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

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Abstract
This paper focuses on university inventors mobility in the EU countries. It is the first quantitative assessment of this phenomenon and is the basis for a set of econometric models that try to explain how different factors affect the mobility of academics and their choices: to stay, to move to the private sector, to move to a different public research organisation (including another university). Mobility away from academia is a significant phenomenon, at least for the sub-sample of university researchers that hold patents from the European Patent Office. Among other results, the econometric models provide some evidence that the more valuable the patent the higher the probability of a move to a company. We found that the younger researchers (with less experience and less seniority) are more likely to move, and tend to move soon after the application or the granting of a patent . Also, the more cumulative (or incremental) the knowledge, the higher the probability of moving to a company. Finally, in all models developed scientific and technological output and scientific quality seem not to have any impact (neither positive nor negative) on the mobility of academic inventors. These results are interpreted in the framework that combines aspects of career mobility and technology transfer.

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

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 less attention has been given to 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; marginal consideration is given to the mechanisms of transmission. 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 the move to other employments of the researchers and scientists involved in the scientific creation.

A few empirical studies have looked at the mobility of high skilled labour (Almeida and Kogut, 1999; Moen, 2000; Rosenkopf and Almeida, 2003; Palomeras, 2004) and particularly focused on the geographic aspects (regional localisation, US versus non-US firms), and the technological characteristics of the originating and receiving firms. Mainly qualitative case based evidence has been gathered on mobility between academia and business: the only paper, to our knowledge, that develops theoretical and econometric analyses of the mobility of researchers between universities and firms is Zucker et al.'s (2002) study on the biotechnology industry. However, little is known about academics' mobility in the European context.

This paper addresses this issue by analysing the determinants of mobility from universities for a sample of European academic inventors. We use the PatVal database, a unique dataset of information about inventors of a sample of about 9,000 European Patent Office (EPO) patents issued in the mid nineties.

Although it has not been the focus of much study, the mobility of scientists is accepted as being most important for the transfer of knowledge, and especially the tacit knowledge embedded in the researcher, which is difficult to codify and transfer (or is purposely not codified to extract economic benefit from the move to a new job (Breschi and Lissoni, 2001). Zucker et al.'s (2002) study subsumes labour mobility within the broader group of university–industry research collaboration. In this paper we focus on 'real' labour mobility among academics, who after involvement in the development of a subsequently patented invention, become employees in (or owners of) a firm. This phenomenon has been rather overlooked in much of the literature on career moves and knowledge transfer. Our unique database enables us to make a first quantification of this phenomenon at the European level and allows us to test a set of preliminary hypotheses about the characteristics of these 'mobile' inventors, to shed some light on the interesting process of knowledge transfer from academia, and the career paths of academic inventors.

Based on these data, we can offer some preliminary evidence on European academic patenting focusing on: (1) What is the relative importance between patents owned by the university and patents with an academic inventor? and (2) What are the technological and country specificities of European academic inventors? On the basis of an original theoretical framework encompassing both factors relating to career move decisions, 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) relating to the occupational choices of European academic inventors. First we estimate a simple standard discrete time duration model to explain the probability of moving; next we apply a competing risk model to the decision problem faced by an academic researcher: move to a company or to another public research organisation (PRO).

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 and main results relating to academic mobility 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 20 years the US and EU countries' governments have developed a set of policies to create incentives for the transmission of knowledge from universities to society at large. The dominant policy view has been that universities do not play a sufficiently active role in the process of knowledge diffusion. New institutional agreements have been put in place to help the flow of knowledge from universities into firms' innovation processes.[1]

Patents have become to be viewed as one solution to the problem. Higher levels of university patenting would allow quicker and easier access to the discoveries made by academic inventors. Starting with the US Bayh-Dole act, which was 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 intellectual property rights (IPR).[2]

Given the poor financial returns from academic patenting, the recent policy and academic literature supporting third stream activities has embraced academic spin-offs as one way to efficiently transfer knowledge and also to make money for the university.[3] Some studies include a large number of heterogeneous organisations within the term 'spin-offs'. The early literature, which was more interested in the broader issue of technology transfer (TT) than university IPR management, considered spin-offs to be all companies that had some form of affiliation with a university, including being set up by an ex-student or an employee of the university (Stankiewicz, 1996). The more recent literature tends to regard spin-offs as only those organisations where the university owns the property rights of its output.

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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. Leydesdorff and Etzkowitz (1996) is 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 TTO activities. See Mowery et al. (2004) for statistical and qualitative evidence on the small revenues (licensing income) generated at the 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.

Clearly there are many more knowledge transmission mechanisms than patents and spin-offs. Although consultancy, contract research and mobility of students and researchers are considered 'traditional' mechanisms, this does not automatically mean that they are less efficient (or less needed) than other means.

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. One reason for this may be that academic mobility is intrinsically related to both career path decisions and knowledge transfer, which are intertwined and difficult to disentangle. There is some limited evidence 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, if we exclude the analyses of mobility of post-graduate or post-doctoral students (Mangematin, 2000; Zellner, 2003), and a few sociological case based studies that marginally examine mobility as part of the broader process of knowledge exchange; the only evidence for the academic sector comes from the series of studies published by Zucker 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 and the comparative analysis of the US and French systems by Gittelmand (2005).[4] Building on this research, Zucker and colleagues modelled the probability of a star scientist moving away from academia, including both part-time collaboration with a company, and a '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 decided to concentrate only on those academic inventors who actually changed jobs. We acknowledge that knowledge transfer also occurs through other forms of mobility (such as temporary secondments or affiliations with a firm), which are generally subsumed under the broad category of university-industry collaboration. However, in our view real mobility (i.e. change of employment) is a different means of knowledge transfer, complementary with other forms, but different, and relatively less studied.

