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WORKERS’ INNOVATIVE PRODUCTIVITY AND JOB MOBILITY
EVIDENCE FROM A SURVEY OF ITALIAN INVENTORS

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ABSTRACT

Technology transfer issues are of great interest in researchers and policy makers agenda because of its implications in terms of innovation diffusion and economic welfare. Among the others, workers’ mobility, namely highly skilled ones, is considered as one of the most influential channels for knowledge transmission.

This paper examines the patterns of mobility of a group of Italian inventors in the pharmaceutical sector. New empirical evidence is discussed and results of the analysis support the idea that workers’ mobility is an important mechanism of valuable knowledge diffusion. Moreover, the paper critically discusses methodological issues concerning measures of inventors’ mobility through patent statistics.
1. INTRODUCTION

The innovation studies literature considers the mobility of workers as one of the most important sources of knowledge flows and an influential means of knowledge transfer. Indeed, individuals ultimately mediate knowledge transfer. Individuals accumulate knowledge while working through a process of learning, thereby increasing their productivity and their stock of human capital. In addition, the characteristics of knowledge are such that, mainly in high tech sectors, it is frequently tacit, complex and specific. Hence, knowledge tends to be embodied in workers. When moving from one firm to another, they may establish a knowledge flow from the firm of departure to that of destination. Therefore, they may act as ‘pollinators’ and diffuse the knowledge they have. This consideration particularly applies to knowledge workers such as scientists, researchers, inventors, and technicians; in other words, it applies to those skilled workers that are responsible and deeply involved in innovative activities. In sum, workers’ mobility can be an important channel for knowledge transfer to the extent that knowledge is largely tacit and embodied in individuals. Unfortunately, only a few works consider and examine the implications of this type of knowledge transfer mechanism and even fewer works analyse the reasons why it occurs. On the contrary, given its consequences on firms’ innovative activities and mainly on the management of innovation, this is a key issue that needs further exploration.

Empirical evidence from labour economics literature points out that, to what concerns Italy, job-to-job moves are much more frequent in more innovative sectors than in more traditional ones, as well as more common among non-manual workers than among non-manual ones (Pacelli et al., 1998). Knowledge workers are obviously non-manual workers and are usually employed by firms that carry out innovative activities. They are also generally employed in innovative sectors. Therefore, the patterns described above are likely to apply also to them. However, in this line of reasoning, the differences among job-to-job mobility rates do not reflect individual characteristics or motivations but depend on existing differences at the industry or firm level.
This paper, differently from others, explores the reasons for different patterns of job-to-job mobility among inventors and aims at providing new empirical evidence on the relationship between workers’ innovative performance and their mobility decision. The implementation of a survey permits the collecting of new and original data on inventors’ characteristics and career paths that are complementary to information on their innovative behaviour (i.e. patent statistics). The econometric application allows for testing the relevance and the direction of the impact of different factors on the mobility outcome.

This paper is composed of four sections.

In the first section, I briefly review some contributions about productivity of workers and job mobility issues. In the second section, I present a model to explain the mobility decision. In the third section, I describe the motivation, the research design and the results of the survey I conducted on a sample of Italian inventors. In the last section, I discuss the results of the econometric applications. Conclusions follow.

2. WORKERS’ PRODUCTIVITY AND JOB MOBILITY

The productivity of scientists and more in general of knowledge workers is a key issue from many points of view and, in particular, for firms, it does not simply involve human resources and hiring strategies. This is also a crucial aspect that concerns the existence of a firm, its production and innovation activities, and it has strong impacts in terms of organisation and management of innovation.

The sociology of science extensively studied the scientists’ productivity issue since the seminal work of Lokta (1926); the author showed that productivity is highly concentrated within a small number of researchers.

Lokta’s law is a sort of inverse power law; more in details, given the number of researchers N with n publications,

\[ N \propto 1/n^2 \]

This means that the number of researchers with n publications is inversely proportional to the squared number of their publications.
This holds true also for inventors; indeed, a small number of inventors are responsible for most of the patents (Narin and Breitzman, 1995). Also the USPTO\(^1\) data confirms this result (Trajtenberg, 2005).

It follows that scientific and technological production is highly concentrated in a few individuals. Very productive workers represent a sort of scarce resource for firms that compete in order to attract and keep them.

Within innovation studies, most of authors focused on the productivity of scientists and technological transfer issues, by stressing the potential trade-off that they face between publishing and patenting activities. Indeed, publishing and patenting are two different knowledge dissemination means that are based on two different sets of norms, rules, incentives and evolutionary logics that regulate the production of knowledge (Gittelman and Kogut, 2003). These works are related to the traditional distinction between the production of science and the production of technology and try to assess to what extent patenting activities of universities may hamper research activities or, alternatively, may incentive technological transfer.

Only recently, some empirical studies explored the relationship between productivity and mobility of highly skilled workers. In effect, despite the literature on technology transfer being rather extensive, it is much more concerned with the beneficial effects of information diffusion than with the mechanisms through which it occurs. (e.g. knowledge diffusion via intellectual human capital). These empirical studies rely upon the assumption that given its tacit nature, knowledge is embodied in individuals (mainly highly skilled workers) and therefore, it can be transmitted across firms through workers’ mobility. Some of these works are focused on the characteristics of the originating and receiving firms while others on the geographical patterns of job mobility; most of the evidence is about the academic sector (Zucker et al., 1996, 1998; Crespi et al., 2005).

For instance, the presence and the geography of star scientists (i.e. highly productive scientists) strongly affected the localisation and the performance of biotechnology firms in California. This result suggests that productive scientists may play an extremely relevant role in the creation and success of firms and supports the idea that very productive individuals are a key asset for firms (Zucker et al., 1998).

