J Technol Transf (2010) 35:651–670
DOI 10.1007/s10961-009-9130-6

Workers' mobility and patterns of knowledge diffusion: evidence from Italian data

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Published online: 26 June 2009

Abstract The channels through which firms access and acquire new and relevant knowledge for their innovative activities is a critical issue to the geography and the management of innovation. In this regard, recent studies have suggested that the mobility of workers across firms is a primary source of new knowledge for the hiring firm and, more in general, of knowledge diffusion across firms. However, little evidence has been presented and discussed about the role and the impact of workers' mobility on the processes of knowledge transfer across firms. The present paper, thus, aims precisely at contributing to this stream of research by making use of unique data on Italian inventors' *curriculum vitae*. The results of the empirical analysis indicate that the mobility of inventors is a mechanism that spurs processes of cumulative knowledge and innovation building from the departure firm to the destination one and significantly impacts on knowledge diffusion across firms.

Keywords Patent · Inventor · Mobility · Knowledge diffusion

JEL Classification J60 · O30

1 Introduction

The increasing importance of knowledge in the contemporary society makes companies successfully competing on the market only if they are able to continuously create new knowledge out of existing capabilities and translate it in new products and processes;

The author is grateful to Valerio Sterzi and Andrea Vezzulli for valuable suggestions and comments. The comments of an anonymous referee significantly helped me to finalise the paper.

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indeed, new knowledge creation and exploitation are at the core of firms' competitive advantages (Nonaka 1991 and 1994; Nonaka et al. 2000). Thus, the channels through which firms access and acquire new and relevant knowledge for their innovative activities is a critical issue that has some relevant implications on the geography and the management of innovation. In this regard, recent studies have suggested that the mobility of workers across firms is a primary source of new knowledge for the hiring firm and, more in general, of knowledge diffusion across firms.

Previous works on US data, by exploiting extensive datasets on inventors, their patents and citations, have shown that the innovations developed by the hiring firms significantly and positively depend upon past mobility behaviour of newly hired inventors. In other words, the more dispersed is the working experience of a newly hired inventor, the greater is the benefit for the hiring firm in terms of cumulative innovation building, as captured by the propensity to cite previous art developed by other innovators. Moreover, the higher the technological distance between the inventor's departure and destination firms the greater is this effect (Rosenkopf and Almeida 2003; Song et al. 2003a).

This evidence suggests that the mobility of workers could facilitate and spur a mechanism of cumulative knowledge creation and innovation building specifically from the departure firm to the destination one, thus significantly impacting on knowledge diffusion between the two. Unfortunately, the literature in this field has rarely explored this knowledge inheritance effect of workers' mobility from one specific firm to another. Rather, this effect has been frequently taken for granted rather than tested.

The present paper, thus, aims precisely at exploring this aspect.

Differently from most of the literature on this topic, this paper does not rely exclusively upon patent data but integrates information on inventors' innovative behaviour with information on their professional career, namely their *curriculum vitae*.

Patent data are extracted from the EP-Cespri dataset that collects data on all patent applications registered at the European Patent Office (EPO) since 1978.

Information on inventors' career path is derived from a survey addressed to a group of Italian inventors in the pharmaceutical field. This type of data is extremely useful mostly because of two reasons. Firstly, it provides an extremely precise description of inventors' mobility path. Secondly, it allows overcoming the limitations of patent statistics in computing and depicting inventors' mobility patterns. On the other side, this choice unfortunately imposes a reduction of dataset size compared to previous studies in the field.

Data show that inventors' mobility across firms is not very frequent but their moves significantly impact on the patterns of citations made by the hiring firms. This suggests that the mobility of inventors brings about a considerable knowledge inheritance and turns into a mechanism that spurs processes of cumulative innovation building, thus, ultimately representing a valuable means of knowledge diffusion across firms.

The remainder of the paper is articulated as follows. The second section provides a short review of the background literature. The third section describes the data used in the empirical analysis and provides descriptive statistics. The fourth part of the paper reports on the results of the econometric analysis. The last section summarises the main findings and indicates implications for the management and the geography of innovation.

2 Background literature

Arrow (1962) is one of the first authors referring to workers' mobility across firms as an influential means of knowledge transfer and one of the main sources of knowledge spillovers. His contribution pointed out that the mobility of workers may have implications on a large number of phenomena such as the organization, the management and the appropriability of the knowledge and innovations developed within firms, the localisation choices of firms and the formation of clusters of production and innovation, and, ultimately, the competitiveness of regions and countries.

After this seminal work, a few scholars have dealt with the issue of workers' mobility and its implications for innovative activities; most of the contributions are empirical while the theoretical ones are still limited.

Much of the empirical works have focused on the effects of workers' mobility at the geographical level of analysis, in particular, on the localisation of knowledge flows in order to examine its impact on the formation of clusters. Saxenian (1994) is one of the first to observe that the high rates of job mobility in Silicon Valley were an influential source of agglomeration economies. The anecdotic and ethnographic evidence she provided is also supported by Fallick et al. (2005) who find out a significantly higher rate of job mobility among college educated employees in the computer industry in California. Moreover, Almeida and Kogut (1999) show that the localisation of knowledge flows, as captured by the patterns of patent citations[1] among firms, is significantly and positively affected by the level of intraregional mobility of highly skilled workers (i.e. inventors in the semiconductor industry). Relatedly, mobile inventors are more likely to be cited by patents of the geographical area they come from rather than others. In fact, the citations they receive come disproportionately from their previous sites and this further confirms the idea that knowledge flows tend to follow the mobility trajectories of those people that produce, possess and master it (Agrawal et al. (2006) on US data and Song et al. (2003b) on the Taiwanese case both based upon US data and a slightly revised version of Jaffe et al. (1993)'s methodology).

