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Technology mobility and job mobility: A comparative analysis between patent and survey data

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Abstract
In recent years, increasing attention and resources have been devoted to the analysis of workers' mobility and the collection of new and extensive datasets in order to monitor and appraise this phenomenon. Most of the works in the innovation studies literature make use of information about inventors extracted from patent data that indeed provides details on their geographical location and the applicants of their patents.
This paper complements patent data with unique data on inventors' *curriculum vitae* collected through a survey addressed to a group of Italian inventors in the pharmaceutical field.
Results seem to suggest that patent and survey data might capture complementary aspects of inventors' career path. In particular, results indicate that survey data describes the whole set of inventors' employers and the knowledge flows across them generated by inventors' moves. Conversely, patent data portrays a different set that is the one composed of those actors directly involved in inventive processes and participating to the production of patented knowledge. More interestingly, these overlap only partially and do not necessarily coincide.

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1. Introduction

In recent years, an increasing attention has been dedicated to the analysis of the characteristics and the implications of the mobility of workers in both researches and policy-makers agenda. As a consequence, growing efforts and amount of resources have been devoted to the collection of new and extensive datasets in order to monitor and appraise this phenomenon.

In particular, the innovation studies literature has primarily looked at skilled workers mobility because of their involvement into innovative activities within firms, their extreme relevance to the creation of new ones, and the eventual impact of their moves for knowledge diffusion processes.

Most of the empirical works in this field has made use of information about patent inventors. In fact, inventors are highly qualified workers that are engaged in research and knowledge intensive activities in the organisations they are employed at, so that they can be considered as a proxy for the larger group of researchers. Additionally, patent data collects detailed information on inventors' geographical location and the applicants of their patents. Data on applicants are thus used in order to trace inventors' mobility by assuming that the applicant(s) listed on the patent document is(are) also (one of) the employer(s) of inventors. Job mobility identification is, ultimately, based upon patents and technology-related criteria and can be referred to as 'technology mobility'.

This notion of technology-based mobility has been employed in order to map and to assess the intensity of knowledge flows across firms and geographical areas, and to look at the implications of inventors mobility for the processes of geographical concentration and distribution of innovative activities (Rosenkopf and Almeida, 2003; Song et al. 2003; Breschi and Lissoni, 2006; Agrawal et al., 2006). A few studies have also investigated the relationship between productivity of inventors and their mobility (Hoisl, 2007; Shankerman et al., 2006; Trajtenberg, 2005).

The present paper complements patent data with unique data on inventors collected through a survey addressed to a group of Italian inventors in the pharmaceutical field, which allows tracking their career path and actual moves across firms on the basis of their *curriculum vitae*. This allows comparing technology mobility patterns to actual job mobility patterns and, ultimately, emphasising similarities and differences in the descriptive and inferential analysis drawn from their respective sources of data.

Moreover, the present paper combines this explorative and comparative outlook with a more specific perspective; in fact, it also studies in depth the relationship between productivity and mobility of the inventors interviewed in order to understand whether it is affected by the notion of mobility adopted (i.e. technology mobility vs. job mobility). This research area is rather unexplored in the innovation studies literature (mostly due to the absence of appropriate data), but there is an abundant anecdotic evidence on the effects of key (i.e. highly productive) workers leaving a firm that calls for a deeper exploration and richer explanation of such phenomena. In fact, when a key worker change job, the hiring firm will enjoy considerable gains in terms of new and additional knowledge, human capital, and competitive position advances, while the departing one will experience a considerable loss in terms of human resources, specific and contextual knowledge, and ultimately, competitive position (Hoisl, 2007).

The results of the analysis suggest that technology mobility and job mobility are likely to capture complementary aspects of an inventor's career. In particular, job mobility seems to describe the whole set of inventors' employers and the knowledge flows across them generated by inventors' moves. In such cases, inventors' moves can be a channel for tacit and embodied knowledge transfer. On the other hand, technology mobility seems to portray the set of actors an inventor is collaborating with (i.e. sharing knowledge with) and that participate to the production of patented knowledge. In such cases, technology mobility could be associated to a channel for the transfer of knowledge that is by some means codified. In fact, in such cases knowledge is transferred within a network of organisations directly involved in inventive processes and which, to a certain extent, share common knowledge and represent, at least in some technological areas such as pharmaceutical, sufficiently close communities.

The remainder of the paper is articulated on four sections. The first one discusses the use of patent data in order to study workers (i.e. inventors) job mobility and puts forward the main issues to be examined in the empirical analysis. The second one introduces and describes the data collected through the survey addressed to a group of Italian inventors in the pharmaceutical field. The third one reports on the results of the comparative analysis between technology mobility and job mobility and is divided in two main sub-sections. The former discusses similarities and differences in descriptive statistics while the latter examines the relationship between mobility and productivity of the inventors interviewed and whether this can be affected by the notion of mobility adopted. The final section summarizes the main findings and concludes.

2. Patents and technology mobility

According to Griliches (1990), patents are one of the major sources of information for the analysis of innovation and technological change. Moreover, the uniformity and the availability of patent data have led to an increase in their use in the innovations studies literature (Jaffe and Trajtenberg, 2002).

Consistently, most of the empirical studies on workers' mobility make use of patent data. The seminal work in this regard is the one by Almeida and Kogut in 1999. They observe that regions differ in the degree of localization of knowledge and interpret this result as the effect of the variability of workers' mobility (i.e. inventors in the US semiconductor industry) within and across regions.

Their exercise relies upon patent data in three respects:

1. inventors are considered as a proxy for researchers and skilled workers because of their involvement into research and knowledge intensive activities in the organisations there are employed at;
2. data on citations are used as a proxy for knowledge flows;
3. data on the applicants of the selected inventors are used in order to track inventors' mobility across organisations and regions. In particular, an inventor is defined as mobile when she applies at least for two patents held by two different applicants.

Consequently, job mobility identification is based upon patents and technology-related criteria. In the remainder of the paper, this notion of mobility will be referred to as technology mobility.

This methodology has been applied by most of later studies (Rosenkopf and Almeida, 2003; Song et al. 2003; Breschi and Lissoni, 2006; Agrawal et al., 2006; Hoisl, 2007; Shankerman et al., 2006; Trajntenber, 2005). The major advantage is that this allows dealing with extensive and already available datasets, such as those maintained by the United States Patent and Trademark Office (USPTO) or the European Patent Office (EPO). Moreover, patent datasets cover several countries, years, and type of organisations. This methodology thus allows following the patenting activity and the technology mobility path of inventors over a very long period of time.

Notwithstanding, the innovation studies literature extensively addresses and deeply discusses patents limitations as indicators of innovation outcome. For instance, patents are deemed to represent only a portion of innovative outcomes because many inventions do not result into patents. Also, patents represent inventions, thus only a portion of innovative activities, and do not entail activities and investments to commercialize new technologies.

Additionally, patents are not considered the most important appropriability mechanism to protect innovations; differently, firms may choose to protect their inventions by other means such as secrecy, lead-time advantages, and marketing (Cohen et al., 2000).

Moreover, motivations for patenting vary across industries, technologies, and firms and may vary over time thus making patent indicators not consistent across sectors. In fact, firms patent for different reasons, not only in order to exploit the commercial value of their inventions, but also to protect them from imitation, to prevent competitors from patenting or pursuing a line of research, or to evaluate the productivity of their R&D activities. Accordingly, patents value varies widely across firms.

Finally, patents commercial value is largely variable (and, consistently, its significance with respect to innovation).

On the other side, the innovation studies literature is less concerned with patents limitations as indicator of inventors' career path and moves across firms and regions. However, there are also a few instances in which technology mobility might not provide a satisfactory description of job mobility (i.e. mobility based upon information extracted from an inventor's *curriculum vitae*).

