DRUID

DRUID Working Paper No. 07-22

Technology Mobility and Job Mobility: A comparative analysis between patent and survey data

By

Camilla Lenzi

Danish Research Unit for Industrial Dynamics

www.druid.dk

Technology Mobility and Job Mobility:
A comparative analysis between patent and survey data

Camilla Lenzi
Cespri – Università Bocconi
Via Sarfatti 25
20136 Milan - Italy
Tel: +39 02 5836 3336
Fax: +39 02 5836 3399
E-mail: camilla.lenzi@unibocconi.it

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 studies make use of information about inventors extracted from patent data. In fact, patent data collects detailed information on inventors, their geographical location and the applicants of their patents.
This paper instead makes use of unique data on inventors' curriculum vitae collected through a survey addressed to a group of Italian inventors in the pharmaceutical field and compares this information to those extracted from patent data.
Results seem to challenge the traditional interpretation of mobility phenomena based on patent data and suggest that patent and survey data might capture different 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. 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, they overlap only partially and do not necessarily coincide.

Key words: Patent; Mobility; Inventor

Jel codes: J60; O30

ISBN 978- 87-7873-251-4

Acknowledgements: The author would like to thank Stefano Breschi, Roberto Camerani, Michael Dahl, Olav Sorenson and the participants to the DRUID Summer Conference 2007 for useful comments and help to finalize this paper. The usual disclaimers apply.

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.

Of what concerns innovation studies, most of the attention has concentrated on skilled workers mobility because of their involvement into innovation activities within firms and their extreme relevance to the creation of new ones. In fact, workers' mobility is a fundamental mechanism of knowledge diffusion, which may take different channels.

In this respect, most of the studies make use of information about inventors extracted from patent data. In fact, patent data collects detailed information on inventors, their geographical location and the applicants of their patents. Patent data on applicants are then 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.

Recent works adopt this data extraction method in order to study and map the geographical extent of inventors' mobility, the knowledge transfer from university to industry, and the paths of knowledge diffusion. There are also a few studies concerned with the relationship between productivity of inventors and their mobility.

However, patent data do not allow capturing more specific information on inventors' *curriculum vitae* and career path such as their educational background, their motivations for changing job, the contractual agreements reached with their employers. On the other side, it is possible to gather such information on inventors by implementing questionnaires or interviews.

This paper makes use of unique data on inventors' *curriculum vitae* derived from a survey addressed to a group of Italian inventors in the pharmaceutical field and compares the information collected through the survey to those extracted from patent data. The main aim is to understand whether these two types of data provide similar information or not, and whether they allow making similar inferences. If this is the case, then patent data are a valuable proxy in order to describe inventors' mobility and career path and additional resources should be invested in the construction of extensive datasets on the basis of patent data. On the other hand, if this is not the case, special attention should be dedicated to the interpretation of the information extracted from patent statistics.

The rest of the paper is articulated on four sections. The first one discusses the use of patent data in order to study 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 patent and survey data. This section is divided in two main sub-sections. The former discusses similarities and differences in descriptive statistics while the latter discusses similarities and differences in inferences that can be drawn from these two sets of data. 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 Trajetenberg, 2002).

Accordingly, most of the empirical studies on workers mobility make use of patent data. The seminal work in this respect is the one by Almeida and Kogut in 1999. They examine the differences across regions in terms of localization of knowledge and interpret this result as effect of the variability of workers' mobility across regions. Their exercise relies upon patent data in two respects: data on citations are used as a proxy for knowledge localisation and information on the applicants of the selected inventors are used in order to track inventors' mobility across organisations[1]. Job mobility identification is then based upon patents and technology-related criteria. Consequently, it can be identified as technology mobility.

[1] An inventor is defined as mobile when he applies at least for two patents held by two different applicants.

This methodology has been applied by most of later studies. The major advantage is that this allows dealing with extensive, free, and already available datasets, such as those maintained by USPTO or EPO[2]. Besides, patent datasets cover several countries, years, and type of organisations. This methodology then allows following the patenting activity and the eventual mobility path of inventors over a very long period of time.

Although the innovation studies literature extensively addresses and deeply discusses patents limitations as indicators of innovation outcome[3], it is less concerned with patents limitations as indicator of inventors' mobility. Nevertheless, there is also a series of limitations in this respect and we would mention the most relevant ones.

Firstly, identifying inventors' affiliation is not always an easy task. In fact, when inventors apply for many patents (held by different applicants) for many different applicants, then it is not straightforward attributing an affiliation to inventors and tracing their movements across applicants.