Other works push further these conclusions (see Breschi and Lissoni 2006a and 2006b on Italy and US data from the EP-Cespri dataset, based upon a slightly revised version of Jaffe et al. (1993)'s methodology, and also Singh (2005) on US data but with a different methodology).

These studies exploit the idea that social and professional collaborations (i.e. collaborative network of research) are a complementary but fundamental means of knowledge diffusion. In this light, the mobility of workers is frequently indicated as a key mechanism able to activate new relationships and knowledge exchanges: network expansion and cohesion is thus supported by the action of mobile workers who connect different and, eventually, distant firms and geographical areas. Thus, knowledge diffusion and its geographical coverage ultimately can depend upon the mobility of workers and its geographical extent; knowledge diffuses locally as long as network ties and the mobility of workers that supports them are so.

These results also couple with findings from the works of Zucker and co-authors on the birth of the biotechnology industry in Silicon Valley. In fact, links with star scientists are found to have a significant and positive effect on firms' entry, localisation and success, also after controlling for other measures of local knowledge stock (e.g. Zucker et al. 1998).

A different stream of research has concentrated on and explored the effect of labour mobility on the generation of knowledge flows across firms. In this regard, two actors should be considered besides the mobile worker: the departure and the destination firms.

[1] In the innovation studies literature, patent citations are largely considered as 'paper trail' of knowledge flows, and are used as proxy in order to measure their intensity and geographical extension (Jaffe et al. 1993).

On the one hand, the departure firm can experience a considerable loss when a worker leaves. In fact, the departing worker can move and exit the labour market; alternatively, the departing worker can move and join another firm that can also be a competitor of the previous one (in fact, mobility is more frequent within than across sectors). Thus, this firm might benefit from the knowledge generated elsewhere, which is exactly a matter of externalities. In such a case, the departure firm risks losing not only an important worker and her knowledge (and human capital) but it also risks that third parties can benefit from this loss. However, 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 mitigate this effect and represent a possible solution (Aghion and Tirole 1994; Anton and Yao 1994; Pakes and Nitzan 1983).

On the other hand, by hiring a new worker, the destination firm can benefit from the knowledge generated elsewhere. This means that hiring strategies as well as human resources policies are of great importance and can be strategically designed and exploited in order to enhance and improve knowledge transfer and acquisition. In fact, knowledge flows across firms, as captured by patent citations, are positively affected by the level of (inventors') mobility within firms' sector of activity and this effect increases with the technological distance between the citing and the cited firms (Rosenkopf and Almeida 2003). Put in other words, firms can benefit from the mobility spillovers arising in their own sector of activity, that is, from those knowledge flows originated by inventors' moves across firms. In this line, Song et al. (2003a) propose that hiring strategies can be even considered as a source of learning for the hiring firms. In fact, they show that knowledge flows across firms are positively influenced by the technological distance between the hiring firm and the newly hired inventor's areas of expertise. This suggests that hiring a new inventor can be though of as a strategy in order to explore technologically distant areas and learn and improve upon it rather than to exploit pre-existing technological areas of expertise (consistently with Rosenkopf and Almeida (2003)'s findings). Thus, firms can act strategically and use hiring strategies in order to tap into specific knowledge, technological and geographical contexts (Rosenkopf and Almeida 2003).

This is also consistent with the relevant literature on knowledge management (see among others Nonaka 1991 and 1994 and Nonaka et al. 2000). These works stress that the process of new knowledge creation always begins with individuals and should be placed at the very centre of human resources strategies. Actually, new knowledge creation is not only a matter of 'processing information' but mainly a matter of tapping individual employees' ideas and expertise and transforming them into organisational knowledge valuable for the whole company. In particular, both employees' strategic job rotation within a company and, more broadly, employees' diverse past working experience are important sources of new knowledge for a firm. On the one side, at the very fundamental level, new knowledge is developed by individuals, on the other, organisations are critical both to provide an adequate context for and to support the creative effort as well as to direct, to articulate and to amplify the new knowledge being developed at the individual and team level.

In the end, the extant literature indicates that, first, individuals are central to the process of knowledge creation and, second, their mobility is a primary channel of knowledge creation and exchange that has relevant implications on knowledge diffusion across firms and geographical areas.

However, there is little focus and debate on the impact of this knowledge transfer means, that is on the knowledge and technological inheritance that a mobile worker can bring from the departure firm to the destination one. As previous studies suggest, this effect can be captured and assessed by looking at the patterns of inventors mobility and citations made by the destination firm; in fact, the innovation studies and strategic management literature extensively use patent citations data as proxy for knowledge flows (see among others Jaffe et al. 1993). The idea exploited in this literature is that "in principle, a citation of Patent X by Patent Y indicates that Patent Y builds upon previously existing knowledge embodied in Patent X. Thus, through patent documents one can infer both organizational and technological influences on a particular invention and thus track knowledge building across people, firms, geographic regions and countries, and time" (Song et al. 2003a, p. 356). Similarly, Rosenkopf and Almeida (2003), in their study on the US semiconductor industry, treat each citation as one instance of the citing firm drawing upon the knowledge developed by the cited firm. Therefore, the transfer and the application of the knowledge an inventor embodies and brings from one firm to another when changing job turns into innovations that eventually lead to patents; in other words, patent citations can be considered the beginning and end points of knowledge transfer (Song et al. 2003a).