We are interested in the probability of a university employee moving to a job in the business sector, 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 PRO (another university, or hospital or government laboratories).

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 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 then:

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

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

[5] Most of the econometric results in 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 than real mobility.

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

$$\phi_{it} = f\left(S_{it}, X_{it}, Z_{it}, E_{it}\right) \quad (2)$$
$$\eta_{it} = g\left(w(X_{it}, Z_{it}), b(X_{it}), c(X_{it})\right) \quad (3)$$

Based on 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 receiving an offer ϕ_{it} is likely to depend on factors such as searching effort (S_{it}), and individual (X_{it}) and environmental labour characteristics (E_{it}). The probability of accepting an offer η_{it} 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 an observable measure of the offered wage (w) or the current or reservation wage (b), but we can assume that earnings (both offered and reservation) depend on the individual's observable characteristics (X_{it}). Finally (Z_{it}) is a vector of the attributes of the knowledge created by the research process 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 ϕ_{it} of receiving an offer and the probability η_{it} of accepting it.

Below we identify the six building blocks explaining the mobility of academic inventors; the first three refer to traditional career path factors, and the last two relate to the process of knowledge transfer. The fourth building block is related to both career mobility and the 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.) which could be interpreted as signalling high individual productivity. The inventor's personal characteristics will affect both the salary being offered (w_{it}) and the individual's opportunity cost, b_{it}. A key determinant of latter is the academic position of the researcher (we would expect non-tenured researchers to be more likely to move than 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 (based on the increase in b_{it} being higher than the potential increase w_{it}). The inventor's personal characteristics can also affect the mobility costs c_{it}. A job change may require skill adjustments. If the inventor's skills are university specific (i.e. not all the routines of the academic research work will be transferable to work in a firm), she must learn how to behave in the new organisation. She must learn new practices, protocols, routines and adjust to a different types and pace of research, for example she must learn how to interact with product managers whose job it is to bring products to market in the shortest possible time. Thus, a period of training or adjustment may be required. Even if these skill adjustments are minor, they can be considered as sunk costs and could deter some inventors from moving. Similarly, the longer the inventor has worked within one particular university the more she will identify with the incentive system and routines in that university, and less willing she will be to continue her academic career in another university. This is especially true for mature academic researchers, who have invested a lot of time in accumulating the skills and reputation needed to succeed in a specific university environment.[6] We can assume that the

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

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 tempted by salary alone to move to a firm. Therefore, the effects of experience and tenure will tend to increase both b_{it} and c_{it},(relative to w_{it}) reducing the probability to move. *Personal characteristics* based on past patterns: willingness to transfer and willingness to move also affect the mobility costs c_{it}. We can expect that inventors that have moved previously, may perceive moving costs as being less important than first-time movers. Finally, research performance is another factor affecting the probability of accepting an offer η_{it}. Publishing is a major determinant of academic reward; although there are some differences across countries (certain European higher education systems rely less than others on research output as measure of quality) career and retention packages generally depend heavily on research output. Researchers with a good publication track record will have better career and retention package prospects; increasing b_{it} and affecting $\eta_{it.}$ However, academic inventors who have more fertile ideas (are more productive) may move to find a more conducive environment. Previous research performance can be seen as signalling a high quality researcher, 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 its effect on b_{it} dominates its effect on w_{it}. Clearly, there are other institutional factors related to career path, which influence mobility from academia. For example in the US context junior faculty face tenure assessment after a period of about 7 years; if they are not successful they are obliged to leave the institution. In Europe the rules are less clearly defined, but some circumstantial evidence points to a 10 year career point at which time researchers will be successful in being awarded a chair, or must decide whether to leave.

Second, the inventor's university can match the outside offer depending on its *retention strategy*. A salary increase as a reward for patenting, a share of the revenues from the patent, etc., would increase $b_{it,}$ and thus lead to less mobility. The Patval database allows identification of those patents that are owned by the university as distinct from those where the inventor is a university employee, but which are not owned by the university (university-invented patents). We assume that in the latter case the university was 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 depend on the existence of a strong *potential demand*. Inventors working in universities in highly industrialised areas will be more likely to receive job offers from companies or another university located nearby, and therefore will be faced with lower moving costs than inventors faced with a move to a different region or country. If this is the case then inventors living in more densely populated areas should have lower searching costs and hence higher mobility. However, inventors in large cities may have higher opportunity costs. In Europe, the highest reputed universities tend to be located in large cities (or nearby), inventors from big cities will have both a higher c_{it} and b_{it} reducing η_{it}, making it more difficult for them to accept an offer than inventors from small cities.