In fact, the notion of university invented and not owned patents (Geuna and Nesta, 2005) suggests that at least for European countries, academic inventors (i.e. academic professors that result to have registered at least one patent application) are not necessarily affiliated to the applicants of their patents. Actually, their patents are frequently assigned to research contractors rather than to the university they are affiliated to. This specific situation could also be extended to those inventors working at public research organisations (PROs), as well as to independent consultants or 'free lance' researchers, which might be in charge of developing research in behalf of third party contractors (which very frequently are private companies). Additionally, the growing number of market transactions involving the use, diffusion and creation of technological knowledge (Arora et al., 2001) suggest that these patterns are increasingly characterising also the private sector. In fact, private firms are more and more active in the exchange of full technology packages such as patents and even more in patent licensing. Similarly, there might the case of inventors working for a subsidiary or a division of a company that files patents only with the name of the company's holding. Thus, in all these cases, the presence of specific technology exchanges or firms' specific patenting strategies can make patent applicants being different from an inventor's employer[1].

This eventually leads to the risk of identifying inventors as movers when they are simply employed at another organisation and perform research or consultancy in behalf of third party contractors, which ultimately is a case of market for technologies. Therefore, technology mobility may overestimate inventors' job mobility[2].

[1] These considerations seem to suggest that multi-applicant inventorship (i.e. inventors filing different patents for different applicants) might describe and encompass different phenomena, as pointed out by a recent paper (Laforgia and Lissoni, 2006). The mobility of inventors can be considered as one specific form of this phenomenon, but neither exhaustive nor the only one.

[2] This can also occur when an inventor patents at different companies and thus moves across them, but the company of destination is the result of a merger or a joint venture between the previous company and another one.

Additionally, if the affiliation recorded in the patent document does not reflect an employment relationship (i.e. an inventor is not employed at the applicant of her patents), there is a mismatch between employer and applicant. It follows that technology mobility may also identify different moves compared to job mobility. As mentioned before, this situation can especially apply to those inventors conducting research in behalf of external organisation to that of employment, for instance inventors working at university or PROs which frequently invent but do not own patents (Geuna and Nesta, 2005)[3]. Consequently, patent data might not provide a satisfactory description of the knowledge flows across organisations originated by inventors' moves. More specifically, technology mobility and job mobility might portray knowledge flows that involve different actors.

Moreover, the notion of technology mobility indicates that an inventor is defined as mobile when she applies at least for two patents held by two different applicants. However, this does not rule out the case that an inventor changed job before patenting the first time, or in between the two patents, or after the last one. In fact, this change might not be recorded in patent data since an inventor does not necessarily patent at all the employers she works for. This consideration holds *a fortiori* for those inventors with only one patent. It follows that technology mobility may signal only a part of inventors' job moves, thus underestimating job mobility and its impact on knowledge diffusion.

Relatedly, technology mobility is more likely to capture indirect knowledge flows rather than direct knowledge flows arising from job mobility. For example, if inventor A signs a patent held by applicant X, next moves to firm Y, and finally to firm Z where A signs another patent. In such a case, the notion of technology mobility would indicate a move from X to Z thus underestimating the intensity of knowledge flows arising from job mobility. Moreover, it would indicate a direct knowledge flow from applicant X to applicant Z while this is actually an indirect knowledge flow mediated by firm Y.

All in all, thus, the identification of an inventor's moves on the basis of patent data (i.e. technology mobility) could differ from the identification of an inventor's moves on the basis

[3] In particular, in the case of academic inventors, this additionally brings to underestimate the contribution of universities to national patenting and innovative activities.

of *curriculum vitae* information (i.e. job mobility) in both the number of moves and the organisations involved.

Of what concerns the relationship between inventors productivity and mobility, this is inherently characterised by endogeneity issues as Hoisl (2007) shows.

On the one hand, it is possible to argue that the causality runs from productivity to mobility: more productive inventors are more likely to change job because they are 'raided' from competitors by means of better job offers. Additionally, as Shankerman et al. (2006) propose, there can be asymmetric information between inventor and employer about the value of the invention developed. In particular, the inventor might be much more aware of the potential impact of the invention (i.e. ex-ante unobservable quality) compared to the employer and this might encourage the mobility decision in order to gain more control over the invention and the profits associated to it. Differently, the employer might not recognise the signals of an invention's potential and not pre-empt an inventor's move.

On the other hand, it is also possible to argue that the innovative activity and performance of inventors can be affected by the innovative environment they are embedded into: moving across firms can expose them to new environments and positively influence their innovative activity. Additionally, the labour economics literature suggests that mobility should increase the matching and the fit between worker and employer; this in turns should imply that an inventor's productivity and the quality of the inventions developed should increase in the post-move period (Topel and Ward, 1992; Hoisl, 2007 and 2008).

However, by using patent data in order to trace inventors' mobility the professional career of an individual collapses into his patenting (innovative) activity track. In fact, technology mobility strictly reflects patenting activity of inventors while tracing their career path and job moves should require to go beyond the patent event and to distinguish between patenting (i.e. innovative) behaviour and professional career[4].

[4] In particular, it is not possible to define precisely time of arrival and time of departure from a given organisation. Put in other words, time of arrival (or departure) coincides with time of patenting: there is simultaneity between the patent event and the mobility event. This makes more difficult to disentangle the effect of time (i.e. experience in the labour market or tenure in a given organisation) on productivity from the pure effect of productivity. Indeed, it is likely that the greater the experience in the labour market the greater the productivity, for instance, in terms of number of patents filed. However, by looking exclusively at patent data, the inventor's patenting life coincides with her labour market experience. Thus, the relationship between the two might turn to be reversed: the greater the productivity the greater the labour market experience.

In particular, the definition of technology mobility applies only to inventors with at least two patents. In fact, for all inventors with only one patent, there is not enough information in order to trace their moves across organisations: by definition, several individuals are excluded from the analysis (most of the inventors have indeed only one patent). Therefore, only more productive inventors are considered and this can introduce a potential bias towards more productive inventors. Thus, there might be the risk that the relationship between productivity and technology mobility is overemphasised compared to the relationship between productivity and job mobility, i.e. technology mobile inventors are more productive than job mobile inventors.

It follows that technology mobility may suffer greater concerns of endogeneity compared to job mobility.

In order to shed new lights on these aspects, the present paper builds upon the results of a survey addressed to a group of Italian inventors in the pharmaceutical field. Its aim is twofold.

At first, it aims at exploring the differences between technology mobility and job mobility in the description of inventors career path and the organisations involved in their moves.

At second, it aims at investigating more in depth the relationship between productivity and mobility and looking whether it is affected by the notion of mobility adopted (i.e. technology mobility vs. job mobility).

The next section describes the methodology applied in order to develop and administer the questionnaire, portrays its structure and reports on its results. It also illustrates the composition of the final dataset and provides short descriptive statistics.

2. The survey: research design and data description

In the innovation studies literature, many surveys have been developed and have collected information on innovative activities. These surveys differ not only according to the extent of their geographical or technology coverage but also according to the target they have been addressed to.

However, at present, most of the surveys implemented have been object-oriented (about innovation activities carried out within firms) rather than subject-oriented (about firms carrying out innovative activities). Moreover, only a little number of them has gathered data at the individual level (about individuals directly involved and responsible for innovative activities).

On the other hand, the survey we developed is one of the first attempts to collect information on inventors that are complementary to patent documents. In fact, differently from previous surveys in the field, this survey collects information at the individual level on inventors' professional experience. As a consequence, this allows overcoming the limitations of object-oriented surveys as well as those of patent statistics in describing inventors' *curriculum vitae* discussed in the previous section. In this case, patent data turn out to be simply a means in order to select the questionnaire's respondents.

In particular, we selected from the EP-Cespri[5] database all Italian inventors with at least one patent in the pharmaceutical field between 1990 and 2000[6].

The pharmaceutical sector is a favourable setting for studying workers' mobility, its characteristics and its impact on innovation. In fact, this is a knowledge-intensive sector where innovation is really one of the most important sources of competitive advantages for firms and a fundamental driver of competition among firms. Moreover, the relevant knowledge in this sector is likely to be complex and specific, thus embodied in individuals and transmitted through their moves across firms. Thus, hiring and keeping people with relevant knowledge for innovative activities is in comparative terms even more important than in other industries.