For instance, Song et al. (2003a) concentrate on the intensity of knowledge flows from the mobile inventor's destination firm to the departure one in order to understand which technological characteristics of the firms involved can favour or hinder inter-firm knowledge transfer.[2]

In particular, this paper aims at investigating whether the mobility of workers turns into a cumulative mechanism of innovation building from the departure firm to the destination one as described in the citations patterns of a group of pharmaceutical firms hiring Italian mobile inventors. This will shed new lights on the knowledge inheritance effect of labour mobility and, thus, on its impact on knowledge diffusion across firms.

3 Data description

In the present work, we identified from the EP-Cespri[3] database all Italian inventors with at least one patent in the pharmaceutical field between 1990 and 2000.[4] We identified about 1,000 inventors that met this requirement.

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

[2] In this work the authors shortly discuss whether knowledge flows go disproportionately to the inventors' previous employer. However, two considerations should be put forward in this regard. Firstly, they consider only inventors that patent at both the departure and the destination firms. Secondly, they use US Patent and Trademark Office (USPTO) data. The relevant literature points out that the rate of citations per patent is systematically greater in this patent system than in the EPO one (Michel and Bettels 2001).

[3] 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 all patent applications registered at the European Patent Office since 1978.

[4] 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.

of the knowledge in this sector seem to be such that knowledge is embodied in individuals and can be transmitted through their moves across firms. Therefore, the channels 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.

The identified inventors were the target of a questionnaire that aimed at collecting information complementary to patent documents, namely, information on their professional experience. In this case, patent data turn out to be simply a means in order to select the questionnaire's respondents.

The survey has been conducted between January and March 2005. We made contact with the selected inventors in relation to the first patent they 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 was a six-page document attached to the email text that the respondents had to fill in and return. We sent 281 emails and obtained 38% response rate that amounts to 106 returned questionnaires.

In the empirical analysis, data collected through the questionnaire were integrated with patent data about each inventor interviewed and their applicants; patent data were extracted from the EP-Cespri dataset.

In order to exclude potential sources of selection on the identified inventors, we looked at the number of patents they filed and the average number of citations received per patent. They do not considerably differ in this respect from the distribution of all Italian inventors in the pharmaceutical field (Table A1 and Fig. 1 in Appendix).

Looking at inventors' mobility, data show that 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.

However, mobility is not a very frequent phenomenon. Almost 40% of respondents never changed their job and most of them changed job once or twice. This data can partly be explained by the fact that most of the respondents entered into the labour market during the '70 s, a time characterised by rather stable labour relationships. Table 1 below shows the distribution of inventors per number of job moves.

Nonetheless, the literature reviewed in the previous section indicates that knowledge flows across firms and geographical areas tend to follow workers (more specifically, inventors) mobility trajectories (Agrawal et al. 2006; Song et al. 2003a). In other words, workers mobility is a mechanism (that operates at the individual level of analysis) that allows for knowledge transfer across firms (that is at the firm level of analysis),

Table 1 Distribution of number of inventors per number of job moves

Number of moves	Number of inventors	
	Absolute number	Percentage
0	40	37.74
1	18	16.98
2	17	16.04
3	17	16.04
4	10	9.43
5	4	3.77

consistently with the knowledge creation process described by Nonaka (1991, 1994). To the extent that we consider patent citations as a proxy for knowledge flows across organisations (Jaffe et al. 1993), we might expect that organisations hiring a new mobile inventor tend to cite (i.e. to source knowledge from) disproportionately her previous employers. Put in other words, when the citing(*hiring*) firm and the cited firm are linked through an inventor's move, we expect the intensity to which the former sources knowledge from the latter to increase. This would attest that an inventor's move (i.e. individual level of analysis) imply some knowledge inheritance from the departure employer to the destination one (i.e. firm level of analysis), that is, mobility between the two firms generates a cumulative innovation building process, as captured by patent citations patterns.

In order to explore whether and to what extent firms hiring a new inventor are more likely to cite and to source knowledge from her previous employer, we stand in the tradition of innovation studies and consider patent citations as 'paper trail' of knowledge flows and use them to map knowledge flows across organisations (Jaffe et al. 1993; Almeida and Kogut 1999; Breschi and Lissoni 2006a and 2006b; Rosenkopf and Almeida 2003; Song et al. 2003a and Song et al. 2003b; Singh 2005; Agrawal et al. 2006; Stolpe 2002; Corredoira and Rosenkopf 2006).

Despite not all knowledge building results into patents, incentive to patents in the pharmaceutical sector are strong and pharmaceutical firms are among the most prolific patentees (Malerba 2004). On the other side, not all patent citations represent pure knowledge flows since they might be added by patent examiners or simply to protect from patent litigation. In fact, citation behaviour may not reflect pure knowledge transfer but rather legal tactics and strategies aimed at reducing the risk of litigation or at building up stronger intellectual property hedge and sounder foundation for defence. Notwithstanding these limitations, the uniformity and availability of patent and citation data increased their use in the innovation study literature to track knowledge flows (Rosenkopf and Almeida 2003). Thus, the existence of a considerable body of research using patent citation data to capture knowledge and its transfer motivated the use of such data in the present paper.

Following Song et al. (2003a) and Agrawal et al. (2006), hiring firms patents' assigned to the identified mobile inventors are selected; in the following these patents are referred to as *originating* patents.[5] However, patents assigned to the first employer are excluded because in this case, by definition, it is not possible to identify a previous employer.