Fourth, the more connected the inventor is to a densely populated *network* of public and private organisations the more likely she will move to another job as she will be well informed about the 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 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 inventors. This means that the probability of moving will depend on the *value of the patent*. As not all knowledge can be codified in the patent, hiring the inventor gives the new employer access to the tacit components of the knowledge that the inventor is unable or unwilling to transfer by other means. Mobility from academia to companies is driven by the knowledge that, willingly or not, is imbedded in the inventor. We can expect that the higher the value of the invention the higher will be the salary that is offered (w_{it}), and hence the higher probability of the offer η_{it} being accepted and the higher the probability of moving.[7]

Sixth, the *knowledge characteristics* of the specific patent and of the knowledge base of the inventor will also affect ϕ_{it}. We refer particularly to the degree of cumulativeness or separability of knowledge and its degree of generality or scope. We expect that more cumulative (and less separable) knowledge makes the inventor a key element in the TT. That is, the more cumulative the inventor's knowledge, the more it is embodied in the inventor, making her more valuable and hence increasing the probability of mobility (by also increasing the offered wage w_{it}). A wider scope of knowledge leads to more ambiguous predictions. On the one hand, greater generality could mean wider scope and more possibilities (for the new employer) to innovate from a given knowledge set, increasing the transfer value of the invention (Palomeras, 2004). On the other hand, high generality, interpreted as more basic knowledge, might require more complementary research in order to extract some value 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 that 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 levels 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 survey of inventors in France, Germany, Italy, the Netherlands, Spain and the UK with an EPO patents registered in the period 1993-1997 (see Appendix 1 for further details).[8] These six countries accounted for about 80% of EPO patents, whose first inventor has an address in one of the EU-15 countries.

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. Based on previous work (Geuna and Nesta, 2004), we distinguished between patents owned

[7] The only reason we can foresee of a higher patent value being negatively correlated with the probability of moving is the case that the opportunity costs also increase with the value. As we explicitly control in the regressions for retention strategy at university level we expect that patent value will have a positive impact on inventor mobility.

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

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). We found that in total 433 patents, which is 4.8% of the total sample, had a university inventor; we consider these to be academic patents. University-invented patents may come about either as a result of a decision by the TTO not to patent them, or as a result of the inventor not informing the TTO about the invention, because the work was carried out 'at home'. Considering these as academic patents involves the implicit assumption that the work done 'at home' is related to the academic's university research. Only a very small percentage of inventors conduct research at home that is completely unrelated to their university job.

Table 1 presents patents by participation and property rights for the whole sample, and for the university sample. In the case of 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 (356 patents, or 82%) 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 PROs OECD, 2003).

{INSERT TABLE 1 APPROXIMATELY HERE}

It is interesting to note the considerable variation in patenting frequency across countries and technologies. In terms of country distribution of university patents, UK university researchers are involved in patent significantly more than their European counterparts (139 patents, approx. 32% of university patents, almost double the UK's share in the total sample) whereas the share of German patents in the total sample is 12 percentage points lower than its share in the total sample. In terms of aggregate technology classes (Table 3), when we compared university patenting to the total sample, the former mainly occurs in chemistry and pharmaceuticals (36% versus 19%) and instruments (21% versus 11%), whereas the share of patents in mechanical engineering is significantly lower in the case of universities (10% versus 30%). 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 PROs, 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 where, although there is mention of university participation, the respondent was working in a private organisation during 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 having undertaken further studies as 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 have retired, but this does not represent job mobility. Fourth, we exclude 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, on which we based our analysis.

Table 2 shows the type of organisation joined after patent application, and also reports 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 shows that university inventors are less mobile (81% versus 74%). This may reflect the nature of their positions; in many European countries, faculty researchers are civil servants. 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 of some kind (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}

Table 3 presents further evidence about the specificity of our sample, based on distribution of technologies and countries across disciplines, and points to the particularity of the UK. The UK share in the PatVal sample is 17%, 36% in the university sample, and 48% in the sample of mobile inventors. One in two mobile university inventors is from the UK, while the situation is reversed for France and Italy. In terms of technology, there is no significant difference in professional mobility for the whole sample and the university sample. Mobility is slightly higher in electrical engineering (higher share of mobile than non mobile). When comparing mobile with non mobile, the share of pharmaceuticals and chemistry remains constant, which is quite surprising in the light of policy makers emphasis on knowledge transfer in these technologies. These preliminary results suggest that mobility is marginally influenced by technological field, and strongly affected by country. While we expected a strong country effect due to different regulation of the job market and historical reasons (idiosyncratic systems of innovation), we were surprised by the small technological effect. Technologies should have an effect in terms of job market opportunities as the organisation of research is technology specific, and the involvement of universities in downstream development varies widely from one discipline to another. However mobility seems to be only marginally affected by technological field.

{INSERT TABLE 3 APPROXIMATELY HERE}

Table 4 presents the descriptive statistics, decomposing the full sample by types of sub samples. Note that the number of observations drops to 198 due to the fact that first, some academic inventors had more than one patent and thus more than one entry, and second, information concerning date of labour transition was missing or inconsistent for some inventors.[9] In the case that an inventor 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 can see 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 no immediate or authoritative benchmark. However, in terms of the feasibility of our econometric assignment, these figures

[9] The inconsistencies were that in the cases when asked when they joined the university, and when they joined their new employer after developing the patent they entered the same year. One explanation might be that these inventors were working part time in firms and part time in a university laboratory such as in a few cases of German professors.

are very satisfactory, with an ideal split between ‘PRO-mobile’ and ‘industry-mobile’ inventors.