\(^1\) USPTO is the US Patent and Trademark Office, the institution in charge of granting patents in US.
Moving ahead from this work, Zucker et al. (2002) explore the causes of a scientist’s movement from a university to a firm and find out that their productivity (measured as the number of human genetic sequences discovered) and the quality of their scientific production (measured as the number of citations received) positively affect the probability of moving away from academia. The authors highlight that these movements are an extremely important source of knowledge transfer from academia to business. Moreover, they interpret this result as an explicit strategy adopted by scientists in order to appropriate and exploit the economic returns of the knowledge they developed and possess. Finally, they argue that it is the presence of formal and informal links between universities and firms, through scientists’ movements, that create localised effects of university research and it is not the pure occurrence of localised knowledge spillovers from universities to firms.

Three main points emerge from these contributions:

1. Productivity is unevenly distributed across individuals not only because of their different talents but also because it follows and it is constrained by a set of social norms.
2. Productivity of knowledge workers is an essential input for firms’ creation and success.
3. Productivity may influence mobility choices and, as of consequence, it may impact on knowledge transfer via job mobility.

On the other hand, the literature on labour economics is much richer and more concerned with mobility patterns and determinants. Jovanovic (1979a) hypothesises that individuals are utility-maximiser agents and then they can leave a firm in search of a better job match; it follows that a job change occurs when they maximise their expected utility in doing so. By assuming that jobs are a sort of experience good and since experience increases with age, Jovanovic finds out that job mobility is expected to be decreasing with job tenure and experience. The basic argument is that individuals gain and accumulate knowledge while working and so increase their productivity and their stock of human capital. This human capital is partly firm specific and it is better exploited within the firm rather than elsewhere. Then, employer and employee can share these productivity gains and the rate of job separations is lowered (Becker, 1962).
However, information about workers’ ability evolves and increases over time. It follows that also the probability that an outsider recognises the ability of a given firm’s workers increases over time and therefore also the probability it makes a job offer increases over time. This particularly applies to those workers whose productivity can be easily observed by both insiders and outsiders such as scientists who publish their ideas or inventors who patent their innovations. It follows that the greater the performance, the higher the number of actual or perceived job offers received by a worker. Then, the best workers are more likely to be raided (Lazear, 1984). This effect partly offsets the job tenure effect that instead goes in the opposite direction.

Furthermore, this result couples with findings from managerial studies about the relationship between job performance and voluntary turnover. While involuntary turnover (or turnover that is recorded as voluntary but in the end is no-volitional) is more likely when job performance is low, voluntary turnover is positively related with job performance and the probability of a job change increases with a worker’s productivity (Jackofsky, 1984; Williams and Livingstone, 1994; Ernst and Vitt, 2000). Put in other words, it exists a curvilinear relationship (inverse U-shaped relationship) between performance and job mobility.

Finally, it is worth mentioning that factors such as, race, gender, educational attainment, wages, a firm’s size, regional differences and personal characteristics (marital status and number of children) have been largely proved to influence the patterns of job mobility. These patterns are affected both in terms of probability of moving and occupational choice (Topel, 1991; Topel and Ward, 1992; Parent, 1999).

This paper aims at testing the effect of workers’ productivity on job mobility outcome, by presenting new evidence from a survey addressed to Italian inventors in the pharmaceutical industry. This is a rather new field of interest within innovation studies but it is extremely relevant because of its implications in terms of appropriability issues, knowledge diffusion and technology transfer, and, ultimately, in terms of a firm’s innovative performance and innovation management strategies and policies.
3. MODELLING WORKERS' MOBILITY

According to Jovanovic (1979a), workers may leave a firm in search of a better job match; in other words, workers stay in their current job until they find a better match. This process can be described in this way. Each time the worker contacts a new employer and on the basis of this match the employer proposes a wage offer that should therefore reflect the marginal product of the worker within the new firm. In the long-run equilibrium, wage offer and marginal product will be equal; lower offers would be perceived as a negative signal and so workers would not select these firms, while higher wages would generate losses for the employer.

Topel and Ward (1992) extend this model to examine the career patterns of young men. They assume that the decision of mobility is affected by the value of staying (that can be thought of as the evolution of wages) as well as the outside offers from new employers. These offers are generated in their model from a known offer distribution that depends on individuals' characteristics and their cumulative labour market experience. On the other hand, the evolution of offers within the current firm depends on the current wage, the labour market experience and job tenure.

The authors are more concerned with the effects of labour market experience and wages, then they abstract from individual differences. On the contrary, my primary concern is to understand the effects of differences in inventors' innovative behaviour on mobility decisions. Using their notation, the external offer can be described in this way:

\[
\text{Prob} (w^o < z; X) = G(z; X), \quad G_i(z; X) \leq 0
\]

Where \(w^o\) is the outside wage offer and \(X\) the labour market experience.

The internal job offer follows this evolution:

\[
\text{Prob} (w < y; w, X, T) = F(y; w, X, T)
\]
Where $w$ is the internal wage counter-offer, $w$ the current wage, $X$ the experience in the labour market, and $T$ the tenure in the current firm.

Zucker et al. (2002) adopt a version of this model, but they focus only on the first equation, i.e. on the new employer side; they do not mention the current employer side. They model the decision of moving as function of the external job offer, but differently from Topel and Ward (1992) they are able to measure a vector $Q$ of indicators of expected value of marginal product. This vector includes variables that are proxy of the quantity and the quality of the research activity and that are expected to increase the scientist’s marginal value to a new firm (as well as to the current firm).

\[
\text{Prob}(w^e < z; Q) = G(z; Q), \quad G'(z; Q) \leq 0
\]

In contrast to Topel and Ward (1992), I am concerned with inventors’ characteristics, and mainly with their innovative activity and its quality. Moreover, I am interested not only in the new employer’s side (that is the focus of Zucker et al., 2002), but also in the current employer’s side.