Next, we look at the patents cited by these *originating* patents (i.e. citations made), build the citing(*originating*)-cited patents pairs and 'unbundle' for the applicants of both the citing(*originating*) and cited patents. This allows building the citing(*originating*)[6]-cited applicants pairs; we identified 302 of such pairs.[7]

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[5] We considered only those patents that do make citations to previous patents as Agrawal et al. (2006).

[6] In short, the citing(*originating*) applicant coincides with the hiring firm; in what follows we will refer to as citing(*hiring*) firms.

[7] These 302 pairs are originated from 60 different applicants firms (and 131 patents) that cite 201 different firms (and 246 patents). We excluded both firm-level self-citations as well as inventor-level self-citations. We are bound to consider only citing(*hiring*) firms' patens assigned to mobile inventors' patents because we do not have information about the mobility behaviour of the inventors of other patents of the citing(*hiring*) firm. In these cases, we could not assess whether citing(*hiring*) and cited firms are linked by an inventor's move (i.e. whether there is match or not between cited firm and inventor's previous employer).

This step enables identifying whether the citing(*hiring*) firm cites the newly hired mobile inventor's previous employer. Actually, 13.33% of citing(*hiring*) firms cite the newly hired inventor's previous employer at least once.

Additionally, this step enables assessing whether each citing(*hiring*)-cited applicants pair is linked by an inventor's move (i.e. whether the applicant of the cited patent coincide with an inventor's previous employer). As a matter of example, let's suppose that inventor X moves from firm B to firm A (i.e. hiring firm) in 1989; let's also suppose that firm A files patent number 7 in 1990, held by inventor X, which cites patent number 5 applied for by firm B in 1988 (but not assigned to inventor X). In such a case, firm A's citation to firm B (i.e. knowledge flow from B to A) can be associated to inventor X's move from B to A.[8]

Three point thirty-one percent (3.31%) of the citing(*hiring*)-cited pairs are linked by an inventor's move (i.e. cited applicant and inventor's previous employer coincide). Although quite limited, previous works in this stream of research have identified very similar level of mobility, still associated to effects statistically significant and of considerable magnitude (Breschi and Lissoni 2006b; Agrawal et al. 2006; Rosenkopf and Almeida 2003; Corredoira and Rosenkopf 2006).[9] These results can be explained by a series of factors.

First, inventors do not file patents at all the organisations they are employed at nor their previous employers are necessarily patent holders. Second, inventors are not always formally affiliated to the applicant of their patents: they might simply conduct research contract or be independent inventors and ultimately file patents held by others than their employer. Thus, the previous employer will result with fewer patents and fewer chances to be cited. Both these effects, ultimately, point to a possibility of under-representation of an inventor's previous employers in the applicants' sample that, eventually, may turn into a lower possibility to receive a citation. However, though weakened, this result holds true also for those inventors that have already patented at the companies they were previously employed at.

[8] Stated in other words, we detect an instance of mobility when the applicant of the patents cited by A (i.e. citing(*hiring*) firm) after inventor X's move coincides with inventor X's previous employer (i.e. firm B); in short, we compare cited applicant to inventor's previous applicant. We argue that when citing(*hiring*) and cited firms are linked by an inventor's move the knowledge inheritance that inventor X brings from firm B into firm A leads to a greater propensity of firm A to build upon (i.e. to cite) firm B's knowledge stock.

[9] For instance, Breschi and Lissoni (2006b) use the EP-CESPRI data on the US pharmaceutical industry and find that citing and cited patents are related by inventors' mobility in 4.95% of the examined cases (which include also personal self-citations). Also, Agrawal et al. (2006) use the USPTO-NBER data and find that patents citing mobile inventors' patents come from their previous location only in 5% of the examined cases. This percentage is greater compared to the one found in the present work. The greater propensity to cite in the USPTO systemas compared to the EPO one and the greater propensity to move in US compared to Europe can explain a greater frequency of the matching between cited applicant and an inventor's previous employer compared to similar percentages computed on EPO data, especially for Italy, which is characterised by rather little level of labour mobility (Michel and Bettels 2001; European Foundation for the Improvement of Living and Working Conditions 2006). Moreover, Rosenkopf and Almeida (2003) and Corredoira and Rosenkopf (2006) find that, on average, citing and cited firms in the US semiconductor industry are linked by inventors' mobility in 1% of the examined cases.

Despite the size of the phenomenon being quite limited, the magnitude of its effects is rather substantial. For instance, Rosenkopf and Almeida (2003) find that the mobility of an inventor from firm A to B leads to a 32% increase (up to 43%, according to the specification of the model estimated) in the expected number of citations from B to A, holding all other variables at their mean; Corredoira and Rosenkopf (2006) find as well a positive effect, though somehow smaller; in fact, in their setting, the mobility of an inventor from firm A to B leads to a 14% increase in the expected number of citations from B to A, holding all other variables at their mean.

[10] Indeed, most of the inventors moved within the national borders (82.5% of the sample).

Moreover, while most of the citing patents are held by Italian companies, most of the cited patents are held by foreign companies. In this case, it is even more difficult to associate the knowledge flows between the citing(*hiring*) and the cited firms to the geographical mobility patterns of inventors, which instead mostly occurs within national borders (i.e. within Italy).[10] However, this result might be also partly explained by a relatively weaker innovative activity of Italian companies and the different and more restrictive rules adopted by the EPO in order to indicate a patent's references compared to USPTO (Michel and Bettels 2001).

In the next section, the idea of workers mobility as a mechanism of knowledge diffusion across firms and its impact on the patterns and intensity of such knowledge flows is further investigated by presenting the results of the econometric analysis.