{INSERT TABLE 4 APPROXIMATELY HERE}

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; second we apply 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 first model 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 the patent application is filed, that is from the moment the researcher became an *inventor* (Zucker et al. (2002).

We estimate a duration model for grouped data following the approach introduced by Prentice and Gloeckler (1978), 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:

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

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 a set of time dummies variables that capture the influence of unobserved time-varying factors affecting inventors’ labour mobility. This model is the discrete time counterpart 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 such 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:

    (ii) *Gender*: A dummy variable with value 1 if the inventor was a female.

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

(iv) *PhD*: A dummy variable with value 1 if inventor's highest academic degree is a PhD.

(v) *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 of graduation from the highest degree (this variable includes also years of not 'proper' employment, such as years of unemployment, or doing a post-doc).

(vi) *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.

(vii) *Mobility Before*: A dummy variable with value 1 if the inventor answered positively to the question about previous employment in firms/organisations or had been self-employed.

(viii) *Publications*: Total (cumulative) number of inventor's publications up to the year before the patent application.

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

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

2. Retention strategy operated by the university:

(i) *Compensation*: A dummy variable with value 1 if the inventor received personal monetary compensation expressly because of the results of the invention.

(ii) *University-Owned*: A dummy variable with value 1 if the university owns the patent (university-owned patent).

3. Potential demand:

(i) *City*: Defined as a dummy variable with value 1 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 dummy variable has value 1 if the inventor answered that the 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 put on the patent by the inventor. To be more precise, each respondent was asked '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 €30,000 to more than €300 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.[10]

(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.[11]

6. Knowledge characteristics of the patent:

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

(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.

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.

Table 5 below presents the results of estimating several different versions of the duration model. The first column shows the results obtained 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 combined 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 individual country dummies only for Germany, the Netherlands and the UK. It can be seen 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 all three cases the findings were significantly different from the base category.[12]

[10] 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).

[11] We tried other proxies for value, such as including the number of states where patent protection for the invention was applied for, and the number claims in the last version of the granted patent; none were significantly different from zero in the model estimation.

[12] It is important to note that this result does not conflict with the findings presented in Table 3. The UK is shown to be the country with the higher frequency of mobile inventors. However, this did not take account of the length

The third column in Table 5 gives the results for the variables measuring the characteristics of the inventor. These variables tend to be highly significant. Firstly, there is some influence from life cycle effects evidenced by the fact that *education*, *experience* and *tenure* are significant and negatively correlated with the hazard rates, the younger the inventor, the more quickly she will move. An additional year of education reduces the likelihood of moving out of the current university. Also, inventors with more *experience* before entering their current university were less likely to move,[13] and those inventors with more years of *tenure* in their current university, showed the lowest probability of moving. Contrary to our expectations, those that had 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 re-run the most complete model in column (8) replacing these variables with 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 with a LR-test with a P-value of 0.09. Some information in our current specification is lost when the three variables are replaced by age.

Finally, and in contrast to Zucker et al.'s (2002) results, scientific production (in terms of both quantity and impact/quality) of academic inventors does not affect the probability of moving. When publication and citation stocks are included in the model one at the time, the coefficients are negative but not significant (results not reported here). When they are both included, such as in the result reported, the coefficients are not significant, although inventors with a good publication record in terms of quantity before the patent were more likely to move than those showing high impact/quality. Similarly, a high invention record has a negative, but not significant impact on the probability of moving. Overall, our results seems to indicate that it is not the high-production/high-quality researchers who are moving to find a better job for their high productivity; on the contrary, it seems that the higher the scientific and technological output the lower the chances of moving.

Column four adds a control variable for the university's retention strategy. 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 of (or not interested) in the invention. In an analysis not reported here we used the dummy variable *university-owned* expecting that as the university must be aware of the invention it would have developed some retention strategy. The variable was never significant, and as it was weakly positively correlated with the dummy for licence we did not include it in this model.

We do not find any significant result when we control (column five) for the potential demand. Although inventors working in large cities at the time of the patent application were less likely to move, the results were not significant.

The sixth column includes a set of proxies for the inventor's network. The variable capturing collaboration with co-inventors working in the private sector is positive and significantly

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of time before the inventor moved. The hazard rates given by model (4) control for this by including a non-parametric time function $\theta(t)$. In summary, while the descriptive analysis was concerned with whether technological fields and countries had an impact on mobility levels, here we focus on explaining if and when an inventor moves out of academia.

[13] 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).

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 organisation.

The last two columns in the table relate to the mobility of academic inventors as a function of the process of knowledge transfer. Column seven shows the results when controlling for the value of the patent. Both proxies for the value of the patent used in this model are positive and significant. The higher the ‘subjective’ expected patent-value, the higher the probability of moving to a new job.[14] Similarly, an academic inventor of a patent that has been licensed (a patent of at least some value) has a higher probability of becoming mobile.

Finally, column eight controls for the knowledge characteristics of the patent. 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 highly cumulative knowledge. Cumulative knowledge is embodied in the inventor (willingly or not) in a tacit form and therefore makes her the vehicle of knowledge transfer increasing her probability of moving to a new job. The other two variables capturing knowledge characteristics were not significantly different from zero.