Finally, it is worth noting that according to the search theory (Mortensen, 1987), workers face a cost for the search of a new job and, eventually, moving to a new employment.

Then, according to these contributions, the decision of moving may be modelled in this way: it depends on the outside job offer ($V$), on the current employer’s counter-offer ($W$) and on the cost of mobility ($C$). More specifically, a job change occurs when the expected value of the outside job offer exceeds the sum of the expected value of the current employer’s counter-offer plus the cost of mobility.

\[
\text{Pr}(\text{Mobility} = 1) \equiv \text{Pr}(V > W + C) = f(V, W, C)
\]

where $f_v > 0$, $f_w < 0$ and $f_c < 0$

Factors that increase $V$ or reduce $W$ or $C$ increase the probability of mobility, while factors that decrease $V$ or increase $W$ or $C$ reduce the probability of mobility.
I cannot directly measure these variables; however, it is possible to think of a series of factors affecting some or all of them:

- Workers’ characteristics.
- Knowledge characteristics.
- Retention and attraction strategies of firms.
- Network effect.
- Local demand.

**Workers’ characteristics**

Topel and Ward (1992) argue that the effect of *experience* is not linear and show that during the first 10 years of a career, workers frequently change job, but afterwards the probability of mobility tends to decline. Then, it is likely to increase W, because the worker’s value is already known to the current firm that may prefer paying a slightly higher wage rather than searching for a new worker. Finally, it also can increase C, because moving may require skills adjustment costs, mainly if skills are highly firm or task specific. In this case workers may perceive them as a sunk cost and decide not to move.

The effect of *productivity* is expected to be positive both on V and W. *Education* and number of previous *patents* granted can be considered signals of high individual productivity.

The *gender* effect of mobility is largely agreed: being female decreases the probability of mobility mainly due to sociological factors.

The type of *current employer* may affect the probability of mobility; working at university, in a private company or in public organisations requires the adoption of different sets of norms, practices, and routines. Consequently, changing job, mainly when it occurs across different types of organisations, implies some costs.

Finally, being an owner of a *firm* obviously increases C, and it decreases the probability of mobility.

**Knowledge characteristics**

Knowledge characteristics can be evaluated according to two basic dimensions of analysis: *quality* and *incrementality*. The former refers to the economic value of a specific bit of
knowledge and the latter to the incrementality of a specific bit of knowledge compared to the state of the art of technology. The effect of quality is expected to be positive on V and W as well as the effect of incrementality.

Patents quality indicates the economic/technological value of patent. It can be captured by the citations received from other patents. The higher the number of citations received, the higher the quality of a patent and the higher V and W. The degree of incrementality indicates its suitability to be actually implemented by a firm (Palomeras, 2004; Crespi et al., 2005) and should therefore increase the value of a worker both to the hiring firm and the current one. Then, the higher the degree of incrementality is the higher V and W. This aspect can be captured by the number of citations made.

Retention and attraction strategies of firms

The presence of retention strategies implemented by firms in order to keep employees may be viewed as an increase in C and sometimes, also in W (for instance when extra-rewards are paid for the innovative efforts of workers). The presence of attraction strategies however increases the value of V and therefore the probability of mobility.

Network effect

If a worker is well connected in a dense network of relationships with other actors (i.e. workers), either from the same organisation or from different ones, she is more likely to be informed of new vacancies and has more probability of moving. This effect operates by reducing the costs of information and search that are mobility costs. In this case, this effect can be captured by the number of co-inventors. On the other hand, a high number of co-inventor may be perceived by the hiring firm as a negative signal of low contribution to the innovative output, thus reducing the value of V. Finally, a number of co-inventors can highlight that the inventor is deeply involved in a firm’s projects, thus increasing W.

Geographical location – potential demand

The geographical location of workers affects the cost of moving. On the one side, working in highly industrialised regions where many firms, universities, research centres are located, makes less costly to move from the current job to a new one within that area; on the other side, it also has a higher opportunity cost of moving outside it.
The table below summarises these relations.

<table>
<thead>
<tr>
<th>Variables</th>
<th>V - outside offer</th>
<th>VV - inside counteroffer</th>
<th>C - cost of mobility</th>
<th>NET EFFECT on mobility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>Education</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Productivity</td>
<td>+</td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Gender</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Current employer</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Firm ownership</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Quality</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Incrementality</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Retention strategies</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Attraction strategies</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Network effect</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Geographical location</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

3. THE DATA

3.1. Introduction and motivation of the survey

Within innovation studies, many surveys have been conducted in order to monitor and to collect new evidence on innovation activities; some of them only have had state-level coverage, while others have been designed and also implemented at the European level.

Innovation surveys are very useful because they provide complementary data about innovative activities (in terms of inputs and outputs) that are not captured in the usual statistics such as patents or R-D expenditures. However, most of the survey implemented were object-oriented (the focus is on innovation activities performed within firms) rather than subject-oriented (about firms carrying out innovation). Moreover, none of them aimed at collecting data at the individual level about those individuals directly involved and responsible for innovation activities. More recently, the PATVAL survey—Patent Value—tried to fill this gap. PATVAL is a patent survey that collected data in six European countries (UK, Italy, Spain, Germany, France, and Netherlands) about patents and their inventors. On the one hand, this is one of the first attempts to gather information about inventors that is complementary to patent documents; on the other hand, the focus of the survey is about
patents, their value and the incentive for patenting. Given this research objective, the
information about inventors is relatively limited compared to those available about patents.

The survey I developed, unlike others, is addressed at individuals and it aims at collecting
data not about their innovative performance, but mainly about their professional experience
(i.e. their curriculum vitae); patent data in this case is simply a means in order to select the
questionnaire’s respondents.