Patent data are available in the EP-Cespri dataset from 1978. As a consequence, we tried to select people that entered the labour market around that time or, at least, not too

[5] Cespri - Centre of Research on Innovation and Internationalisation Processes - is a research centre hosted by Bocconi University, in Milan (Italy). The EP-Cespri database collects patent data registered at the European Patent Office.

[6] Every patent is attributed to one or more technological classes according to the International Patent Classification (IPC) that is the technological classification adopted by the EPO. We considered only the primary class. In order to identify all the patents corresponding to the field of interest (i.e. pharmaceutical), we followed a 30 technological field classification. This is a technology-oriented classification, jointly elaborated by Fraunhofer Gesellschaft-ISI (Karlsruhe), Institut National de la Propriété Industrielle (INPI, Paris) and Observatoire des Sciences and des Techniques (OST, Paris). This classification aggregates all IPC codes into 30 technology fields.

many years before that time. Indeed, our primary concern was to select the respondents in a way that they have the same potential exposure time to patenting activity and possibly a similar labour market experience (that is the number of years spent in the labour market after entry). Thus, we selected those inventors that patented at least once between 1990 and 2000 in the pharmaceutical field, regardless of their region of residence, their affiliation or the number of patents filed. Assuming some time lag between entry in the labour market and the first year of patenting activity, we selected 1990 as the lower bound. Moreover, given that the distribution of patents over time is uneven and rapidly falls in the later years, we chose 2000 as the upper bound. It follows that the selected inventors may have patented also before 1990 and after 2000. We identified approximately 1000 inventors that met this requirement.

The survey has been conducted between January and March 2005. We made contact with the respondents in relation to the first patent filed in the pharmaceutical sector between 1990 and 2000 and administered the questionnaire by email. As a consequence, this choice limited the number of people interviewed because we were not able to collect the email address for all of them. The questionnaire is a 6-page document attached to the email text that the respondents had to fill in and return. Overall, we sent 281 emails and obtained 38% response rate that amounts to 106 returned questionnaires.

The main goal of the questionnaire is to trace the career path of respondents. In the empirical analysis, data collected through the questionnaire are integrated with patent data about each inventor interviewed; patent data are extracted from the EP-Cespri dataset, namely the number of patents filed, their applicants, the citations received and the number of co-inventors.

The final dataset is composed of 106 individuals; on average, they are 51 years old. The gender distribution is 80 men and 26 women. Forty-eight of them work for private companies, 35 for universities, 22 for PROs or hospitals, and 1 is retired. There is one independent consultant; all the others are employed by firms, universities or other organisations. Inventors almost always changed job voluntarily (there is only one case in which mobility is due to a firm's failure), and all cases but two are cases of upward mobility.

In order to exclude potential sources of selection on the interviewed inventors, we compared the distribution of the number of patents per inventor in the survey sample to two different samples. At first, the whole pharmaceutical sample, which spreads from 1978 onwards, and then to a restriction that covers the years from 1990 to 2000. This has been done in order to check whether our sample captures specific characteristics of this interval of time. The selected sample perfectly replicates the distribution of the number of patents per inventors of both the whole population of Italian inventors in the pharmaceutical and its restriction, as the figure reported below shows.

[Figure 1 about here]

This consideration also holds true when comparing the rate of technology mobility in the three samples, as Table 1 shows.

[Table 1 about here]

Finally, this consideration also applies to the number of citations received in the first five years per patent, as Table 2 shows.

[Table 2 about here]

Thus, the selected sample is pretty similar to the original population of inventors in the pharmaceutical (also when it is restricted to the years 1990-2000). This holds true according to a series of dimensions of analysis, which are also very relevant variables in our analysis such as the number of patents, the rate of technology mobility and the number of citations per patent. Therefore, we expect that the inferences drawn from this sample are rather robust and do not seem to be affected by selection bias.

Notwithstanding this evidence, it is worth pointing out that also questionnaire data might have a number of limitations and drawbacks in absolute and comparative terms (especially with respect to patent data). In particular, questionnaire data frequently imply a strong reduction in the sample size. In the present case, this imposes considering a small sample in one country and one sector and the analysis would certainly benefit from an extension of the research to other geographical and technological contexts.

Moreover, survey data are likely to be based on personal judgements and feelings of respondents that, in some circumstances, might affect the reliability of the answers provided. In the present case, however, the strong similarities between the original population and the survey sample according to the three relevant variables above mentioned make this concern less tight. Additionally, the questions to be answered in the survey (i.e. to fill in the employment record) are unlikely to be affected by personal judgements. Notwithstanding, respondents typing errors are conceivable and, unfortunately, cannot be controlled for by the researcher.

In the next section, we carry out a comparative analysis between technology mobility and job mobility. Firstly, we look at the differences with respect to the issues discussed in section 2. Secondly, we investigate the relationship between productivity and mobility and look whether it is affected by the notion of mobility adopted (i.e. technology mobility vs. job mobility) by means of an econometric exercise.

3. A comparative analysis between technology mobility and job mobility

3.1. Descriptive evidence

According to patent data, 81 inventors never moved and 25 moved at least once; on the other hand, according to the survey, 41 inventors never changed their job while 65 did, up to five times[7]. The rate of technology mobility is on average 0,38 while the rate of job mobility is on average 1,46. Their difference is statistically significant at 1% level, also if we consider only inventors with two patents, those that can be defined as mobile according to

[7] The rate of technology mobility is computed by controlling for two potential sources of error. At first, we have checked for the presence of M&A processes between applicants; in fact, without controlling for these cases, the actual number of moves could turn out to be inflated. Next, we have checked whether it is a case of market for technology. In this respect, we have not considered an inventor as a mover in two cases, as proposed by Laforgia and Lissoni (2006): 1) one of the applicants is a PRO or a university and the others are private companies; 2) the inventor signs patents either in its own name or for a private company as well as for a university or a PRO.

the notion of technology mobility[8]. Technology mobility is thus much less frequent than job mobility. It means that inventors do not file patents for all their employers.

More specifically, technology mobility under-estimates job mobility in 60 cases out of 65. Also, technology mobility over-estimates job mobility (7 cases out of 106); it is highly probable that this group captures phenomena of market for inventions. In fact, the inventors in this group either work at university or PRO while patenting for third party organisations, or work at the private sector and patent for a joint venture of their employer with other companies. The rate of technology mobility and job mobility ultimately coincides only in 39 cases out of which 34 are cases of no mobility. The following table illustrates these figures.

[Table 3 about here]

Additionally, inventors are not always affiliated to the applicants of their patents. By construction, in the cases in which technology mobility underestimates job mobility, an inventor's applicants do not mirror all the employers; thus, the matching between applicants and employers is at least partial. However, it might also be the case that there is no match at all between these two. This happens in 34 cases out of 106, which amounts to 32% of the sample. In such cases thus, technology mobility signals different moves compared to job mobility. The following table indicates the cases in which there is match between applicant and employer (Y column) or there is no match (N column), broken down by the rate of technology mobility and job mobility.

[Table 4 about here]

We also have looked more in depth at this figure in order to understand whether the frequency of the matching could depend upon the type of institution of actual employment and/or the patterns of job mobility across organisations.

Lets first consider only inventors that never moved across different type of organisations (i.e. cases of inter-sector mobility are excluded). Those inventors that never moved and for which there is no match at all between applicant and employer, all work

[8] In the one tail t-test the average rate of technology mobility is significantly lower than the rate of job mobility at 1% level.

either at university or at a public research lab. Moreover, inventors which always worked at the public sector (university or PRO) are more likely to show a mismatch between employer and applicant (61,3% of cases), compared to inventors which always worked at the private sector (18,75% of the cases)[9]. However, it is worth pointing out that this count has been computed without taking into accounts the number of an inventor's moves. In fact, the risk of mismatch is likely to be higher the greater the number of employers and applicants an inventor records (therefore, for job mobile and technology mobile inventors).