Moreover, this consideration can be even reinforced. In fact, inventors are not necessarily affiliated to the applicants of their patents. This situation can apply to inventors working at university or public research organisations, which might be in charge of developing research in behalf of private companies, as well as to consultants or a 'free lance' researchers. Additionally, this can also be the case of inventors working for a subsidiary or a division of a big company that files patents only with the name of the company's headquarters[4].

In particular, of what concerns the appraisal of technology transfer from university to industry, the presence of university invented but not owned patents leads to two risks.

---

[2] USPTO: United States Patent and Trademark Office. EPO: European Patent Office.

[3] Patents indeed represent only a portion of innovative outcomes: not all inventions are patented. In fact, many inventions do not result into patents and patents are not considered the most important appropriability mechanism to protect innovations. Differently, firms may protect their inventions by other means such as through secrecy, lead-time advantages, and marketing. (Cohen et al. 2000)

Motivations for patenting vary across industries, technologies, and firms and may vary over time. 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. On the other side, also patents commercial value is largely variable (and, consistently, its significance with respect to innovation).

Finally, patents represent inventions, thus only a portion of innovative activities and do not entail activities and investments to commercialize new technology.

[4] 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.

On the one side, there is the risk of underestimating technology transfer from university to industry (Geuna and Nesta, 2005). On the other side, there is the risk of identifying inventors as movers when they are employed at another organisation and simply perform research or consultancy in behalf of third parties, which is a case of market for technologies.

Therefore, there is not only the risk of underestimating the mobility of inventors across organisations but also the risk of overestimating it, as in the case of market for technologies mentioned above. Moreover, this can also be the case of mobility across two companies where the company of destination is the result of a merger or a joint venture between the previous company and another one.

Finally, patent data contains information on the geographical location of inventors, namely their address. The ordinary hypothesis is that the address listed on the patent document is the address of residence of inventors. However, this is not always the case. In fact, there are a few companies that are used to ascribe their own location as inventors' address. This can affect the attribution of an inventor to a given geographical area and this risk increases with the number of applicants an inventor is patenting for. Therefore, this especially holds true for inventors who sign patents for many applicants, i.e. technology mobile inventors.

In all these cases then, technology mobility (i.e. mobility based upon patent data) could differ from pure job mobility (i.e. pure job change).

Despite these factors being rather relevant limitations of the use of patents data, these limitations could be somehow overcome through accurate and extensive data cleaning. On the other hand, there are other elements, say 'structural' elements, which cannot be overcome even through extensive data cleaning.

Firstly, 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 movements across organisations: by definition, several individuals are excluded from the analysis (most of the inventors have only one patent). Therefore, only more productive inventors are included in the analysis and this can introduce a potential bias towards more productive inventors. Moreover, even when considering only inventors that patent at two different applicants, 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 he 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 pure job mobility and the knowledge flows it give rise.

Secondly, if the affiliation recorded in the patent document does not reflect an employment relationship, a mismatch between employer and applicant will emerge. It follows that technology mobility may also identify different moves compared to pure 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 public research organisations which invent but do not own patents (Geuna and Nesta, 2005). Consequently, using patent data in order to describe the knowledge flows across organisations originated by labour mobility could be somehow misleading. More specifically, technology mobility and pure job mobility might indicate knowledge flows that involve different actors.

Thirdly, by using patent data in order to trace inventors' mobility, the professional career of an individual collapses into his patenting (innovative) activity track. Thus, technology mobility strictly reflects patenting activity of inventors. Conversely, tracing their career path and job moves requires going beyond the patent event and distinguishing between patenting (i.e. innovative) behaviour and professional career. In particular, this implies that 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 can affect the reliability of the inferences drawn by the econometric exercises based upon this type of data and cumulates to the restriction on inventors with at least two patents. Moreover, this adds up to endogeneity issues that are particularly relevant when studying the relationship between productivity and mobility of inventors. 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. 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: moving across firms then can expose to new environments and positively influence their innovative activity (Hoisl, 2007). It follows that technology mobility may suffer from greater concerns of endogeneity compared to pure 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 patent and survey data in describing inventors' professional career. At second, it aims at testing the differences between the inferences drawn from these two sets of data with specific reference to the above mentioned relationship between inventors' productivity and 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

Within innovation studies, 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). Unfortunately, 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 present survey is one of the first attempts to collect information on inventors that are complementary to patent documents. In fact, differently from previous ones, 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*. In this case, patent data turns out to be simply a means in order to select the questionnaire's respondents.