{INSERT TABLE 5 APPROXIMATELY HERE}

To verify the robustness of our estimations we checked for the potential problem of individual level unobserved heterogeneity. Although we included a large set of control variables, it is probable that there are several others that affect the probability of leaving the actual job. We tested for this problem and found that our findings are robust to the omission of unobserved heterogeneity.[15]

An intuitive way of representing our results is by plotting the hazard function. 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.[16] The plot suggests that there is non-monotonic negative time dependence in the hazard rates. In other words, the probability to exit the current academic job becomes very high, soon after the inventor is ‘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 there is a second spike in exit behaviour. This spike lasts for about two years, and declines again by year 6. A plausible explanation for this pattern relates to the granting process; it normally takes 2 to 3 years after the year of application to obtain a granted patent. Some inventors (the majority of those that decide to move), with highly valuable and maybe technology complex findings (possibly developed in collaboration with company inventors) move immediately after the application. However there is a second group of academic inventors that move after the application has been approved and the patent granted; this may be due to the fact that the diffusion of information about their invention induces demand (if they did not have it before) or stronger demand for their knowledge, and therefore better conditions for their mobility.

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[14] Given the model’s assumptions, in order to get an idea of the economic impact of each of the explanatory variables it is necessary to take account of 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).

[15] See Appendix 3 for the test.

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

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 for all countries. However, there are some interesting differences across countries. The highest exit probability, and hence the quickest mobility, is observed for the Netherlands, followed by Germany. The UK occupies an intermediate position. Finally, mobility seems to be lowest in the base categories (Italy and Spain). It might be that this pattern reflects profound differences in the academic labour market institution of the different countries, which requires further research to confirm or refute. According to the results from the corresponding survival functions (not shown here), less than 1% of Spanish and Italian researchers had moved after five years, while the percentages were 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 in inventor's characteristics and expected patent value. The first two top panels show the baseline hazard function for an inventor without experience (no employment before the current job) (left hand side) and for an inventor without tenure (right hand side); the mean hazard function is drawn to make the comparisons easier. It is clear from these two panels that inventors without experience and with no tenure have a higher probability of moving. The effects are larger for tenure than for experience. The bottom left panel compares the mean baseline hazard function with that for no publications (and citations). Both hazards overlap almost perfectly, suggesting small relevance of these two variables in explaining mobility. Finally the bottom right panel shows the hazard for inventors that produce patent with the expected value in the lowest interval (€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 of the estimates of the standard discrete time duration model 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 and seniority, and who are younger, are likely to move to a new job sooner. Career path explanations are, however, not sufficient to explain 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 found some evidence to support the view that the mobility of academic inventors is driven by career-path type determinants, and 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 to. In this section we advance the analysis of the determinants of inventors' mobility by controlling for 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 PRO (e.g. another university, a government research laboratory or a hospital) or moving to a private company (large, small or start up).[17]

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

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 sufficiently different jobs to support this assumption (which is also tested below). In practical terms, the independent competing risk framework treats both 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* respectively, depending on whether the move is to a private company or to a PRO. Finally, a cautionary note about the interpretation of the coefficient estimates. In CMR models, interpretations of the coefficients are not always as straightforward as in case of the pooled model in the previous section because the results depend on all the parameters in the model. If the CMR model has a proportional hazard form (as is the case in (5)), then an increase in *W* will increase the conditional probability to move, for instance to a private company if the estimated coefficient for the hazard of exit via a private company is larger than the corresponding coefficient for the hazards of moving to a PRO (see Thomas, 1996, for details).[18]

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

The first column of Table 6 reproduces the result of the single destination (or pooled) model. Columns two and three show the results for the exits towards business and other PROs. The first important result is that most of the variables tend to have a higher significance when used to explain mobility to business; the model estimated seems to be more robust to explaining mobility to business than mobility to PROs.

The results of the estimates show that the three countries with the highest mobility (Germany, Netherlands and UK) have a higher mobility to private businesses than to another PRO, however the dummy variable is only significant in the case of The Netherlands.

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 to 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 rather than a business. In other words, business firms tend to hire less experienced and more junior academic inventors. Finally, the results for publications are interesting. The CRM results indicate that a high number of existing publications tends to

[18] It should be noted 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 assume that we have intrinsically discrete time data we can estimate (5) using a 'multinomial logit' competing risk model; this estimation produced basically the same results.

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.

The results relating to expected patent value are interesting and indicate that inventors involved in more valuable patents have a higher probability of moving to the private sector, while although patent value was also a positive indicator of a move to another 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 to a private business, leaving unchanged the probability of moving towards a PRO. The result was similar when value was measured in terms of licensing.

A third set of findings regards networks effects. The results for collaboration indicate that academic inventors involved in collaborative networks (as measured by involvement with other researchers from another organisation in the process of invention) have a higher probability of moving to another PRO than to a private firm. The findings that the larger the size of the patent team the lower the chances of moving to a firm may indicate that if the inventive process involves a large set of researchers the knowledge developed may became easier to access by firms and thus reduces the chances a good job in a company based on the unique tacit knowledge of the specific academic inventor.

Regarding knowledge characteristics we found that knowledge cumulativeness increases the likelihood of moving from academia to 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 breadth) reduces the odds of moving to the private sector rather than 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 score for patent breadth may reduce its applicability, thereby reducing the attractiveness of those inventors for companies.