[Table 5 about here]

Next, we have looked at inventors which moved across sectors. Differently from the previous case, it is not possible to describe a clear pattern for the two categories of 'partial match' and 'perfect match'. In fact, these categories equally apply to inventors which have moved across private sector and university, private sector and PRO, or university and PRO. Moreover, it seems that inventors do not follow any specific path or, put in other words, there is not any particular sequence at place. However, it is rather clear that the rate of technology mobility and job mobility and the actors involved differ at most for those inventors which have worked either at university or at a PRO and moved across these types of organisations.

In conclusion, these figures seem to complicate and enrich the interpretation of mobility phenomena based on patent data and suggest that job mobility and technology mobility might capture complementary aspects of inventors' career path.

Firstly, inventors do not patent at every organisation they work for or, put differently, technology mobility is less frequent than job mobility. As a consequence, technology mobility underestimates the knowledge flows generated by inventors' job mobility. On the one side, job mobility describes the knowledge flows not only between organisations that contribute to the production of new patented knowledge but also between those that do not and indicates the whole set of organisations that benefit from the knowledge flows originated by inventors' moves. On the other, technology moves still do capture knowledge

[9] The proportion test (one tail) shows that the proportion of mismatch for inventors in the public sector is significantly greater compared to inventors in private sector at 1% level.

flows but only those occurring across organisations that directly participate to the production of patented knowledge.

Secondly, the match between applicant and employer might be partial, that is technology mobility and job mobility might involve different actors. In fact, it might be the case that technology moves are not associated (or only partially) to knowledge flows from the departure organisation to the destination one but they may involve different organisations (this turns to be reinforced given that technology mobility captures only a portion of an inventor job moves and employers). Moreover, since this especially applies to inventors working at PRO or university, there is the additional risk of underestimating the technology transfer from university to industry. Conversely, it might be argued that this occurrence applies much more to the category of 'market for technology' rather than to that of job mobility. This ultimately suggests that market for technologies are rather widespread and interrelated with inventors' career path and their innovative behaviour and productivity.

3.2. Econometric analysis

Technology mobile inventors hold on average 13 patents while job mobile inventors hold on average 6,8 patents. On average, technology mobile inventors are almost twice more productive than job mobile inventors. Their difference is statistically significant at 1% level (also if we consider only inventors with at least two patents, those that can be defined as mobile according to the notion of technology mobility)[10]. Thus, the notion of technology mobility is likely to pick up more productive inventors while dismissing the rest and might introduce a bias towards more productive inventors that in turns might overemphasise the relationship between productivity and mobility.

This sums to the relevant problem of endogeneity that characterises the two-way relationship between productivity and mobility (Hoisl, 2007).

Accordingly, in this work, we aim at studying both whether productivity of inventors affects their mobility decisions and, *vice versa*, whether inventors' mobility has any effect on

[10] In the one tail t-test, the average productivity of technology mobile inventors is significantly greater than the average productivity of job mobile inventors at 1% level. Additionally, technology mobile inventors are significantly more productive than no technology mobile inventors at 1% level (also if we consider only inventors with at least two patents), while this does not occur when comparing the average productivity of job mobile and no job mobile inventors (also if we consider only inventors with at least two patents).

their productivity. While measures of productivity of the innovative output are derived exclusively from patent data, measures of mobility are derived from both patent (i.e. technology mobility) and survey data (i.e. job mobility). We thus aim at studying whether the use of these two notions of mobility can influence the relationship between productivity and mobility and the causality direction of this relation.

At first, we have looked at the factors that influence the rate of technology mobility and job mobility, i.e. the number of moves an inventor records in his career according to patent and data survey respectively. Since we are studying the cumulative number of moves, we are interested in modelling an event count; in fact, this can also be viewed as the rate of occurrence of the event. In this type of context, linear regression models have been frequently applied, but they lead to inefficient, inconsistent and biased estimates (Long et al., 2004). On the contrary, specific models for count data must be applied and they all have a benchmark model that is the Poisson distribution.

In this model μ is the rate of occurrence or the number of times an event occurs over a given period of time; y is a random variable and indicates the number of times the event occurred. The Poisson distribution gives the relationship that links μ and y:

$$\text{Prob}\ (Y = y) = (e^{-\mu}\mu^{y})/y! \qquad y = 0, 1, 2, \ldots$$

In this distribution, μ is the only parameter defining the distribution. Moreover, $E(Y) = Var(Y) = \mu$: mean and variance are equal. This property is known as equi-dispersion; when variance is greater (lower) than mean there is over-dispersion (under-dispersion).

The Poisson regression model can be viewed as an extension of the Poisson distribution: the difference is that μ can vary across observations depending on some regressors.

Then, the dependent variable y is distributed with density

$$f(y_i | x_i) = (e^{-\mu}\mu^{y})/y! \qquad i = 1, \ldots, n$$

and in the log-linear version of the model the mean parameter for the i^{th} individual is

$\mu_i = E(y_i \mid x_i) = \exp(x_i\beta)$

This assures that μ_i is positive and that y_i is 0 or positive. Moreover, the property of equi-dispersion signals that the model is intrinsically heteroschedastic and a robust estimator is required.

We excluded from the analysis retired inventors and those who entered the labour market before 1970. This is because we tried to limit the effect of inventors' time exposure and patent data is available from 1978. This reduces the sample to 97 subjects (more specifically, the definition of technology mobility can be applied only to inventors with at least two patents; in this case, the sample amounts to 60 individuals).

Therefore, following Trajtenberg (2005), the rate of occurrence (e.g. the number of moves) can be described as follows[11]

$\mu_i = E(y_i|x_i) = \exp(x_i\beta) = \exp(\text{productivity}_i\theta_1 + \text{experience}_i\theta_2 + \text{experience}^2_i\theta_3 + \text{co-inventors}_i\theta_4)$.

The rate of mobility, the dependent variable, either technology mobility or job mobility, can be affected by several factors; the variable we are interested most is productivity. We considered two different aspects: the number of patents filed and their quality. Productivity is thus proxied, first, by the number of patents filed and, second, by the number of patents' citations received (i.e. a measure of patents quality; for a discussion, see for instance Haroff et al., 2003)[12]. We also control for a number of factors which can affect the number of moves. At first, we control for an inventor's experience in the labour market that is captured through the number of years of inventive activity up to 2005 when using patent data and by the number of years in the labour market up to 2005 when using survey data. In fact, more experienced inventors are more likely to have repeatedly changed job and in the sample there are inventors with different labour market experiences. A squared term is

[11] We consider only one specific sector and country and, accordingly, we do not need to control for countries' and technological fields' fixed effects.

[12] Citations received are computed as the cumulative number of citations received in the first five years after patent application.

added since the literature of labour economics indicates a quadratic effect of labour market experience on the probability of a job change (Jovanovic, 1979; Topel and Ward, 1992). Secondly, we also consider the number of co-inventors per patent in order to capture the size of an inventor's network of relationships; being more connected can increase the chances to be informed about new vacancies and therefore of changing job. Measures of geographical location as well as type of organisation of employment are excluded since they can vary over time, precisely for inventors that do change job. Controls for education, type of contractual agreements, motivations are excluded too since this information would be available only when we use survey data.

It is worth noting that the effect of variations in the regressors depends on the value of all other covariates and, differently from linear models, it is not equal to the estimated parameters. Interpretation in count data models thus looks like that in binary outcome models. The effects of the variations of the independent variables on the expected count can be interpreted in several ways: factor or percentage change in the rate, marginal or discrete effects (Cameron and Trivedi, 1998; Long et al., 2004).

Table 6 and 7 provide a short description of the variables used in the econometric analysis and summary statistics for them[13].

[Table 6 about here]
[Table 7 about here]

Table 8 and 9 show the estimates obtained respectively for technology mobility and job mobility. The measures of the number of moves and the labour market experience differ according to the data used, while three variables do not change, namely the two productivity variables and the network variable.