4 Results

In order to explore this idea, we look again at the identified pairs of citing(*hiring*)-cited applicants. However, we now aim at studying the factors affecting the intensity to which one builds upon the knowledge developed by the other, i.e. the strength of the knowledge inheritance, as captured by the number of citations made by the citing(*hiring*) applicant to the cited one. Our idea is that not only whether one cites the other but mostly the number of times this occurs could depend upon the mobility of an inventor from the cited to the citing(*hiring*), i.e. whether the cited and the citing(*hiring*) applicants are linked by an inventor's move from the former to the latter.[11]

Since we are studying the number of citations made, we are interested in modelling an event count. In this type of context, linear regression models have been frequently applied, but they lead to inefficient, inconsistent and biased estimates (Long and Freese 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 particular, we consider only cases in which citations occur. Therefore our model of reference is the zero-truncated Poisson model that is based on a modified Poisson regression model[12] which takes only values greater than zero. This model, as the baseline Poisson regression model, is inherently heteroschedastic, and requires a robust estimator.

However, given the distribution of the number of citations made (which takes value 1 in more than 80% of cases), we decided to reframe the dependent variable and, accordingly, the model setting. Our interest, thus, concentrated on the factors affecting the probability to make more than one citation. Accordingly, the dependent variable becomes a binary outcome variable which takes value 1 if this occurs (i.e. the citing(*hiring*) applicant cites

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[11] More precisely, we compute the number of citations made as the number of times that the citing(*hiring*) firm cites another with reference to different patents. For instance, if one firm cites four times a firm always with reference to the same patent, the count variable would take value 1 and not 4.

[12] The Poisson regression model can be viewed as an extension of the Poisson distribution where the mean parameter varies across observations depending on some regressors. The dependent variable is a random variable and indicates the number of times a given event occurs. The mean parameter is the only one defining the distribution and it is supposed to be equal to the variance (equi-dispersion property). This implies the necessity of a robust estimator.

more than once another applicant; **citations_made**) and 0 otherwise and we decided to use a probit model.

In the specification of the model we mainly refer to the works by Rosenkopf and Almeida (2003) and Song et al. (2003a).

Our attention primarily concentrates on the effect of mobility (**mobility**), which is a dummy variable that takes value 1 when citing*(hiring)* and cited firms are linked by an inventor's move (i.e. the inventor moved from the cited to the citing(*hiring*) firm, or, stated differently, an inventor previous employer and the cited firm coincide) and 0 otherwise. We expect mobility to have a positive and significant effect on the hiring firm capability to build upon the knowledge developed by a mobile inventor previous's employer. In other words, we expect that the mobility of inventors from the cited to the citing(*hiring*) firm might significantly facilitate and spur a mechanism of cumulative knowledge and innovation building, thus resulting in a higher citation rate and a higher probability that the citing(*hiring*) applicant cites (i.e. sources knowledge from) the cited applicant more than once.[13]

Furthermore, the number of citations between two firms can depend upon other factors and we insert controls for them.

Firstly, the technological distance (**tech_dist**) between citing(*hiring*) and cited firms can affect the cumulative number of citations across firms. Firms tend to build new knowledge on the ground of the results of past researches; also, bounded rationality and rather stable routines tend to constraint the search space to somehow close areas. As a consequence, firms tend to show patterns of technological local search, to cite and to draw primarily on the knowledge stocks of technologically close firms. According to Rosenkopf and Almeida (2003) and Song et al. (2003a) findings, we expect a negative effect of technological distance on the intensity of knowledge flows across firms: the higher is the technological distance the lower the probability to make more than one citation.[14] Additionally, controlling for technological distance is relevant because mobility is more frequent within than across sectors.

Secondly, the higher the number of patents and citations received by a firm, the higher the probability of being cited more than once (**cited_firm_pat** and **cited_firm_cited**). Thirdly, it depends upon the number of patents the citing(*hiring*) firm files and upon its attitude towards citing (**citing_firm_pat** and **citing_firm_citing**): the higher the number of patents and citations made the higher the probability to cite any single firm more than once. These effects are found to be of a great importance in both Rosenkopf and Almeida (2003) and Song et al. (2003a). However, differently from these authors, patent counts are all computed as stock averaged on the number of years an inventor spent in a specific employment (i.e. tenure). More precisely, patents of the citing(*hiring*) firm are averaged on the number of years the inventor spent in this firm while patents of the cited firm are averaged on number of years the

[13] It is worth mentioning that there could be a potential risk of endogenity. In fact, it could be argued that the mobility of an inventor from one specific firm to another occurs because of the pre-existing knowledge proximity and exchanges between the two, which is a factor that in turn may result in a higher citation rate between the two and a higher probability that the citing(*hiring*) applicant cites the cited applicant more than once. However, in the model specification we precisely take in to account this aspect by controlling for the technological distance between citing and cited applicant. Moreover, in 90% of the examined cases there is no citation from the citing to the cited firm before hiring the new inventor. This suggests that in most of the instances inventors' mobility behaviour is not related to previous knowledge relationships between the citing and the cited applicants.

[14] More specifically, in Rosenkopf and Almeida (2003) the joint effect of mobility and technological distance has a positive effect on the citations rate while the pure technological distance among firms a negative one.

inventor spent in the previous employment. The citation counts are computed respectively as average number of citations made or received per patent.

We also control for inventors previous patenting activity (**patent_inventor**) since we expect more prolific inventors to have more knowledge to transfer (Song et al. 2003a).