{INSERT TABLE 6 APPROXIMATELY HERE}

We also tested whether the mobility to the two identified destinations, PROs and industry, are behaviourally 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:

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

The test is given by the following expression:

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

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 $j=1,\dots j$ destination states. This test statistic is distributed Chi-squared with degrees of freedom equal to the number of restrictions.[19] Using information from Table 6 plus the above formulas, the Chi-squared value is 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 evidence to support the view that different factors affect the mobility of academic inventors depending on the organisation offering the job. For academic inventors moving to another PROs traditional factors related to the career of the academics, such as experience, seniority and tenure, play a major role while for a move to a company factors related to knowledge transfer are also relevant. Variables such as the value of the invention and knowledge characteristics are necessary to predict the mobility of academic inventors to business companies. We found some evidence to suggest that network effects are more important for mobility to another PRO.

5. Conclusions

This paper provides initial representative information on academic patenting in Europe. Our analysis was based on a sample of inventors of EPO patents, located in six European countries with significant innovative activities. On the basis of the information in the PatVal database, we 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 develops a set of econometric models to explain how different factors affect the mobility of European academic inventors.

We identified a total of 433 patents with a university inventor, which is 4.8% of the total sample. Less than one third of academic patents are owned by the university which employed the inventor at the time of the invention. 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.

Academic inventors tend to be less mobile than company inventors, about 20% of academic inventors do move (in the ten year period following the granting of the patent) with a 50:50 split between companies and PROs. We do not analyse whether this is a high or low level of mobility; however, 10% mobility away from academia seems significant, at least for the sub-sample of university researchers that were the inventors of EPO granted patents. This phenomenon requires further research, to compare with other knowledge transfer mechanisms in order to develop a better and broader understanding of the process of knowledge exchange between science and industry.

We developed two sets of econometric models. First we estimated a simple discrete time duration model to explain the probability of moving; second we estimated a CRM to explain the mobility to a company or PROs. We found 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. Being a successful inventor can be considered as an opportunity for an academic to decide what to do: to stay in academia or to move to a company. The opportunity occurs either at the time of filing the patent or when the patent is granted. However, we cannot rule out the possibility that mobility is the result of a process of self-selection by those

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

academic researchers who are less productive or less interested in academia, and who decide to invest in patenting with a view to obtaining a better job elsewhere. The consequence of this would be a bias in the baseline hazard function. We investigated the effects of this sort of unobserved heterogeneity, but did not find strong evidence that it seriously affected our results.

The econometric models provide some evidence indicating that the more valuable the patent the higher the probability of moving to a company. We found that younger, less experienced, more junior academic inventors are the more likely to move, and tend to move very soon after the patent application or after the patent was granted. The more cumulative (or incremental) the knowledge involved, the higher the probability of moving to a company. Contrary to the results of previous studies focusing on the US context, we found some evidence of a negative impact of scientific productivity on mobility. Estimations including number of publications, citations and patents, tend to confirm the result that highly productive (in terms of quantity and quality/impact) academic inventors tend to have a lower probability of changing their academic job and especially of moving to the private sector.

These results point to the existence of two explanatory sets of factors that affect the mobility of academic inventors. The first includes traditional career related factors such as seniority. The second explains mobility in relation to the process of knowledge transfer from science to industry and is related to the tacit knowledge that is embedded in the scientist. For example, one of the reasons why the value of the patent affects mobility relates 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 cases they already own the patent, and thus the codified knowledge it contains, but they want to appropriate of the tacit knowledge that is embedded in its academic inventor. This interpretation is confirmed by the fact that academic inventors of patents with a large number of co-inventors tend to have a lower probability of moving to firms because their knowledge is not so unique and the firm has less incentive to hire them. Similarly, 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 the previous knowledge of the inventor the company has a greater incentive to hire the academic to appropriate the tacit knowledge.

The results of the CRM, although very preliminary and requiring further validation due to the small number of observations, confirm that knowledge transfer factors are important in explaining mobility to companies while they are not significant in mobility to other universities. Career related factors are the driving forces behind the latter, more traditional type of mobility.

Finally, we found strong country effects, indicating that regulation supporting or not mobility and tradition, are important determinants of mobility and therefore of knowledge transfer. Contrary to our expectations we did not find important technology effects. It seems that mobility of academic inventors is only marginally affected by the specificities of the technological sector of involvement, but strongly dependent on national characteristics.

These results can be problematic for the European innovative system. If researcher mobility is a very important mechanism of knowledge transfer (as claimed by most of the literature), then our results indicate that the knowledge transfer may be not of the top quality as they are not the high calibre researchers that move to companies, but those of lower scientific and technological output that seems to opt for an industrial carrier. Moreover, though we have found some evidence of mobility from academia to industry this tend to be concentrated in a few countries indicating that the institutional set up of a large set of European countries is clearly not supportive of mobility and therefore limiting the innovative potential of those countries.

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Appendix 1: The PatVal Survey

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 memberships, etc.) and the characteristics of the invention process.

The total number of EPO patents with priority date between 1993 and 1997 was 49,078. When there were several inventors, the first inventor was contacted first. If no response was received, the second inventor was contacted, and so on until a response was obtained. Most countries concentrated on a sub-sample of patents whereas others, like the UK, decided to send the questionnaire to all patent inventors. During the PatVal project, we contacted 27,531 patent inventors and obtained responses relating to 9,017 patents. This equates to a 33% response rate (at the inventor level) and represents 18% of all granted EPO patents with a priority date 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 under-estimating 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.