[13] We decided to report summary statistic and estimates for the sample including all inventors (97 individuals) and not for the sample including inventors with at least two patents (60 individuals) because estimates do not change very much in the two samples.

At first we have focused on technology mobility and we have progressively estimated the full model. Estimates show that the experience in the labour market affects the number of moves in an inventor's career. This exhibits a non-linear effect, consistently with the relevant literature, though, the quadratic term is weakly significant (it is significant only in model 2). When labour experience is limited (young people, new entrants in the labour market) the number of moves is higher, but when experience is sufficiently higher, labour positions become more stable and the number of moves decreases. The number of co-inventors has a positive sign but is never significant. A possible explanation for this result is that here we do not (and we cannot) distinguish between internal network and external network to the organisation of employment. The former should have a negative effect on the probability of a move (i.e. the more an inventor is embedded in an organisation the higher the costs of moving away, the lower the probability of a move). On the other hand, the latter should have a positive effect on the probability of a move (i.e. the higher the number of contacts outside the organisation the lower the costs of information about job openings and the greater the opportunities ti change job). Unfortunately, patent data on co-inventorship do not allow us to distinguish these aspects; in fact, as discussed above, applicant and employer do not always coincide.

The two measures of productivity are firstly introduced separately (model 2 and model 3). In both cases, their sign is positive and their effects are statistically significant; this means that more productive inventors change job more frequently. Next, they are jointly introduced (model 4); however, they are both less significant.

In conclusion, we do find a statistically significant and positive association between productivity, as measured by the number of patents filed, and technology mobility as Trajtenberg (2005), but differently from Hoisl (2007) and Shankerman et al. (2006), which find out a significant and negative effect. These differences could in part be driven by the different settings examined (in particular Hoisl (2007) and Shankerman et al. (2006) study only inventors employed at the private sector while the present sample includes also inventors working in the public sector). Moreover, the literature shows mixed evidence on the effect of productivity on labour mobility (see also Crespi et al. (2007) and Zucker et al. (2002)).

Finally, the positive effect of the number of citations received is consistent with findings of Trajtenberg (2005) and Shankerman et al. (2006), thus supporting the idea of asymmetric information as a key driver of mobility decisions. In fact, the number of citations received might capture ex-ante unobservable aspects of an invention; in case of asymmetric information about the value of an invention between inventor and employer, an inventor might be better at evaluating its potential impact and might probably move in order to better exploit it and appropriate the returns it generates while the employer might not be able to recognise the signals of the invention's quality and not pre-empt an inventor's move.

[Table 8 about here]

We next turned to look at job mobility. Table 9 shows the estimates. Again, we progressively estimated the full model. The overall fit of the model decreases compared to previous estimates. In model 1, the only significant variable is the linear term of experience. Nevertheless, the effect of experience is consistent with the predictions of the relevant literature and the effect of the number of co-inventors is positive though not significant. We next introduced separately the two measures of productivity that have both a positive effect (model 2 and model 3); however only quality has a statistically significant effect, also when they are jointly introduced (model 4)[14]. In conclusion, we find again a statistically significant (though less robust) and positive association between productivity and mobility.

[Table 9 about here]

As a consequence, the comparison between these two sets of estimates suggests that both technology and job mobility are associated in a statistically significant way with productivity variables.

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[14] In a related paper, we find that the number of patents significantly affects the probability of a move while the number of citations does not (Lenzi, 2008). A possible explanation for this result is that on the one side patent record might be more easily included in a *curriculum vitae* compared to the number of citations received and thus increase the probability of receiving a job offer and facilitate a specific move. On the other side, when we consider an inventor's whole career and the cumulative number of moves what ex-post really discriminates is the quality of the inventions made; additionally, the number of citations received is positively influenced by the number of patents filed.

Next, we investigated the effect of technology and job mobility on an inventor's productivity. In particular, we study the effect of previous moves on the number of citations each patent receives in the first five years.

We decided to use only this measure of productivity instead of the number of patents filed mainly because this allows overcoming a problem of simultaneity between technology mobility and patents (as we discussed in section 2).

Since we are studying the number of citations received per patent, we are again interested in modelling an event count. As discussed above, this type of events can be described through a Poisson model. Again, we excluded from the analysis retired inventors and those who entered the labour market before 1970, in order to limit the effect of inventors' time exposure and because patent data is available from 1978. This reduces the sample to 97 subjects (more specifically, the definition of technology mobility can be applied only to inventors with at least two patents; in this case, the sample amounts to 60 individuals).

Therefore, following Trajtenberg (2005), in the log-linear version of the model the mean parameter for the i^{th} patent is

$$\mu_i = E(y_i|x_i) = \exp(x_i\beta) = \exp(\text{application\_year}_i\theta_1 + \text{previous\_patent}_i\theta_2 + \text{previous\_patent\_citations}_i\theta_3 + \text{inventors\_team}_i\theta_4 + \text{mobility}_i\theta_5)$$

The most relevant independent variable is mobility that controls for the effect of the exposure to different working environments and should positively influence the innovative productivity of an individual. In such a case, mobility may improve the match between employer and inventor turning into a better innovative performance. Mobility is measured in two different ways: either as the cumulative number of moves before the examined patent or as a dummy variable which takes value 1 if mobility ever occurred before that patent and 0 otherwise.

Application year indicates the year of application of the patent whose we are counting the citations received. We expect that more recent patents are less likely to be cited. This should also control for potential trends in patent data. Previous patent controls for an inventor's attitude towards patenting. No clear effect is expected in the sense that it is likely that inventors with more patents are more likely to be cited; on the other hand, it might also be the case that there is a potential trade-off between number of patents and their quality as captured by the number of citations. We thus consider also this aspect and include the number of citations received by previous patents. This should introduce a further control for individual abilities. Finally, we control for the size of the inventing team. Also in this case, one might expect that the effect is positive, on the other side there can be a sort of 'congestion' effect at place. This could also give some insights on the 'optimal' size of inventing teams. Finally, Table 10 and 11 provide a short description of the variables used in the econometric analysis and summary statistics for them.

[Table 10 about here]

[Table 11 about here]

Table 12 shows the estimates obtained respectively from the baseline model (model 1), technology mobility (model 2 and model 3) and job mobility (model 4 and model 5). All variables but one are equal in these two sets of estimates. The only variable that differs is the one related to the mobility effect. In fact, this can differ according to its measurement through patent (i.e. technology mobility) or survey data (i.e. job mobility). We estimated the model by introducing separately different measures of mobility in order to avoid risk of multicollinearity among these variables.

[Table 12 about here]

The overall fit of the model is rather good. The estimates indicate that the number of citations received per patent is significantly but negatively affected by the year of application. As expected, more recent patent are less likely to be cited. This result is consistent across all models. The effect of the number of patents is significant and negative in all models. It seems that there is a sort of trade-off between number of patents filed and their quality, consistently with Trajtenberg (2005) and Shankerman et al. (2006). We have also introduced a squared term in order to control for non-linear effects, but it is never significant and with the same sign of the linear term. Therefore, we decide to not report these estimates. Differently, the effect of the number of citations received is positive and significant in all models suggesting that patents of inventors with greater quality inventions are more likely to be cited. The effect of the number of co-inventors is positive though never significant, suggesting that larger teams produce better patents and excluding the presence of 'congestion' effects. We also introduced a squared term in order to inspect the presence of a non-linear effect. However, the coefficient remains not significant and the fit of models decreases. Therefore, we do not report these estimates.