In the present work, 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 characteristics of the knowledge in this sector seem to be such that knowledge is embodied in individuals and can transmitted through their movements across firms. Therefore, the channel through which firms acquire new and relevant knowledge for innovative activities is a critical issue. Hiring and keeping people with this knowledge 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 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). Then, 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

[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.

inventors may have patented also before 1990 and after 2000. We identified approximately 1000 inventors that met this requirement.

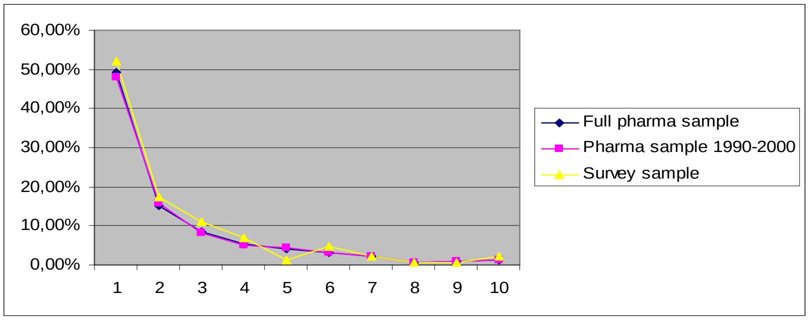
The survey has been conducted between January and March 2005. We contacted the respondents in relation to the first patent filed in the pharmaceutical sector between 1990 and 2000 and administered the questionnaire by email. As a consequence, this choice limited the number of people interviewed because 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 send back. 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 is integrated with patent data about each inventor interviewed; patent data is 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. 48 of them work for private companies, 35 for universities, 22 for public research organisations (PRO) 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 have 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 features 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. Distribution of number of patents per inventors



This consideration also holds true when comparing the number of moves across assignees (i.e. technology mobility) in the three samples, as Table 1 shows.

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

	Inventors with one patent	Inventors with more than one patent but the same applicant	Inventors with more than one patent and different applicants
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

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

Table 2. Frequency of the number of citations received per patent in the first five years, self-citations excluded (%)

	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

The selected sample then 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 such as the number of patents, the number of moves across assignees 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.

In the next section, we carry out a comparative analysis of patent and survey data. Firstly, we look at the differences between these two sets of data in the description of inventors' mobility. Then, we compare the results of a set of estimates based on these two groups of data.

3. A comparative analysis between patent and survey data

3.1. Descriptive statistics

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]. Technology mobility is thus much less frequent than pure job mobility.

More specifically, technology mobility frequently under-estimates pure job mobility (60 cases out of 65). It means that inventors do not file patents for all their employers. The rate of job mobility according to survey data is indeed much higher than the rate of job mobility according to patents data. Besides, technology mobility also over-estimates pure job mobility (7 cases out of 106); it is highly probable that this group

[7] Technology mobility is computed by controlling for two potential errors. 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. Then, 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 his applicants is a public research organisation 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 public research organisation.

captures phenomena of market for inventions. In fact, the inventors in this group either work at university or public research organisation while patenting for third party organisations, or work at the private sector and patent for a joint venture of their employer with other companies. Technology mobility and job mobility thus coincides only in 39 cases out of which 34 are cases of no mobility. The following table illustrates these figures.

Table 3. Computing job mobility: differences between patent and survey data

	Technology mobility (patent data)				
Pure 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	-	-

Technology mobile inventors hold on average 13 patents while pure job mobile inventors hold on average 6,8 patents. On average, technology mobile inventors are almost twice more productive than pure job mobile inventors.

Additionally, inventors neither patent for all the organisations they are employed at nor they are always affiliated to the applicants of their patents. By construction, in the cases in which technology mobility underestimates pure job mobility, an inventor's applicants do not mirror all his 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 this information. This happens in 34 cases out of 106, which amounts to 32% of the sample. In such cases then, technology mobility signals different moves compared to pure job mobility. The following table indicates the cases in which there is at least partial match between applicant and employer (Y column) or there is no match at all (N column), broken down by number of moves computed both according to patent and survey data.

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

	Technology mobility (patent data)									
	0		**1**		**2**		**3**		**4**	
Pure 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	-	-	-	-

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

For instance, among those inventors that never moved and for which there is no match at all between applicant and employer, all work either at university or at a public research lab. Moreover, inventors which worked always at the public sector (university or PRO) are more likely to show a mismatch between employer and applicant (61,3% of cases). On the other hand, inventors which always worked at the private sector almost always show a match between employer and applicant (18,75% of the cases, as Table 5 shows). However, it is worth pointing out that this count has done without taking into account the number of an inventor's moves. Moreover, we consider only inventors that never moved across different type of organisations (i.e. cases of intra-sector mobility are excluded).