There are different motivations for the decision of implementing a new survey addressed to
inventors. Firstly, most of the studies on inventors’ mobility rely on patent data in order to
extract information about inventors’ career path. However, there are some distortions and
limitations related to the use of patent data in order to trace inventors’ mobility. I would
highlight the most important ones:

1. It restricts the analysis to those inventors with at least two patents; for those with
   only one, there is not information to trace their career path.
2. It is not possible to define time of arrival and time of departure from a firm. There is
   simultaneity between arrival or departure and patenting.
3. Affiliation does not always imply that the inventor is employed in one of the applicant
   firms or organisations: inventors can simply be consultants or ‘free-lance’
   researchers. In particular, in the case of university researchers, they might simply
   perform research on behalf of private companies that are listed as applicants. These
   researchers are listed as the inventors of patent, but their university is not the
   applicant.

In addition, I realised there is lack of more qualitative information about inventors; for
example education, motivations for quits, importance of covenants not to compete and the
presence of incentive schemes for innovation production. This information is probably as
relevant as innovative performance in explaining their decision for changing jobs. Finally and
partly linked to this point, tracing their career path requires going beyond the patent event
and distinguishing between patenting (i.e. innovative) behaviour and professional careers.
3.2. Research design

In this work, I selected from the EP-Cespri\(^2\) database all Italian inventors with at least one patent in the pharmaceutical field in the period 1990-2000.

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. I considered only the primary class. In order to identify all the patents corresponding to the selected field, I followed a 30 technology fields classification\(^3\).

Pharmaceutical is a knowledge-intensive sector where innovation is really one of the most important sources of competitive advantages for firms and an engine of competitive processes. 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. Finally, the characteristics of the knowledge in this sector seem to reflect the idea of embodied knowledge introduced and discussed earlier. These considerations make the pharmaceutical sector a favourable setting for studying workers’ mobility and its impact on innovation.

Patent data are available in the EP-Cespri dataset from 1978; I tried to select people that entered the labour market around that time or, at least, not too many years before that time. Indeed, my 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, I selected those inventors that patented at least once between 1990 and 2000. Assuming some time lag between entry in the labour market and the first year of patenting activity, this led me to select 1990 as the lower bound. Moreover, given that the distribution of patents over time is uneven and rapidly falls in the later years, I chose 2000 as the upper bound. It follows that the selected inventors may have patented also before 1990 and after 2000.

\(^2\) Cespi - 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.

\(^3\) 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 et des Techniques (OST, Paris). This classification aggregates all IPC codes into 30 technology fields.
I identified 1136 inventors active in the pharmaceutical sector between 1990 and 2000. Inventors have been selected regardless of their region of residence, their affiliation or the number of patents filed. I started to search and collect their personal contacts. Overall, I collected 700 contacts and I implemented a pilot study on 32 individuals. I decided to contact them in relation to the first patent they filed in the pharmaceutical sector between 1990 and 2000 and to submit the questionnaire by email. The questionnaire is a 6-page document attached to the email text that the respondents had to fill in and send back. The pilot test had a 25% response rate. I then decided to submit all the questionnaires by email. As a consequence, this choice limited the number of people interviewed because I was not able to collect the email address for all of them. Overall, I sent 281 emails. 20/25 days after the first contact, I sent a reminder email with the questionnaire attached. In the end, I obtained 38% response rate (106 returned questionnaires), with at least 80% response rate per question. This result probably underestimates the response rate; indeed, I suspect that among those who did not answer the questionnaire there are cases of homonymy that I could not exclude before submitting the questionnaire.

The questionnaire is composed of 3 main sections. The first one aims at collecting personal information. The second section aims at tracing the career path of the respondent. In section three I added some questions about the type of agreements reached with the organisations they worked for (i.e. covenants not to compete, reward scheme for inventive activity).

In the empirical analysis, data collected through the questionnaire is integrated with patent data of each inventor interviewed extracted from the EP-Cespri dataset, namely the number of patents filed, the citations made and received and the number of co-inventors.

3.3. Description of the data

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 centres or hospitals, and 1 is retired. There is one independent consultant; all the others are employed by firms, universities or other organisations. These inventors are affiliated to 32 different firms, 21 universities and 12 public organisations (out of which 3 are hospitals). This implies that some inventors work in
the same place. Looking at their complete career up to 2005, they have been affiliated to 50 different firms, 34 universities and 22 public organisations.

Of what concerns their geographical distribution, 2 of them now work abroad (Switzerland), 65 in the North of the country (among which 43 in Milan), 29 in the Centre and 10 in the South and the Islands. The following figure shows their geographical distribution according to the workplace (Figure 3.3.1).

**Figure 3.3.1. Geographical distribution of inventors according to their workplace**

![Geographical distribution of inventors according to their workplace](image)

Almost all of them hold a degree (there are only two inventors with high school diplomas); more interestingly, many of them (60 individuals, around 60%) hold also a post-graduate qualification such as a masters, PhD or similar (Medical School).

Looking at inventors’ mobility, the data shows that inventors almost always changed job voluntarily (there is only one case in which mobility is due to firm’s failure). More interestingly, the information collected with the questionnaire allows us to compare real mobility to that measured through patent data. On the one hand, according to patent data, 71 inventors never moved and 35 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.

It follows that using patent data to calculate job mobility implies the risk of both underestimation and overestimation of real mobility and the statistics are obviously biased according to the number of patents filed by the inventor. Since the definition of mobility applies only to inventors with at least two patents, the major problem is that of simultaneity of measurement of mobility and productivity (i.e. number of patents). It is highly probable that in these cases mobility increases with the number of patents, while mobility is by
definition zero, and probably underestimated, for all of them with only one patent. In the examined cases, patent data overestimates mobility in 12 cases and underestimates it in 58 cases; only 36 cases (34%) are correctly predicted, out of which 29 are cases of no mobility. The table below illustrates the differences between patent and survey data in calculating job mobility.