The most interesting information concerns the effect of the mobility variables. Technology mobility has a significant and positive effect on the number of citations received; *ceteris paribus*, it gives a premium in terms of number of citations received by later patents. This result holds true by using either of the two measures of technology mobility; moreover, the statistical level of significance does not decrease. Being technology mobile increases the expected quality of patents by a factor of 1,37; this means that being technology mobile leads to 37% increase in the number of citations, holding all other variables at their mean. If the number of moves is taken into account, every additional move leads to 16,74% increase in the expected number of citations, holding all other variables at their mean. Moreover, an additional move increases the number of citations by a factor of 1,16. These results are consistent with previous findings by Hoisl (2007 and 2008) about mobility as a mechanism to improve the matching between inventor and employer that in turns increases the inventor innovative performance.

On the other hand, job mobility does not have a significant (though positive) effect. This result holds true by using either of the two measures of job mobility.

As a consequence, there is a rather statistically robust relationship between technology mobility and productivity that is not confirmed when we use data on job mobility. Rather, estimates from table 9 and table 12 (model 4 and model 5) indicate that the causal relationship seems running from productivity to job mobility. Differently, estimates from table 8 and table 12 (model 2 and model 3) indicate that the causal relationship between productivity and technology mobility is bi-directional, consistently with Hoisl (2007)'s findings.

Therefore, these results seem to complicate and enrich further the interpretation of mobility phenomena based upon patent data. In fact, technology mobility and job mobility suggest rather different pictures. One possible interpretation for this challenging result is that these data capture complementary aspects of inventors' career path. In particular, it might be the case that technology mobility catches relational aspects of the inventive process (i.e. people and organisations an inventor is working and sharing knowledge with) rather than a true and formal labour relationship with the applicant of the patents. In this line of reasoning, technology mobility may describe the set of actors involved in the inventive process (inventive network) rather than describe the set of inventors' employers and track inventors' *curriculum vitae* (professional network). The wider the inventive set the greater the probability of being cited because of the joint effect of reputation and a higher attitude towards patenting within the network. Conversely, a more diverse professional experience (i.e. a higher number of job moves) does not necessarily lead to a significantly higher probability of being cited. Moreover, the evidence from the previous sections suggests that these two networks can sometimes overlap and share the same actors but do not necessarily coincide. Therefore, technology mobility and job mobility are likely to capture different aspects of inventors' professional career and may thus indicate different implications and predictions as long as they are meant to describe the same phenomenon.

4. Conclusions

The increasing interest and resources dedicated in recent years to the analysis of workers' mobility is at the basis of the present paper. Indeed, workers' mobility, namely highly skilled ones, is a fundamental mechanism of knowledge diffusion across firms and may eventually lead to the creation of new firms.

In the innovation studies literature most of the works on this issue concentrate on inventors' mobility and make use of patent data in order to extract information on inventors' career path. Patent data, in fact, collects detailed information on inventors, their geographical location and the applicants of their patents.

This paper instead complements patent data with unique data on inventors' *curriculum vitae* collected through a survey addressed to a group of Italian inventors in the pharmaceutical field, and carries out a comparative analysis between patent and survey data.

Results from descriptive statistics show that patent data frequently underestimate the rate of job mobility across firms: technology mobility (i.e. identification of job moves on the basis of patent data) is less frequent than job mobility (i.e. identification of job moves on the basis of *curriculum vitae* data). Moreover, inventors are not always affiliated to the applicants of their patents. This especially holds true for inventors that have always been employed at universities or PROs as well as for inventors that change job across these types of organisations.

This has two important implications. Differently from job mobility, technology mobility explains only a fraction of the knowledge flows generated through workers' job moves. In particular, it captures only those flows occurring across organisations that actively participate to the production of patented knowledge. Secondly, it might also be the case that technology mobility does not reflect at all a knowledge flow from the firm of departure to that of destination but it might involve two different organisations. We suggest that this occurrence applies much more to the category of 'market for technology' rather than to that of workers' mobility. In particular, since this especially holds true for inventors working at universities, this leads to the additional risk of underestimating the technology transfer from university to industry.

Results from the econometric analysis indicate that both technology and job mobility are associated in a statistically significant way with productivity variables. Furthermore, technology mobility has a significant and positive effect on the number of citations each patent receives; *ceteris paribus*, it gives a premium in terms of number of citations received. This result holds true by using either of the two indicators proposed for technology mobility. As a consequence, there is a rather statistically robust causal relationship from technology mobility to productivity that instead is not confirmed when we use data on job mobility. Rather, estimates indicate that the causal relationship seems running from productivity to job mobility, whereas the causal relationship between productivity and technology mobility seems to be bi-directional.

This paper provides some contributions to the current debate on workers' mobility, by qualifying the interpretation and use of patent data in order to describe inventors' career path. In particular, it puts forward a number of differences between technology and job mobility in both the descriptions and the predictions that can be drawn and proposes an interpretation for them. More specifically, it suggests that job mobility might describe the whole set of inventors' employers and the knowledge flows across them generated by inventors' moves; in such cases, it is a channel for tacit and embodied knowledge transfer. On the other hand, technology mobility portrays the set of actors directly involved in inventive processes and directly participating to the production of patented knowledge; in such cases, it could be associated to a channel for the transfer of knowledge that is by some means codified. In fact, in such a case knowledge is transferred within a network of organisations directly involved in inventive processes and which, to a certain extent, share common knowledge and represent, at least in some technological areas such as pharmaceutical, sufficiently close communities. Finally, these two sets overlap only partially and do not necessarily coincide.

Further research should be devoted to the study of the mobility of knowledge workers. In particular, it would be helpful to enlarge the analysis to other countries and sectors in order to understand whether these findings could be generalised. Additionally, it could be interesting to investigate whether an inventor's move from an organisation to another enhances the chances of co-patenting or citations. These refinements would certainly improve our understanding of the characteristics of workers' mobility and its implications on knowledge diffusion phenomena.

BIBLIOGRAPHY

Aghion P. and Tirole J. (1994), "The management of innovation", *The Quarterly Journal of Economics*, 109(4): 1185-1209.

Agrawal A.K., Cockburn I.M., McHale J. (2003), "Gone but not forgotten: Labor flows, knowledge spillovers and enduring social capital", NBER WP n. 9950.

Almeida P. and Kogut B. (1999), "The localization of knowledge and the mobility of engineers in regional networks", *Management Science*, 45(7): 905-917.

Arora A., Fosfuri A., Gambardella A. (2001), *Markets for Technology*, MIT Press, Cambridge, MA.

Arrow K.J. (1962), "Economic welfare and the allocation of resources for invention", in R.R. Nelson (ed.), *The Rate and Direction for Inventive Activity. Economic and Social Factors*, Princeton University Press, Princeton.

Becker G. (1962), "Investiment in human capital: A theoretical analysis", *Journal of Political Economy*, 70: 9-49.

Breschi S. and Lissoni F. (2006), "Mobility and social networks: Localised knowledge spillovers revisited", *Annales d'Economie et de Statistique,* forthcoming.

Cameron A.C. and Tirvedi P.K. (1998), *Regression analysis of count data*, Cambridge University Press, Cambridge, UK.

Cohen W., Nelson R.R., Walsh J.P. (2000), "Protecting their intellectual assets: appropriability conditions and why U.S. manufacturing firms patent (or not)", NBER WP N. 7552.

Corredoira, R. and L. Rosenkopf. 2005. "Gaining from your losses: The backward transfer of knowledge through mobility ties", mimeo, Wharton Business School.

Crespi G., Geuna A., Nesta L. (2007), "The mobility of university inventors in Europe", *Journal of Technology Transfer*, 32(3): 195-215.

Franco A.M. and Filson D. (2005), "Spin-outs: Knowledge Diffusion through Employee Mobility", Federal Reserve Bank of Minneapolis, Research Department Staff Report 272 –modified.

Geuna A. and Nesta L.J.J. (2005), "University patenting and its effects on academic research: The emerging European evidence", *Research Policy*, 35(6): 790-807.

Giuri P., Mariani M. et al. (2005), "Everything you always wanted to know about inventors (but never asked): Evidence from the Pat-Val survey", LEM WP n. 2005-20.

Greene W.H. (2000), *Econometric analysis*, Fourth Edition, Prentice Hall International, New Jersey.