Appendix 2: Variables description

Variable Name	Measure
Expected Patent Value	The expected patent values estimated by the inventor
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
Citations	Number of citations to scientific papers of inventor, normalised by the number of publications
Size of Patent Team	Number of co-inventors involved in the patent
Collaboration	Dummy variable set to 1 if the inventor has answered that co-inventors were employed by other organisations.
Compensation mechanisms	Dummy variable set to 1 if the inventor received any personal monetary compensation expressly because as a result of the 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 the research

Appendix 3: Test for unobserved heterogeneity

What happens to parameter estimates if one (mistakenly) ignores unobserved heterogeneity? The theoretical literature suggests two results. First, the (increasing) time trend captured by the dummy variables in (4) will be underestimated. This is basically a selection effect. For instance, imagine that there are two classes of researchers: slow and fast movers. As time passes, the conditional sample contains more and more slow movers and hence generates 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, 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:

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

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 5. It can be seen that the results barely change. In other 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).

A remaining issue is related to the impact of unobserved heterogeneity in the CMR model McVicar and Podivinsky (2001) and Boheim and Taylor (2000) argue that the distributional assumptions for including unobserved heterogeneity are even stronger for the CRM than the standard single risk case, and 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 did not implement 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%

Source: Crespi, Geuna and Nesta, 2007

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-offs)	335	3.7%	17.7%	9	3.9%	20.5%
Hospital, Foundation, or PRO	13	0.1%	0.7%	1	0.4%	2.3%
Government Research Organisation	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	-0.1	-0.113	0.016	0.482	0.201	0.055	0.049
Fixed Effects		[0.77]	[0.87]	[0.16]	[0.18]	[0.02]	[0.67]	[0.33]	[0.08]	[0.07]
	Chem/Pharm (0/1)	-0.169	-0.121	0.667	0.676	0.686	0.884	0.661	0.696	0.694
		[0.35]	[0.24]	[1.10]	[1.10]	[1.13]	[1.31]	[1.02]	[1.04]	[1.11]
	Proc Eng (0/1)	-0.135	-0.065	1.036	1.068	1.125	1.459	1.265	1.265	1.252
		[0.25]	[0.12]	[1.47]	[1.45]	[1.51]	[1.73]*	[1.69]*	[1.58]	[1.71]*
	Mech Eng (0/1)	-0.709	-0.704	-0.362	-0.389	-0.447	0.046	0.108	0.447	0.471
		[0.88]	[0.86]	[0.47]	[0.48]	[0.54]	[0.05]	[0.11]	[0.44]	[0.48]
Country	Germany (0/1)		1.117	1.644	1.608	1.561	1.862	2.287	2.721	2.731
Fixed Effects			[2.07]**	[2.30]**	[2.20]**	[2.14]**	[2.44]**	[2.63]***	[2.48]**	[3.19]***
	Netherlands (0/1)		0.887	1.457	1.401	1.395	2.007	2.5	2.873	2.895
			[1.51]	[2.26]**	[2.11]**	[2.13]**	[2.32]**	[2.31]**	[2.29]**	[3.08]***
	UK (0/1)		0.611	1.275	1.239	1.257	1.742	1.77	1.944	1.968
			[1.11]	[2.09]**	[1.97]**	[2.00]**	[2.12]**	[1.96]*	[1.86]*	[2.36]**
Iventor	Gender (0/1)			0.183	0.135	0.273	-0.033	-0.195	-0.464	-0.468
Background				[0.23]	[0.16]	[0.28]	[0.03]	[0.17]	[0.41]	[0.48]
	Education (yrs)			-0.095	-0.094	-0.086	-0.099	-0.101	-0.089	-0.091
				[2.15]**	[2.16]**	[1.84]*	[1.97]**	[1.88]*	[1.64]	[1.61]
	PhD graduated (0/1)			-0.331	-0.322	-0.367	-0.38	-0.509	-0.579	-0.594
				[0.64]	[0.63]	[0.73]	[0.64]	[0.90]	[1.01]	[0.97]
	Experience (yrs)			-0.184	-0.185	-0.182	-0.214	-0.236	-0.237	-0.238
				[4.23]***	[4.16]***	[3.97]***	[3.50]***	[3.07]***	[2.39]**	[3.30]***
	Tenure (yrs)			-0.114	-0.115	-0.112	-0.13	-0.141	-0.15	-0.151
				[3.75]***	[3.66]***	[3.70]***	[3.65]***	[3.84]***	[3.60]***	[4.43]***
	Mobility Before (0/1)			-0.665	-0.679	-0.643	-0.66	-0.632	-0.881	-0.891
				[1.34]	[1.34]	[1.30]	[1.26]	[1.33]	[1.58]	[1.72]*
	Publications (Stock)			0.02	0.018	0.015	0.01	0.016	0.001	0.001
				[0.71]	[0.63]	[0.49]	[0.28]	[0.46]	[0.03]	[0.02]
	Citations (Stock)			-0.003	-0.003	-0.003	-0.002	-0.003	-0.003	-0.003
				[1.14]	[1.08]	[0.99]	[0.96]	[1.13]	[0.97]	[1.19]
	Past Patent applications			-0.012	-0.013	-0.013	-0.018	-0.019	-0.035	-0.034
				[0.55]	[0.58]	[0.60]	[0.75]	[0.87]	[1.23]	[1.44]
Retention	Compensation (0/1)				-0.212	-0.215	-0.265	-0.241	-0.218	-0.229
Strategy					[0.33]	[0.34]	[0.40]	[0.35]	[0.33]	[0.39]
Potential	Ciy (0/1)					-0.291	-0.234	-0.424	-0.328	-0.335
Demand						[0.57]	[0.45]	[0.97]	[0.65]	[0.70]
Networks	Size of the Patent Team						-0.118	-0.095	-0.053	-0.052
							[0.58]	[0.45]	[0.27]	[0.31]
	Co-ownership						-0.705	-0.72	-0.795	-0.838
							[0.75]	[0.87]	[0.79]	[0.84]
	Collaboration (0/1)						1.109	1.377	1.526	1.524
							[1.94]*	[2.09]**	[2.20]**	[2.36]**
Value of Patent	Expected Patent Value							0.204	0.252	0.251
								[2.18]**	[2.71]***	[2.15]**
	Licensed (0/1)							0.848	0.941	0.933
								[1.92]*	[1.74]*	[1.78]*
Knowledge Characteristics	Cumulativeness (0/1)								0.999	1.008
of the patent									[1.77]*	[2.13]**
	Patent Breadth								-0.022	-0.029
									[0.08]	[0.11]
	Incrementality								-0.036	-0.036
									[0.24]	[0.32]
	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	-110.98	-110.9	-110.67	-108.19	-104.28	-101.9	-102.05
Chi2	32.28	37.55	147.3	145.45	145.93	129.98	150.22	183.66	72.74
ρ									5.06E-07
Chi2-ρ=0									0.0000