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

Affiliation matching	Private sector	University	Public sector
Perfect	26	10	2
Partial	4	1	-
Not at all	2	14	4

When we look at inventors which moved across sectors, the picture is somehow more blurred. 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 technology mobility and job mobility 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 challenge the traditional interpretation of mobility phenomena based on patent data and suggest that pure job mobility and technology mobility might capture different aspects of inventors' career path. Firstly, this applies to the calculation of the number of moves. In fact, inventors do not patent at every organisation they work for or, put differently, technology mobility is less frequent than pure job mobility. As a consequence, the knowledge flows generated by inventors' pure job mobility are underestimated by technology mobility. On the one side, pure job moves describe the knowledge flows not only between organisations that do 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' mobility. On the other, technology moves still do capture knowledge flows but only those occurring across organisations that directly participate to the production of patented knowledge. Secondly, the match between applicant and employer is frequently partial or even incorrect, that is technology mobility and pure job mobility frequently involve different actors. This implies that relying exclusively upon patent data in order to depict the knowledge flows arising from inventors' mobility can be somehow misleading. This might have implications for the study of the hiring strategies implemented by organisations as well as for the study of the geographical concentration of innovative activities. In fact, it might be the case that technology moves are not associated (or only partially) to knowledge flows from the firm of departure to that of destination but they may involve different organisations. Conversely, it might be argued that this occurrence applies to the category of 'market for technology' rather than to that of pure job mobility. 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.

3.2. Econometric analysis

This part of the paper examines more in depth the differences between patent and survey data by looking at a group of estimates drawn from these two sets of data.

In particular, we explore the relationship between inventors' productivity and mobility. At first, we study whether productivity of inventors affects their mobility decisions; then, we analyse the effect of inventors' mobility on 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. pure job mobility). We then examine whether the use of these two measures of mobility can influence the relationship between productivity and mobility and the causality direction of this relation. In fact, it is possible to argue that the causality runs from productivity to mobility: more productive inventors are more likely to be 'raided' from competitors by means of better job offers. 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: moving across firms then can expose to new environments and positively influence their innovative activity.

Therefore, a relevant problem of endogeneity emerges as result of this two-ways relationship between productivity and mobility (Hoisl 2007). This paper aims at shedding new lights precisely on this aspect.

At first, we have looked at the factors that influence the numbers of moves an inventor records in his career. Since we are studying the cumulative number of moves, we are interested in modelling an event count. 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:

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

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

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

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

We tried to study the effect of different measures of productivity on the number of an inventor's moves. We excluded from the analysis retired inventors and those who entered the labour market before 1970. This is because we tried to limit the pure effect of inventors' time exposure and patent data is available from 1978. This reduces the sample to 97 subjects.

Therefore, following Trajetenberg (2005), the rate of occurrence (e.g. the number of moves) can be described as follows[8]

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

[8] We consider only one specific sector and country and we then do not need to control for countries and technological fields fixed effexts.

The dependent variable is the number of moves. This can be affected by several factors: the variable we are interested at most is productivity. We consider two different aspects: the number of patents filed and their quality. Productivity is thus proxied by the number of patents filed and patents' citations received (i.e. a measure of patents quality)[9]. 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 more patents and in this sample there are inventors with different labour market experiences. A squared term is added since the literature of labour economics indicates a quadratic effect 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 then looks like that in binary outcome model. 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.

[9] Moreover, we consider a maximum five year lag between a patent and it(s) citation(s).

Table 6. Description of the variables

Name of the variable	Description
EXP_PAT	Number of years in the labour market proxied as 2003-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[10]	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[11]	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 and 9 show the estimates obtained respectively for technology mobility and pure job mobility. The measures of the number of moves and the labour experience differ according to the data used. On the other side, three variables do not change according to the data used, namely the two productivity variables and the network variable.

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.

---

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

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

What is really interesting to the purpose of this paper is the effect of the two measures of productivity. Firstly, they are 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. Secondly, 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 and technology mobility, as Trajtenberg (2005), but differently from Hoisl (2007), which finds out a significant and negative effect. These differences could in part be driven by the adoption of different measures of productivity[12] and by the different settings examined (in particular Hoisl (2007) studies the effect of productivity on the probability of a single move).