Griliches Z. (1990), "Patent statistics as economic indicators: A survey", *Journal of Economic Literature*, 28: 1661-1797.

Haroff D., Scherer F.M, Vopel K. (2003), "Citations, family size, opposition and the value of patent rights", *Research Policy*, 32: 1343-1363.

Hoisl K. (2007), "Tracing mobile inventors: The causality between inventor mobility and inventor productivity", *Research Policy*, 36(5): 619-636.

Hoisl, K, (2008): "Does Mobility Increase the Productivity of Inventors?", *Journal of Technology Transfer*, forthcoming.

Jaffe A.B. and Trajtenberg M. (2002), *Patents, Citations and Innovations: A Window on the Knowledge Economy*, Cambridge: MIT Press, 2002.

Jaffe A.B., Trajtenberg M., Fogarty M.S. (2000), "Knowledge spillovers and patent citations: Evidence from a survey of inventors", *American Economic Review*, 90(2): 215-218.

Jovanovic B. (1979), "Job matching and the theory of turnover", *The Journal of Political Economy*, 87(5): 972-990.

Kim J. and Marschke G. (2001), "The labor market for scientists and the recent raise in patenting", State University of New York at Albany Discussion Paper n. 01-03.

Klepper S. and Sleeper S. (2005), "Entry by spinoff", *Management Science,* 51: 1291-1306.

Laforgia F. and Lissoni F. (2006), "What do you mean by mobile? Multi-applicant inventors in the European bio-technology industry", DRUID WP n 06-15.

Lambert D. (1992), "Zero-inflated Poisson regression, with an application to defects in manufacturing", *Technometrics*, 34(1): 1-14.

Lenzi C. (2008), "Patterns and determinants of skilled workers' mobility: Evidence from a survey of Italian inventors", *Economics of Innovation and New Technology*, forthcoming.

Long J.S. and Freese J. (2004), *Regression models for categorical dependent variables using STATA*", Stata Press, College Station, Texas.

Murray F. (2002), "Innovation as overlapping scientific and technological trajectories: exploring tissue engineering", *Research Policy*, 31(8-9): 1389-1403.

Moen J. (2000), "Is the mobility of technical personnel a source of R&D spillovers?", NBER WP n. 7834.

Oppenheim A.N. (1992), *Questionnaire Design, Interviewing and Attitude Measurement*, Pinter Publishers, London.

Pacelli L., Rapiti F., Revelli R. (1998), "Employment and mobility of workers in industries with different intensity of innovation: Evidence on Italy from a panel of workers and firms", *Economics of Innovation and New Technologies*, 5(2-4): 273-300.

Pakes A. and Nitzan S. (1983), "Optimum contracts for research personnel, research employment, and the establishment of 'rival' enterprises", *Journal of Labor Economics*, 1(4): 345-365.

Rosenkopf L. and Almeida P. (2003), "Overcoming local search through alliances and mobility", *Management Science*, 49(6): 751-766.

Shankerman M., Shalem R., Trajtenber M. (2006), "Software patents, inventors and mobility", mimeo.

Sing J. (2005), "Collaborative networks as determinants of knowledge diffusion patterns", *Management Science*, 51(5): 756-770.

Song J., Almeida P., Wu G. (2001), "Mobility of engineers and cross-border knowledge building: The technological catching-up case of Korean and Taiwanese semiconductor firms". Henry Chesbrough and Robert Burgelman (Eds.), *Research in Technology and Innovation Management*, Elsevier, New York, 59-84.

Song J., Almeida P., Wu G. (2003), "Learning by hiring: When is mobility more to facilitate knowledge transfer?", *Management Science*, 49(4): 351-365.

Stolpe M. (2002), "Determinants of knowledge diffusion as evidenced in patent data: The case of liquid crystal display technology", *Research Policy*, 31(7): 1181-1198.

Topel R.H. and Ward M.P. (1992), "Job mobility and the careers of young men", *The Quarterly Journal of Economics*, 107(2): 439-479.

Trajtenberg M. (2005), "Recombinant ideas: the mobility of inventors and the productivity of research", in Proceedings of the CEPR Conference, Munich, May 26–28, 2005.

Zellner C. (2003), "The economic effects of basic research: evidence for embodied knowledge transfer via scientists' migration", *Research Policy*, 32(10): 1881-1895.

Zucker L.G., Darby M.R., Armstrong J. (1998), "Geographically localized knowledge: Spillovers or market?", *Economic Inquiry*, 36(1): 65-86.

Zucker L.G., Darby M.R., Torero M. (2002), "Labor mobility from academe to commerce", *Journal of Labor Economics*, 20(3): 629-660.

TABLES and FIGURES

Figure 1. Distribution of number of patents per inventors

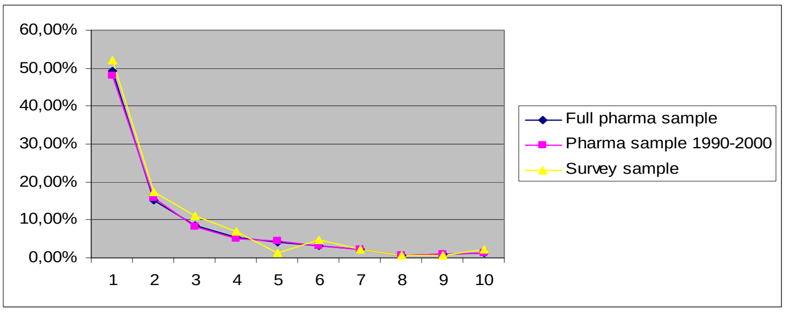

Table 1. Distribution of number of moves per inventors (%)

	Inventors with one patent	Inventors with more than one patent but no technology mobile	Inventors with more than one patent and technology mobile
Pharma sample 1978-2002	49,22	20,64	30,13
Pharma sample 1990-2000	48,00	20,47	31,53
Suvey sample	52,08	18,06	29,86

Table 2. Frequency of the number of citations received per patent in the first five years

	Pharma sample 1978-2002	Pharma sample 1990-2000	Survey sample
0	93,33	92,72	94,05
1	5,34	5,74	5,29
2	1,02	1,17	0,00
3	0,21	0,24	0,33
4	0,06	0,07	0,00
5	0,03	0,04	0,17
6	0,01	0,01	0,00
7	0,00	0,00	0,00
8	0,00	0,00	0,17

Table 3. Comparison between the rate of technology mobility and the rate of job mobility

	Technology mobility (patent data)				
Job mobility (survey data)	**0**	**1**	**2**	**3**	**4**
0	34	2	4	-	-
1	15	3	-	-	-
2	13	4	-	-	-
3	10	2	2	2	1
4	7	2	1	-	-
5	2	1	1	-	-

Table 4. Matching between employer and applicant broken down by the number of moves

	Technology mobility (patent data)									
	0		**1**		**2**		**3**		**4**	
Job mobility (survey data)	**Y**	**N**	**Y**	**N**	**Y**	**N**	**Y**	**N**	**Y**	**N**
0	24	10	-	2	1	3	-	-	-	-
1	10	5	2	1	-	-	-	-	-	-
2	9	4	3	-	-	1	-	-	-	-
3	6	4	2	-	2	-	2	-	1	-
4	5	2	1	-	1	-	1	-	-	-
5	1	1	1	-	-	1	-	-	-	-

Table 5. Affiliation matching broken down by the type of organisation of employment

Affiliation matching	Private sector	Public sector (University and PROs)
Perfect	81,25%	38,71%
Partial/Not at all	18,75%	61,29%

Table 6. Description of the variables

Name of the variable	Description
EXP_PAT	Number of years in the labour market proxied as 2005-year of the first patent
EXP_PAT2	Squared EXP_PAT
CUM_EXP	Number of years in the labour market proxied as 2005-year of entry in the labour market
CUM_EXP2	Squared CUM_EXP
LOG_PAT	Natural logarithm of the cumulative number of patents
AV_CITED[15]	Categorical variable that takes value 0 if the average number of citation received is 0 1 if the average number of citation received is greater than 0 and lower or equal to 1 2 if the average number of citation received is greater than 1
AV_CUM_COINV[16]	Categorical variable that takes value 0 if the average number of co-inventors is lower or equal to 1 1 if the average number of co-inventors is greater than 1 and lower than 3 2 if the average number of co-inventors is greater or equal to 3