Finally, we control for the effect of geographical distance of inventors' moves (within or outside national borders, i.e. domestic versus international mobility: **dom_mob**) and the co-location of citing(*hiring*) and cited applicants at the state level (**geog_match**) since knowledge flows are likely to be geographically bounded (Jaffe et al. 1993).

There are also a few differences from the specification implemented in the present paper and the one implemented by Song et al. (2003a). In fact, we do not insert control for technological distance between citing(*hiring*) firm and an inventor's patent portfolio (as well as for technological distance between previous employer and an inventor's patent portfolio) since all inventors move across firms active in the pharmaceutical field and most of them did not patent in their previous employment (70% of them, which amounts almost to 50% of the observations in the sample). Accordingly, measures of technological distance between firms and inventors patent portfolio could not be derived consistently for all inventors in the sample.

In sum, the probability that the citing(*hiring*) applicant cites more than once another applicant can be described as follows:

$$\begin{aligned}\mathrm{Prob}[\mathrm{citations\_made}_i = 1] = F(&\mathrm{cited\_firm\_pat}_i\theta_1, \mathrm{cited\_firm\_cited}_i\theta_2, \mathrm{citing\_firm\_pat}_i\theta_3,\\ &\mathrm{citing\_firm\_citing}_i\theta_4, \mathrm{patent\_inventor}_i\theta_5, \mathrm{tech\_dist}_i\theta_6,\\ &\mathrm{dom\_mob}_i\theta_7, \mathrm{geog\_match}_i\theta_8, \mathrm{mobility}_i\theta_9)\end{aligned}$$

where F is the normal cumulative density function and is estimated through a probit model.

Tables 2 and 3 report the list of variables as well as descriptive statistics for them; the correlation matrix is reported in Table A2 of Appendix.

The full model is estimated in four different steps. In the first two models, we introduce only controls and in the latter we introduce the mobility variable. Table 4 shows the estimates.

Consistently with previous findings (Rosenkopf and Almeida 2003; Song et al. 2003a), the first model indicates that the intensity of knowledge flows across two firms positively and significantly depends on the patenting activity of both firms. The more innovative are both the cited and citing(*hiring*) firms the higher the probability to make more than one citation. Moreover, the higher the propensity to cite the higher the probability to make more than one citation; this effect is statistically significant. On the other hand, the average number of patents of the inventor in the previous employment does not have a significant impact over the probability to make more than one citation, as in Song et al. (2003a). Also, the effect of technological distance is not significant as in Song et al. (2003a). Additionally, the two controls for the geographical distance of the move and the geographical co-location of citing(*hiring*) and cited applicants are not significant. Surprisingly, the higher the propensity to be cited the lower the probability to make more than one citation. In order to inspect further this aspect, we modified this independent variable—average number of citations received (cited firm)—into four dummy variables (model 2). The first one takes on value 1 when the categorical variable assumes value 0 and 0 otherwise (no citations received category); the second one takes on value 1 when the categorical variable assumes value 1 and 0 otherwise (little citations received category); the third one takes on value 1 when the categorical variable assumes value 2 and 0 otherwise (medium citations received category); the last one takes on value

Table 2 List of the variables

Variable	Description
Average number of patents (cited_firm_pat) [see foonote no. 14]	Categorical variable that can take four different values: 0 when the average number of patents is 0 1 when the average number of patents is greater than 0 and lower than 5 2 when the average number of patents is greater than 5 and lower than 20 3 when the average number of patents is greater than 20
Average number of citations received (cited_firm_cited) [see foonote no. 14]	Categorical variable that can take four different values: 0 when the average number of citations is 0 1 when the average number of citations is greater than 0 and lower than 1 2 when the average number of citations is greater than 1 and lower than 2 3 when the average number of citations is greater than 2 Or, alternatively, four dummy variables: Dummy 1 that takes value 1 when cited_firm_cited = 0 and 0 otherwise Dummy 2 that takes value 1 when cited_firm_cited = 1 and 0 otherwise Dummy 3 that takes value 1 when cited_firm_cited = 2 and 0 otherwise Dummy 4 that takes value 1 when cited_firm_cited = 3 and 0 otherwise
Average number of patents (citing_firm_pat)[a]	Categorical variable that can take three different values: 0 when the average number of citations is lower than 1 1 when the average number of citations is greater than 1 and lower than 3 2 when the average number of citations is greater than 3
Average number of citations made (citing_firm_citing) [see foonote no. 14]	Categorical variable that can take three different values: 0 when the average number of citations is than 1 1 when the average number of citations is greater than 1 and lower than 2 2 when the average number of citations is greater than 2
Average number of patents (patent_inventor)	Average number of patents per year an inventor filed in the previous employment
Technological distance (tech_dist)	Euclidean distance between citing(*hiring*) and cited firms' vectors of patents[b]
Domestic mobility (dom_mob)	Dummy variable that takes value 1 when an inventor's previous employer was located in Italy (i.e. domestic mobility) and 0 otherwise (i.e. international mobility)
Geographical match between citing(*hiring*) and cited applicants (geog_match)	Dummy variable that takes value 1 when citing(*hiring*) and cited applicants are both located in Italy and 0 otherwise

Table 2 continued

Variable	Description
Mobility (mobility)	Dummy variable that takes value 1 when citing(*hiring*) and cited firms are linked by an inventor's move and 0 otherwise

[a] The identification of the categories is based upon the distribution of the variable; the identified thresholds, thus, do not represent critical values specifically indicated in the relevant literature. The use of categorical variables instead of continuous variables has been preferred because of the large number of outliers.