Table 8. Poisson regression estimates based on patent data

	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

We then turned to look at pure 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 then introduced separately the two measures of

[12] Trajetenberg measures productivity as the cumulative number of patent applications and Hoisl as the total number of patents divided by age of the inventor at the time of the investigation minus 25 (the age he is expected to enter the labour market).

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). In conclusion, we find again a statistically significant (though less robust) and positive association between productivity and mobility.

Table 9. Poisson regression estimates based on survey data

	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.

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

The second aspect we investigated refers to the effect of technology and pure job mobility on an inventor's productivity. Accordingly, this analysis is performed through both patent and survey data. In particular, we study the effect of previous moves on the number of citations each patent receives in the first five years.

We used 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.

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. We studied the effect of previous moves on the number of patent citations received. Again, we excluded from the analysis retired inventors and those who entered the labour market before 1970, in order to limit the pure effect of inventors' time exposure and because patent data is available from 1978. This reduces the sample to 97 subjects. Moreover, since the definition of technology mobility can apply only to inventors with at least two patents, the sample of inventors is further reduced and amounts to 60 inventors.

Therefore, following Trajetenberg (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. It 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. 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 then 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. 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[13]	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[14]	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= previous mobility as computed through patent data; 0 otherwise)
SMOB_PRE	Dummy variable (1= previous mobility as computed through survey data; 0 otherwise)
MOB_P_PRE	Number of previous job moves as computed through patent data
MOB_S_PRE	Number of previous job moves as computed through 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

Table 12 shows the estimates obtained respectively from the baseline model (model 1), technology mobility (model 2 and model 3) and pure 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. pure job mobility). We estimated the model by introducing separately different measures of mobility in order to avoid risk of multicollinearity among these variables.

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

[14] 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.

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. 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 coefficients remain not significant and the fit of models decrease. 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 constant. Moreover, an additional move increases the number of citations by 1,16 citations, holding all other variables at their mean. These results are consistent with previous findings by Hoisl (2006) and Trajtenberg (2005).

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

As a consequence, it emerges a rather statistically robust relationship from technology mobility to productivity that is not confirmed when we use data on pure job mobility. Moreover, there is not support to the presence of an endogeneity problem between productivity and pure 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 pure 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.

Therefore, these results seem to challenge further the traditional interpretation of mobility phenomena based upon patent data. In fact, patent and survey data suggest rather different pictures. One possible interpretation for this challenging result is that this data captures different 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, patent data 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 pure job moves) does not necessarily lead to a significantly higher probability of being cited. Besides, these two networks can sometimes overlap and share the same actors but do not necessarily coincide. Finally, it is also likely that mobility assumes different connotations and is driven by different motivations in these two settings. Therefore, this could generate a mismatch between the interpretation and predictions obtained by using patent and survey data as long as they are meant to capture and 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 also lead to the creation of new firms.

Within innovation studies 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 indeed collects detailed information on inventors, their geographical location and the applicants of their patents.

This paper instead makes use of unique data on inventors' *curriculum vitae* derived from a survey addressed to a group of Italian inventors in the pharmaceutical field, and compares the information extracted from patent data to those derived from the survey. It has different goals. Namely, it aims at understanding whether these two types of data provide similar information or not, and whether they allow making similar inferences.

Results from descriptive statistics show that patent data frequently underestimate the presence of job mobility across firms: technology mobility is less frequent than pure job mobility. 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 PRO as well as for inventors that change job across these types of organisations. This has two important implications. Differently from pure 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 pure 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 proxies proposed for technology mobility. As a consequence, it emerges a rather statistically robust causal relationship from technology mobility to productivity that instead is not confirmed when we use data on pure job mobility. It follows that there is not support forthe presence of an endogeneity problem between productivity and pure job mobility. Rather, estimates indicate that the causal relationship seems running from productivity to pure job mobility, whereas the causal relationship between productivity and technology mobility seems to be bi-directional.

This paper provides important contributions to the current debate on workers' mobility. In particular, it challenges the traditional interpretation and use of patent data in order to describe inventors' career path. Moreover, it puts forward a number of differences between technology and pure job mobility in both the descriptions and the predictions that can be drawn. It also proposes an interpretation for these differences. In particular, it suggests that survey data might describe the whole set of inventors' employers and the knowledge flows across them; in such cases, pure job mobility is a channel for pure tacit and embodied knowledge transfer. On the other hand, patent data portrays the set of actors directly involved in inventive processes and directly participating 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 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.

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. Finally, 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.

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.

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.

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

Hoisl K. (2006), "Does Mobility Increase the Productivity of Inventors?", Munich Business Research, WP 2006-13.

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.

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.

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

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.