Table 7. Summary statistics

Name of the variable	N. of observations	Mean	Standard deviation	Minimum	Maximum
EXP_PAT	97	11,680	5,996	5	26
EXP_PAT2	97	172,010	171,698	25	676
CUM_EXP	97	22,082	7,442	6	35
CUM_EXP2	97	542,454	319,454	36	1225
LOG_PAT	97	0,478	0,497	0	1,644
AV_CITED	97	0,897	0,797	0	2
AV_CUM_COINV	97	0,979	0,790	0	2

Table 8. Poisson regression estimates based – technology mobility

	Model 1	Model 2	Model 3	Model 4
EXP_PAT	0,394**	0,320*	0,352**	0,310*
	(0,159)	(0,173)	(0,176)	(0,191)
EXP_PAT2	-0,008	-0,008*	-0,007	-0,008
	(0,005)	(0,005)	(0,005)	(0,005)
AV_CUM_COINV	0,015	0,184	0,058	0,165
	(0,236)	(0,251)	(0,240)	(0,255)
LOG_PAT		1,454**		1,147*
		(0,638)		(0,610)
AV_CITED			0,708***	0,629**
			(0,277)	(0,299)
CONSTANT	-4,862***	-4,845***	-5,292***	-5,331***
	(1,322)	(1,400)	(1,594)	(1,652)
Wald χ^2	26,20	41,68	27,38	36,93
Log - likelihood	-66,372***	-63,763***	-63,041***	-61,380***
Number of observations	97	97	97	97

* p<0,1; ** p<0,05; *** p<0,01. Standard errors in parentheses.

[15] We used a categorical variable instead of a log-transformation because of the presence of zeros. Categories are defined on the basis of the distribution of the variable and do not reflect specific threshold already identified in the literature.

[16] We used a categorical variable instead of a log-transformation because of the presence of zeros. Categories are defined on the basis of the distribution of the variable and do not reflect specific threshold already identified in the literature.

Table 9. Poisson regression estimates based – job mobility

	Model 1	Model 2	Model 3	Model 4
CUM_EXP	0,172*	0,154	0,119	0,120
	(0,095)	(0,098)	(0,096)	(0,096)
CUM_EXP2	-0,003	-0,003	-0,002	-0,002
	(0,002)	(0,002)	(0,002)	(0,002)
AV_CUM_COINV	0,181	0,197	0,201	0,198
	(0,136)	(0,142)	(0,137)	(0,137)
LOG_PAT		0,169		-0,038
		(0,194)		(0,223)
AV_CITED			0,266**	0,277*
			(0,123)	(0,143)
CONSTANT	-2,041**	-1,923*	-1,749*	-1,760*
	(1,033)	(1,033)	(1,019)	(1,018)
Wald χ^2	10,35**	10,69**	15,60***	15,62***
Log - likelihood	-158,454	-157,990	-155,605	-155,586
Number of observations	97	97	97	97

* p<0,1; ** p<0,05; *** p<0,01. Standard errors in parentheses.

Table 10. Description of the variables

Name of the variable	Description
ANNO	Year of patent application
LOG_PAT	Natural logarithm of the cumulative number of previous patents
PAST_CITATIONS[17]	Categorical variable that takes value 0 if the cumulative number of citation received by previous patents is lower or equal to 3 1 if the cumulative number of citation received by previous patents is greater than 3 and lower or equal to 8 2 if the cumulative number of citation received by previous patents is greater than 8 and lower or equal to 22 3 if the cumulative number of citation received by previous patents is greater than 22
N_COINV[18]	Categorical variable that takes value 0 if the number of co-inventors is lower than 4 1 if the number of co-inventors is equal to 4 or 5 2 if the number of co-inventors is greater than 5
PMOB_PRE	Dummy variable (1= rate of technology mobility greater than 0; 0 otherwise)
SMOB_PRE	Dummy variable (1= rate of job mobility greater than 0; 0 otherwise)
MOB_P_PRE	Rate of technology mobility (i.e. number of job moves according to patent data)
MOB_S_PRE	Rate of job mobility (i.e. number of job moves according to survey data)

Table 11. Summary statistics

Name of the variable	N. of observations	Mean	Standard deviation	Minimum	Maximum
ANNO	486	1993	5,131	1980	2002
LOG_PAT	486	1,818	1,017	0	3,714
PAST_CITATIONS	486	1,496	1,123	0	3
N_COINV	486	0,768	0,753	0	2
PMOB_PRE	486	0,424	0,495	0	1
SMOB_PRE	486	0,541	0,499	0	1
MOB_P_PRE	486	0,531	0,714	0	4
MOB_S_PRE	486	0,986	1,091	0	4

[17] We used a categorical variable instead of a log-transformation because of the presence of zeros. Categories are defined on the basis of the distribution of the variable and do not reflect specific thresholds already identified in the literature.

[18] We used a categorical variable instead of the log-transformation because of the presence of outliers also in the log-transformation of the variable.

Table 12. Poisson regression estimates

	Model 1	Model 2	Model 3	Model 4	Model 5
ANNO	-0,045***	-0,040***	-0,043***	-0,045***	-0,046***
	(0,012)	(0,012)	(0,012)	(0,013)	(0,013)
LOG_PAT	-0,358***	-0,427***	-0,406***	-0,358***	-0,355***
	(0,130)	(0,142)	(0,141)	(0,130)	(0,133)
PAST_CITATIONS	0,356***	0,352***	0,352***	0,356***	0,348***
	(0,096)	(0,107)	(0,100)	(0,097)	(0,098)
N_COINV	0,146	0,145	0,153	0,145	0,143
	(0,124)	(0,125)	(0,127)	(0,125)	(0,124)
PMOB_PRE		0,316**			
		(0,136)			
MOB_P_PRE			0,155**		
			(0,070)		
SMOB_PRE				0,008	
				(0,165)	
MOB_S_PRE					0,065
					(0,068)
CONSTANT	89,282***	79,822***	85,210***	89,370***	91,723***
	(24,259)	(24,826)	(23,497)	(25,079)	(25,179)
Wald χ^2	31,75***	49,60***	32,86***	38,16***	35,47***
Log - likelihood	-824,521	-819,412	-822,099	-824,517	-823,235
Number of observations	486	486	486	486	486

* p<0,1; ** p<0,05; *** p<0,01. Standard errors in parentheses.

ANNEX

Table A. Correlation matrix

		1	2	3	4	5	6
1	**EXP_PAT**						
2	**EXP_PAT2**	0,979*					
3	**CUM_EXP**	0,355*	0,356*				
4	**CUM_EXP2**	0,329*	0,341*	0,983*			
5	**LOG_PAT**	0,822*	0,818*	0,299*	0,259*		
6	**AV_CITED**	0,486*	0,441*	0,195	0,146	0,547*	
7	**AV_CUM_COINV**	-0,019	-0,051	-0,055	-0,069	-0,088	-0,053

* p<0,05.

Table B. Correlation matrix

		1	2	3	4	5	6	7
1	**ANNO**							
2	**LOG_PAT**	0,217*						
3	**PAST_CITATIONS**	0,154*	0,762*					
4	**N_COINV**	-0,038	0,197	-0,0414				
5	**PMOB_PRE**	-0,062	0,363*	0,348*	0,111			
6	**SMOB_PRE**	0,009	0,393*	0,368*	-0,042	0,868*		
7	**MOB_P_PRE**	-0,027	-0,009	0,094*	0,616	0,439*	0,408*	
8	**MOB_S_PRE**	0,191	-0,010	0,473	0,128	0,367*	0,428*	0,833*

* p<0,05.