Table 3.3.2. Calculating job mobility: comparison between patent and survey data

<table>
<thead>
<tr>
<th>Number of moves (survey data)</th>
<th>Number of moves (patent data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>2</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

It seems that patenting life of inventors describes a different phenomenon from a professional career. When trying to trace inventors’ career paths by using patent data, there is an enormous risk of obtaining partially reliable counts. In this respect, it is possible to say that patenting activity only captures a limited and incomplete aspect of inventors’ professional experience. It is more likely that it is a good proxy for inventors’ technical expertise and competences and for their attitude to team working, knowledge sharing and exchange (relational aspects). On the other hand, it is less likely that is a reliable proxy in order to describe inventors’ curriculum vitae.

The table below illustrates the relationship between productivity and mobility, as measured by patent data and survey data. In this case I do not consider the number of moves but only whether mobility occurred (mobility = 0 if it never occurred, mobility = 1 if it occurred at least once) and I distinguish only between inventors with one patent and inventors with more than one.

Table 3.3.3. Productivity and mobility: comparison between patent and survey data

<table>
<thead>
<tr>
<th>Patent data Mobility = 0</th>
<th>Mobility = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent = 1</td>
<td>27 (25%)</td>
</tr>
<tr>
<td>Patent &gt;1</td>
<td>44 (42%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Survey data Mobility = 0</th>
<th>Mobility = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobility = 0</td>
<td>9 (9%)</td>
</tr>
<tr>
<td>Mobility = 1</td>
<td>32 (30%)</td>
</tr>
</tbody>
</table>

According to patent data, the cases of no mobility are over-represented while the cases of mobility are much under-represented. Moreover, among those with only one patent, real mobility occurs in 2/3 of the cases (66%), while among those with more than one patent it
occurs in $3/5$ of the cases (60%). I also checked that these results are not only due to the time individuals spent in the labour market. It is probable that the longer the time they spent in the labour market, the higher the probability they changed job; moreover, the older the first patent, the higher the probability that the inventor files other patents. In other words, the earlier they entered the labour market, the higher the probability they changed job or they were more productive. Then, I compared the average labour market experience of inventor with only one patent and that of more productive inventors and they are really close (22 years for the former group and 24 for the latter). I made the same comparison for mobile and non mobile inventors and the differences are really small (25 years for the former and 21 for the latter). It follows that this results does not seem to be affected by the time exposure to labour market or patenting activity of inventors.

4. THE ECONOMETRIC ANALYSIS

4.1. The econometric models

I decided to adopt a duration model because it allows us to deal with censored and uncensored observations at the same time. Duration models allow studying a group of individuals for whom a point event of some kind is defined; this point event is generally referred to as a failure. Failure occurs after a length of time that is called failure time. In this case the ‘failure’ event is a job change and the spell length is the duration or occupancy of a given state and is exactly the number of years before it occurs. In other words, it is the number of years spent in a firm, i.e. job tenure.

The hazard function indicates the instantaneous rate of exit from a given state (leaving a firm), conditional on the state being occupied (working for that firm). Put in other words, it is the probability that the failure event (worker leaving the firm) occurs in a given interval, conditional upon the worker having survived to the beginning of that interval, divided by the length of time (Cleves et al., 2004). Then, the hazard may be interpreted not only as the probability of job change, but also as the risk that this event occurs.

The relationship occurring between hazard rate and duration is called duration dependence. Since I do not have any a priori hypothesis on the functional form of the hazard, I decided to
use a Cox semiparametric approach that does not require specifying the baseline hazard. It can assume whatever shape, provided that is the same for every subject. Then, the hazard function can be written as a proportional hazard model

\[ h(t; x_j) = h_0(t) \ h_1(x_j) \quad j = 1, \ldots, n \]

where \( h_0 \) and \( h_1 \) are the same functions for all \( j \) individuals.

In particular, it is possible to set

\[ h_1(x_j) = \exp(x_j \beta_x) \quad j = 1, \ldots, n \]

and then the hazard at time \( t \) for individual \( j \), conditional upon the covariates \( x \), becomes

\[ h(t; x_j) = h_0(t) \ \exp(x_j \beta_x) \]

and, by substituting the covariates,

\[ h(t; x_j) = h_0(t) \ \exp(\beta_1 \text{experience}_j + \beta_2 \text{education}_j + \beta_3 \text{productivity}_j + \beta_4 \text{gender}_j + \beta_5 \text{current_employer}_j + \beta_6 \text{firm_ownership}_j + \beta_7 \text{quality}_j + \beta_8 \text{incrementality}_j + \beta_9 \text{retention_strategies}_j + \beta_{10} \text{attraction_strategies}_j + \beta_{11} \text{network_effect}_j + \beta_{12} \text{geographical_location}_j) \]

Parameters are estimated with a partial maximum likelihood method, suggested by Cox (1972).

I consider the case of repeated job changes. I treat every job change as different from the others: after a job change occurs, the time at risk starts again from 1. It follows that mobile inventors enter the analysis as \( (n + 1) \) different individuals, where \( n \) is the number of job changes. I also inspect the presence of unobserved heterogeneity across inventors. Finally, as observations on mobile inventors are obviously not independent, a robust estimator is used.
The last aspect I investigate is about the factors that influence the number of moves that an inventor records in her career (that is the realisation of the probability examined in the duration model). I am interested in modelling an event count that is the number of times the event mobility occurs; this can also be viewed as the rate of occurrence of the event. In this case, specific models for count data must be applied and they all have a benchmark model that is the Poisson distribution.