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. Column (9) adds to the model a normally distributed random effect to account for unobserved heterogeneity.

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]
Inventor	Education (yrs)	-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 (yrs)	-0.228	-0.298	-0.167
		[2.75]***	[2.36]**	[1.50]
	Tenure (yrs)	-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]
Retention Strategy	Compensation (0/1)	-0.017	-0.016	-0.176
		[0.03]	[0.01]	[0.24]
Potential Demand	City (0/1)	-0.239	0.006	-0.932
		[0.49]	[0.01]	[1.21]
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]**
Patent 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]
Knowledge Characteristics	Cumulativeness (0/1)	0.793	0.819	-0.025
		[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]
	Observations	1348	1348	1348
	LL	-103.69	-51.84	-59.96
	Chi2	145.73	203.76	206.1

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

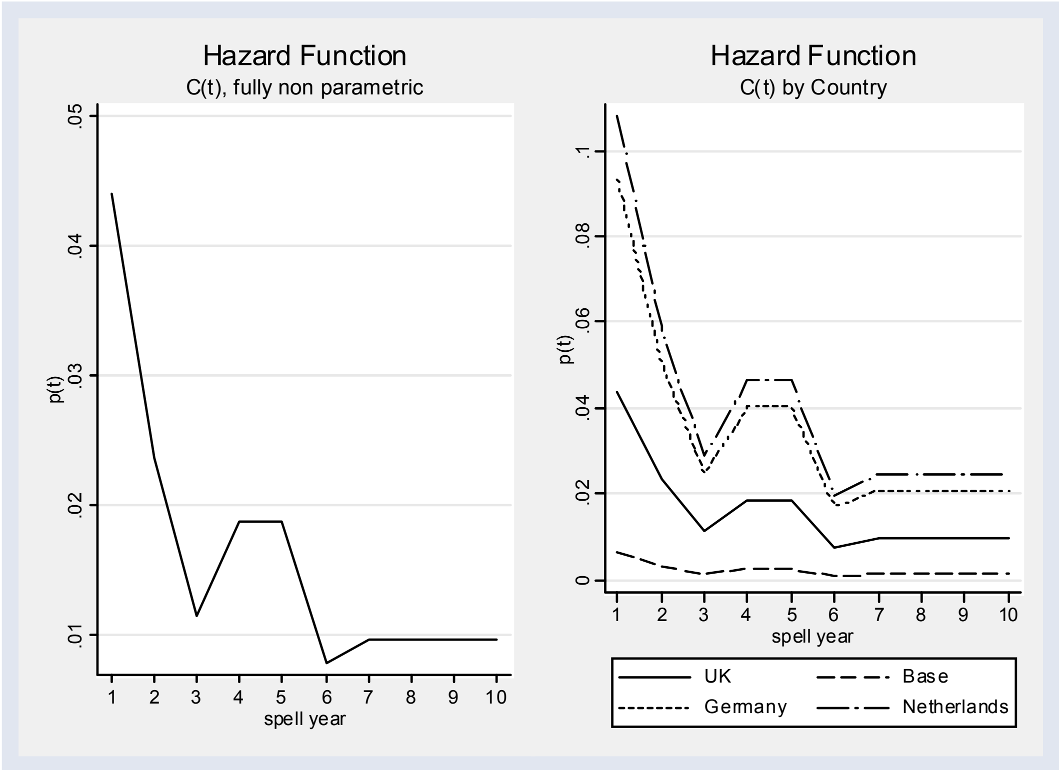

Figure 2.Inventor's Baseline Hazard functions by inventor's characteristics and expected patent value