[b] In order to compute technological distance, we summarised the percentage of patents assigned in each patent class and we computed the Euclidean distance between these patent class vectors. This ranges from 0 (same technological profile) to 1.4 (i.e. the squared root of 2, when the two firms are assigned all their patents in two different classes). This measure is also widely used in the literature (see among others Jaffe 1986 and 1989); in this context, this is preferable compared to other measures based on citations patterns since it allows distinguishing technological similarity and knowledge flows both empirically and conceptually (Rosenkopf and Almeida 2003).

Table 3 Descriptive statistics

Variable	No. of observations	Mean	Standard deviation	Minimum	Maximum
Average number of patents (cited firm)	302	1.416	1.112	0	3
Average number of citations received (cited firm)	302	1.320	1.083	0	3
Average number of citations received (cited firm)—Dummy 1	302	0.310	0.463	0	1
Average number of citations received (cited firm)—Dummy 2	302	0.224	0.418	0	1
Average number of citations received (cited firm)—Dummy 3	302	0.300	0.459	0	1
Average number of citations received (cited firm)—Dummy 4	302	0.166	0.372	0	1
Average number of patents (citing firm)	302	0.841	0.783	0	2
Average number of citations made (citing firm)	302	0.964	0.711	0	2
Average number of patents (inventor)	302	0.615	1.130	0	6
Technological distance	302	0.592	0.331	0	1.414
Domestic mobility	302	0.825	0.381	0	1
Geographical match citing(*hiring*) and cited applicants	302	0.056	0.231	0	1
Mobility	302	0.033	0.179	0	1

1 when the categorical variable assumes value 3 and 0 otherwise (high citations received category). We included the first three dummy variables and considered the last one as reference case. Estimates show that the effect of the propensity to be cited is significant but does not seem to be linear. In fact, being in the little citations received category has a greater effect on the probability to receive more than one citation compared to the

Table 4 Probit regression: estimates

Variables	Model 1	Model 2	Model 3	Model 4
Average number of patents (cited firm)	0.179**	0.092	0.173*	0.091
	(0.090)	(0.150)	(0.093)	(0.152)
Average number of citations received (cited firm)	−0.298***		−0.307***	
	(0.100)		(0.105)	
Average number of citations received (cited firm)—Dummy1		0.673**		0.732**
		(0.333)		(0.341)
Average number of citations received (cited firm)—Dummy2		0.792***		0.806***
		(0.306)		(0.280)
Average number of citations received (cited firm)—Dummy 3		0.209		0.261
		(0.283)		(0.275)
Average number of patents (citing firm)	0.220**	0.245**	0.227**	0.250***
	(0.114)	(0.104)	(0.112)	(0.101)
Average number of citations made (citing firm patents)	0.460***	0.479***	0.502***	0.519***
	(0.140)	(0.134)	(0.137)	(0.132)
Average number of patents (inventor)	0.010	−0.011	0.001	−0.016
	(0.117)	(0.109)	(0.114)	(0.108)
Technological distance	0.065	0.131	0.019	0.075
	(0.212)	(0.229)	(0.212)	(0.225)
Domestic mobility	−0.109	−0.123	−0.124	−0.138
	(0.148)	(0.149)	(0.137)	(0.140)
Geographical match	0.080	0.063	−0.395	−0.391
	(0.349)	(0.364)	(0.314)	(0.289)
Mobility			1.115***	1.075***
			(0.461)	(0.439)
Costant	−1.718***	−2.501***	−1.730***	−2.558***
	(0.224)	(0.398)	(0.244)	(0.422)
Wald χ^2	19.73***	42.73***	22.67***	40.42***
Log-likelihood	−102.595	−101.775	−100.389	−99.775
Number of observations	302	302	302	302

Standard errors in parentheses

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

medium citations received category (the reference category is the high citations received one). However, the average number of patents of the cited firm is anymore significant (although it keeps a positive sign) while the sign and the significance of all other variables but the average number of patents of the inventor in the previous employment do not change.

The third and the fourth model introduce the mobility variable. In both models, the sign of all other variables do not change but the geographical match. Mobility has a significant and positive effect on the probability to make more than one citation. This indicates that the mobility of inventors from the cited to the citing(*hiring*) firm can significantly facilitate and spur a mechanism of cumulative innovation building. *Ceteris paribus*, inventors' mobility can ultimately explain the patterns of citations and knowledge diffusion.[15]

The comparison of these findings with the results of previous works indicates that the operating of the mobility effect can be extended also to those cases where inventors did not patent in their previous employment and EPO data are used. It follows that the mobility of workers allows transferring also knowledge that is not already embedded in an inventor's patents. Moreover, this result holds also in EPO case where citations are primarily added by patent examiners and there is a lower risk of inflation of patent references (Michel and Bettels 2001), which otherwise could lead to overestimate the impact of mobility on the generation of knowledge flows. This result, thus, extends further previous findings about the relevance and impact of workers' mobility across firms as an influential channel of knowledge transfer.

5 Conclusions

The extant literature indicates that workers mobility is a primary conduit of knowledge transmission and exhibits a large consensus on its implications on knowledge diffusion processes across firms and geographical areas.

However, little attention has been dedicated to the assessment of the knowledge inheritance effect it may bring about and, thus, its impact as knowledge diffusion channel. This, instead, has been frequently taken for granted rather than tested.

Differently, this paper investigated precisely this aspect and explored whether the mobility of workers may turn into a mechanism of cumulative innovation building from the departure firm to the destination one.