In this model $\mu$ 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 $\mu$ and $y$:

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

In this distribution, $\mu$ is the only parameter defining the distribution. Moreover, $E(Y) = \text{Var}(Y) = \mu$: 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 $\mu$ can vary across observations depending on some regressors. Then, the dependent variable $y$ is distributed with density

$$f(y_i|x_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!} \quad i = 1, \ldots, n$$

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 $\mu_i$ is positive and $y_i$ is 0 or positive. Moreover, given the property of equi-dispersion, it also signals that the model is intrinsically heteroscedastic; then a robust estimator is required. Finally, I check for two frequent problems in count data: overdispersion and excess of zeros.
Finally, by substituting the regressors\textsuperscript{4}

\[ \mu_i = E(y_i|x_i) = \exp(x_i\beta) = \exp(\text{experience}\theta_1 + \text{education}\theta_2 + \text{productivity}\theta_3 + \text{gender}\theta_4 + \text{current_employer}\theta_5 + \text{quality}\theta_6 + \text{incrementality}\theta_7 + \text{retention_strategies}\theta_8 + \text{attraction_strategies}\theta_9 + \text{network_affect}\theta_{10} + \text{geographical_location}\theta_{11}). \]

\textbf{4.3. Comments of the results}

\textbf{Duration model}

Before commenting on the results of the estimates, I firstly describe the variable adopted in the econometric exercise and how I measured them. Table 4.2 reports this information. Data about attraction and retention strategies are not available for every spell, but for the whole career and cannot be exploited. Finally, I also excluded from the analysis retired inventors and those who entered the labour market before 1970. This is because I tried to limit the pure effect of inventors’ time exposure and patent data is available from 1978. This reduces the sample to 98\textsuperscript{5} subjects that amounts to 234 observations.

It is worth pointing out that there is a potential risk of problems of endogeneity. This brought me to introduce the relevant variables (those related to the number of patents filed by an inventor as productivity, quality, and network effect) with one spell lag.

\textbf{Table 4.2. Description of the variables}\textsuperscript{6}

<table>
<thead>
<tr>
<th>Name of the variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>Number of years in the labour market previous to the current employment</td>
</tr>
<tr>
<td>Exp\textsuperscript{2}</td>
<td>Squared experience</td>
</tr>
<tr>
<td>Education</td>
<td>Dummy variable (1 if the inventor holds a post-lauream qualification, 0 otherwise)</td>
</tr>
<tr>
<td>Productivity</td>
<td>Average number of patents (number of patents filed in the last employment divided by the number of years in that employment)</td>
</tr>
<tr>
<td>Gender</td>
<td>Dummy variable (1 if the inventor is male, 0 if female)</td>
</tr>
<tr>
<td>Current employer</td>
<td>Dummy variable (1 if employer is university, 0 otherwise)</td>
</tr>
<tr>
<td>Firm ownership</td>
<td>Dummy variable (1 if the inventor is the owner of the firm, 0 otherwise)</td>
</tr>
<tr>
<td>Quality</td>
<td>Average number of citations received in the first five years per patent in the last employment</td>
</tr>
<tr>
<td>Incrementality</td>
<td>Average number of citations made per patent in the last employment</td>
</tr>
<tr>
<td>Network effect</td>
<td>Average number of co-inventors per patent in the last employment</td>
</tr>
<tr>
<td>Geographical location</td>
<td>Dummy variable (1 if the inventor works in Milan, 0 otherwise)</td>
</tr>
<tr>
<td>Location</td>
<td>Dummy variable (1 if the inventor works in the North of Italy, 0 otherwise)</td>
</tr>
</tbody>
</table>

\textsuperscript{4} In this model I exclude firm ownership; I expect that this variable strongly affects the decision of moving or not, but it is not extremely relevant in order to understand the reasons for the realisation of a different number of moves.

\textsuperscript{5} In the duration model I am bound to consider only 97 individuals because one of them change job twice during the same year. This originates some problems as the analysis time is measured in year.

\textsuperscript{6} Literature points out that the effect of experience is not linear; this is why I add the square of experience.
The table below reports summary statistics for these variables.

### Table 4.3. Summary statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>N. of observation</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>234</td>
<td>5,453</td>
<td>7,473</td>
<td>0</td>
<td>32</td>
</tr>
<tr>
<td>Experience squared</td>
<td>234</td>
<td>85,376</td>
<td>180,639</td>
<td>0</td>
<td>1024</td>
</tr>
<tr>
<td>Education</td>
<td>234</td>
<td>0,564</td>
<td>0,497</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Gender</td>
<td>234</td>
<td>0,846</td>
<td>0,362</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Current employer</td>
<td>234</td>
<td>0,282</td>
<td>0,451</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Firm</td>
<td>234</td>
<td>0,034</td>
<td>0,182</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Productivity</td>
<td>234</td>
<td>0,165</td>
<td>0,601</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Incrementality</td>
<td>234</td>
<td>0,321</td>
<td>0,880</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Quality</td>
<td>234</td>
<td>0,249</td>
<td>0,764</td>
<td>0</td>
<td>6,75</td>
</tr>
<tr>
<td>Network effect</td>
<td>234</td>
<td>0,482</td>
<td>1,327</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>Dummy 1 - Milan</td>
<td>234</td>
<td>0,345</td>
<td>0,477</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Dummy 2 - North</td>
<td>234</td>
<td>0,184</td>
<td>0,389</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

I progressively estimated the full model in four different steps (Table 4.4).

When only inventor’s characteristics are included (Model 1), there are three variables explaining the decision for changing job: experience in the labour market, gender, and innovative productivity. As the literature highlights, experience has a significant and non-linear effect; when experience is limited (young people, new entrants in the labour market) the hazard of changing job is higher. When experience is sufficiently higher, labour positions become more stable. To what concerns gender, being male significantly increases the hazard of changing job, as the literature points out.

The effect of productivity is more interesting. The average number of patents in the last employment makes the inventor more willing to move: the effect of productivity is greater on V than on W, as suggested by Lazear (1984). The other variables enter with the expected sign although not significantly. Holding a post-graduate qualification increases the probability of moving. Working at university decreases the hazard. Being owner of firm decreases the probability of a move. Overall the model fits well and is highly significant.

Model 2 adds the variables measuring incrementality and quality of inventions. The fit of the model slightly increases. Incrementality and quality variables do not enter significantly. However, looking at the sign of their effect it seems that the more incremental a patent is, the less likely a job move. The higher a patent’s value the higher the probability of a move. It would mean that inventors with more radical and valuable inventions are more likely to
change employment. Experience, gender, and productivity variables are still significant. All the other variables keep their sign, but are not significant.

Model 3 includes the network effect as measured by the number of co-inventors. The variable is not highly significant (significant at 15%) with positive sign. Incrementality is now significant at 10% with the same sign: it reduces the hazard. Neither the significance nor the sign of the other variables change.

Finally, model 4 incorporates the dummy variables for geographical location. I decided to insert only two variables for geographical location that should control for the Italian regions where most of the economic activities (and also pharmaceutical companies) are located. Being located in the North or in Milan decreases the hazard. In particular, being located in Milan significantly decreases the hazard. These results are consistent with the view that moving from a highly industrialised region (North) has higher opportunity costs than moving from less industrialised regions (South). The overall fit of the model increases. Once all the variables of interest are included in the equation, experience, gender, productivity, and incrementality are significant along with dummy for geographical location. Then, mobility ultimately depends on labour market experience, innovative productivity characteristics of inventors and the geographical position.
I also test the robustness of this model to the presence of unobserved heterogeneity. However, the test rejects it. I conclude that the estimates in table 4.4 are robust to the omission of heterogeneity.

**Count regression**

Before commenting on the results of the analysis, I firstly provide summary statistics for the variables used (Table 4.5). In this model, I excluded some variables considered in the duration analysis: I could not insert the dummy for type of employer and the dummies for geographical areas. These variables not only might change over the period of time examined but also they are more likely to change when mobility occurs. This also applies to the dummies for retention and attraction strategies that therefore are excluded from the regression. Productivity is measured through the cumulative number of patents divided by the years in the labour market; incrementality, quality, and network effect respectively through the cumulative number of citations made, citations received, and co-inventors weighed by the number of patents. Again, inventors that entered the labour market before 1970 as well as the retired are excluded.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model1</th>
<th>Model2</th>
<th>Model3</th>
<th>Model4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>0.153***</td>
<td>0.154***</td>
<td>0.146***</td>
<td>0.150***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.046)</td>
<td>(0.047)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Experience squared</td>
<td>-0.004*</td>
<td>-0.004*</td>
<td>-0.004*</td>
<td>-0.004**</td>
</tr>
<tr>
<td>Gender</td>
<td>0.542**</td>
<td>0.542**</td>
<td>0.567**</td>
<td>0.583**</td>
</tr>
<tr>
<td></td>
<td>(0.259)</td>
<td>(0.259)</td>
<td>(0.253)</td>
<td>(0.254)</td>
</tr>
<tr>
<td>Current employer</td>
<td>-0.156</td>
<td>-0.156</td>
<td>-0.156</td>
<td>-0.156</td>
</tr>
<tr>
<td></td>
<td>(0.205)</td>
<td>(0.205)</td>
<td>(0.205)</td>
<td>(0.205)</td>
</tr>
<tr>
<td>Education</td>
<td>0.084</td>
<td>0.084</td>
<td>0.084</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.177)</td>
<td>(0.177)</td>
<td>(0.177)</td>
<td>(0.177)</td>
</tr>
<tr>
<td>Firm</td>
<td>-0.989</td>
<td>-0.989</td>
<td>-0.989</td>
<td>-1.006</td>
</tr>
<tr>
<td></td>
<td>(1.164)</td>
<td>(1.164)</td>
<td>(1.164)</td>
<td>(1.164)</td>
</tr>
<tr>
<td>Productivity</td>
<td>0.174*</td>
<td>0.206**</td>
<td>0.225**</td>
<td>0.204**</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.109)</td>
<td>(0.109)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Quality</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
<td>0.087</td>
</tr>
<tr>
<td></td>
<td>(0.151)</td>
<td>(0.151)</td>
<td>(0.151)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Incrementality</td>
<td>-0.112</td>
<td>-0.179*</td>
<td>-0.173*</td>
<td>-0.173*</td>
</tr>
<tr>
<td></td>
<td>(0.109)</td>
<td>(0.109)</td>
<td>(0.109)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Network effect</td>
<td>0.091</td>
<td>0.091</td>
<td>0.091</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.063)</td>
<td>(0.063)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Dummy 1 - Milan</td>
<td>-0.324*</td>
<td>-0.324*</td>
<td>-0.324*</td>
<td>-0.324*</td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
<td>(0.183)</td>
<td>(0.183)</td>
<td>(0.183)</td>
</tr>
<tr>
<td>Dummy 2 - North</td>
<td>-0.040</td>
<td>-0.040</td>
<td>-0.040</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(0.211)</td>
<td>(0.211)</td>
<td>(0.211)</td>
<td>(0.211)</td>
</tr>
<tr>
<td>Wald $x^2$</td>
<td>41.91***</td>
<td>45.69***</td>
<td>47.41***</td>
<td>54.21***</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-587.685</td>
<td>-587.387</td>
<td>-586.920</td>
<td>-585.532</td>
</tr>
<tr>
<td>Number of</td>
<td>234</td>
<td>234</td>
<td>234</td>
<td>234</td>
</tr>
<tr>
<td>observation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Breslow’s method for ties</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.
As in the duration analysis, I progressively estimated the full model in three steps (Table 4.6). Model 1 considers the effect of inventor's characteristics. Gender and experience significantly enter the regression; productivity and education are not significant but with the expected sign. In model 2, I introduce the variable for incrementality and quality; they enter significantly and with the same sign as in the duration analysis. The more radical and valuable the inventions the higher the number of job moves. Gender is still significant: not surprisingly being male increases the number of job moves during a professional career. On the other side, experience is no more significant; productivity is still not significant and it also changes sign. Finally, the network effect is not significant with a positive sign, as in the duration analysis while all the other variables keep their sign and significance (model 3).

Table 4.6. Poisson regression – estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model1</th>
<th>Model2</th>
<th>Model3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>0.174* (0.096)</td>
<td>0.129 (0.098)</td>
<td>0.129 (0.095)</td>
</tr>
<tr>
<td>Experience squared</td>
<td>-0.003 (0.002)</td>
<td>-0.002 (0.002)</td>
<td>-0.002 (0.002)</td>
</tr>
<tr>
<td>Education</td>
<td>0.085 (0.236)</td>
<td>0.089 (0.262)</td>
<td>0.073 (0.204)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.700** (0.307)</td>
<td>0.585* (0.307)</td>
<td>0.677** (0.313)</td>
</tr>
<tr>
<td>Productivity</td>
<td>0.065 (0.239)</td>
<td>-0.168 (0.287)</td>
<td>-0.108 (0.275)</td>
</tr>
<tr>
<td>Incrementality</td>
<td>0.125* (0.065)</td>
<td>0.129** (0.063)</td>
<td>0.182** (0.093)</td>
</tr>
<tr>
<td>Quality</td>
<td>0.182* (0.094)</td>
<td>0.183* (0.072)</td>
<td>0.183* (0.072)</td>
</tr>
<tr>
<td>Network effect</td>
<td>0.091 (0.072)</td>
<td>0.091 (0.072)</td>
<td>0.091 (0.072)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.394** (1.159)</td>
<td>-2.234*** (1.120)</td>
<td>-2.490** (1.062)</td>
</tr>
</tbody>
</table>

Wald, $\chi^2$ 12.45** (12.45**), 26.81*** (26.81***), 30.98*** (30.98***)

Log-likelihood 156.023, 152.332, 151.317

*p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.
I also checked the robustness of this model against negative binomial and zero inflated models. The model is robust to the presence of unobserved heterogeneity that otherwise would lead to negative binomial regression (and this result is consistent with that of duration analysis). Secondly, the presence of two different processes generating the count is not supported. Then, the estimates are robust to these possible sources of problems.

The basic predictions of the duration analysis are confirmed even if some differences emerge. When looking at the number of job changes the significance shifts from the measure of productivity to the characteristics of the knowledge and the innovation generated namely incrementality and quality. Productivity, as measured in the duration model, is likely to reflect only short term performance while quality and incrementality as measured in the Poisson regression are likely to capture longer term proxies of performance. This could explain the shift of significance from productivity to innovation quality measures when the whole career (and therefore the number of job changes) of an inventor is examined. Finally, the usual measures of experience are no longer a significant predictor of the number of job changes when other variables, such as innovation quality, are taken into account.

5. CONCLUSIONS

This paper examined the relationship between innovative performance of inventors and their decision of changing job. In particular, I focused on their innovative productivity as a key determinant of their mobility decision. This analysis relies on the results of a survey addressed to a sample of Italian inventors; moreover, two econometric applications are discussed in order to assess the significance and the direction of productivity effects.

The results of the survey provide a methodological contribution to the current debate on the relevance of workers’ mobility as a channel for knowledge diffusion. Firstly, they show that job mobility is a much more frequent phenomenon than what emerges from patent statistics. Moreover, they clearly point out that patenting activity patterns of inventors rarely and imprecisely reflect their career path. Therefore, using patent statistics in order to depict the knowledge flows originated by workers’ mobility systematically underestimate the intensity and the size of these phenomena. As discussed in the paper, patent statistics are
probably more suitable in order to capture the relational and collaborative aspects of the inventive process than to illustrate the *curriculum vitae* of an inventor.

The econometric analysis shows that along with traditional explanation of job mobility, inventive productivity and the characteristics of the knowledge produced do matter in order to determine the mobility outcome. It also shows that workers’ mobility allows transmitting ‘good knowledge’ and therefore this is a mechanism of technology transfer that needs to be supported and promoted.

This analysis also suggests that besides the beneficial effects on knowledge diffusion, workers’ mobility also implies some risks for firms since the greater the productivity of an inventor, the higher the risk she will leave a firm. In particular, there is a risk of losing proprietary and highly valuable knowledge. Therefore, these results also highlight a substantial problem of appropriability on the knowledge generated by a worker while working for the firm of departure: knowledge workers’ mobility then may have serious implications for firms’ innovative activities and performance. Moreover, these quits are only a part of the loss experienced by this firm. The departing worker can move and exit the labour market. Alternatively, the departing worker can move and join a new firm that can also be a competitor of the previous one (mobility is more frequent within than across sectors). This implies that the new firm will benefit from the knowledge generated elsewhere and this is exactly a matter of externalities. More interestingly, in this case externalities are mediated by exchanges that take place in the labour market. Organisation and management of innovation should carefully take into account the presence of such a risk. As some contributions point out, a redefinition of property rights on the knowledge and innovations developed within firms as well as a redefinition of the sharing rules of economic returns of innovative outcomes can represent a possible solution (Aghion and Tirole, 1994; Anton and Yao, 1994; Pakes and Nitzan, 1989).
BIBLIOGRAPHY