The analysis made use of two primary sources of data. Firstly, a survey addressed to a group of Italian inventors in the pharmaceutical field that collected data on their career path. Secondly, patent data about the inventors that answered to the questionnaire and the firms they worked for (namely the number of patents and citations made and received).

Results indicated that mobility is not a very frequent phenomenon: almost 40% of respondents never changed their job and most of them changed job once or twice. However, 13.33% of hiring firms source knowledge from the newly hired inventors' previous employers (i.e. cite them at least once).

Also, the econometric analysis showed that the mobility of an inventor from the cited to the citing(*hiring*) firm significantly and positively impacts on the citation rate. It follows that the mobility of inventors brings about a significant knowledge inheritance, that is a mechanism that spurs a process of cumulative innovation building and, eventually, represents a valuable means of knowledge diffusion across firms.

This result, ultimately, has important implications for both the geography and the management of innovation.

[15] In particular, as far as the effect of technological distance is concerned, this result can be interpreted as follows: the mobility of an inventor from the cited to the citing(*hiring*) firm increases the intensity to which the citing(*hiring*) firm sources knowledge from the cited firm besides the firms being technologically proximate (and thus, eventually, better positioned to source knowledge one from the other).

To what concerns the geography of innovation, the literature indicates that knowledge tends to be localised to the extent that also the movement of workers across firms are such. On the other hand, their mobility over longer distances may allow connecting firms and geographical areas far apart from each other while activating and supporting the formation of new relationships and, ultimately, additional knowledge exchanges. The present results support further these considerations and also show that knowledge exchanges across firms significantly rely upon voluntary and market mechanisms (i.e. labour mobility); this has important implications for the debate about the relevance of ‘pure’ versus ‘pecuniary’ externalities in the process of geographical concentration of economic and innovative activities.

To what concerns the management of innovation, these findings support further the idea that the generation of knowledge flows between the departure and the destination firms challenges the management of intellectual property within firms and calls for a better definition, allocation and distribution of property rights over the innovations developed. In fact, the knowledge diffusion effect of workers’ mobility occurs also in those cases where the knowledge and innovation developed in the previous employment are not protected by intellectual property rights (i.e. patents). Finally, these results point out that hiring and human resources policies can be strategically designed and managed within a firm in order to access specific expertises. Since hiring a new inventor gives a premium in terms of knowledge inheritance and cumulative innovation building, this could open a window to access specific knowledge and could be thought of as a strategy to access a precise bit of knowledge and to improve upon it.

Interesting future research directions entail the investigation of the impact of new hirings on firms direction of patenting and, possibly, of research projects.[16] Actually, some hires can be motivated by the exploration of a different technological domain from the one currently at the core of the research done at the citing(*hiring*) firm (thus supporting a pattern of technological diversification and, eventually, impacting on and changing a firm’s patenting and research direction). Differently, others can be motivated by the exploitation of the citing(*hiring*) firm’s core technological domain which requires additional human resources to be invested into (thus supporting a pattern of technological deepening and, eventually, strengthening the current technological profile). In principle, the two effects on a firm’s direction of patenting and research could

[16] Despite this is a very interesting research area to explore, and the impact of hirings on the research direction at the project level are likely to be even stronger than at the patent level, it is worth pointing out that this type of data are scarcely available compared to more ordinary statistics such as patents or R&D expenditures, although, dedicated surveys or in-depth interviews aimed at investigating these specific aspects might allow overcoming such data scarcity. Actually, collecting the complete time series of a firm’s research projects and studying its variation before and after hiring a new inventor would require identifying and interviewing key persons within the firm with deep knowledge of a firm’s story. However, inventors do not necessarily possess detailed information on a firm’s all current and, mostly, past research projects, especially in the case of mobile inventors. In fact, mobile inventors might have very little knowledge (almost none) of research projects developed before she joined a new firm. Therefore, in this research and in the questionnaire implemented, we did not explore these aspects but exclusively focussed on the tracing inventors’ career path.

offset each other, but, unfortunately, in this study, we are unable to observe all inward moves at the citing(*hiring*) firm and to assess which effect actually prevails. In both cases, however, hirings can be regarded as being strategically used to source external knowledge, that is inward mobility is a mechanism of cumulative knowledge and innovation building.

Lastly, comparisons across regions, countries, sectors and organisations would provide additional insights on knowledge workers' mobility besides this evidence based on a rather small sample from one single country and sector and open up further the 'black box' of knowledge spillovers.

Appendix

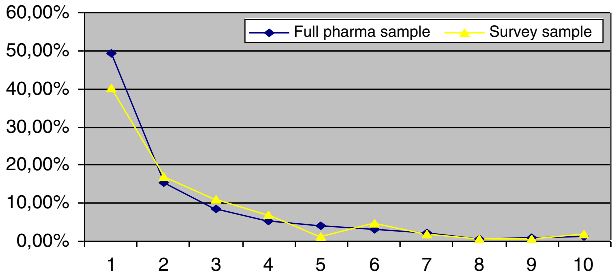

Fig. 1 Distribution of number of patents per inventors

Table A1 Frequency of the number of citations received per patent in the first 5 years, self-citations excluded (%)

	Pharma sample	Survey sample
0	93.33	94.05
1	5.34	5.29
2	1.02	0.00
3	0.21	0.33
4	0.06	0.00
5	0.03	0.17
6	0.01	0.00
7	0.00	0.00
8	0.00	0.17

Table A2 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1	–											
2	0.546*	–										
3	−0.752*	−0.819*	–									
4	0.337*	−0.158*	−0.362*	–								
5	0.379*	0.411*	–0.438*	–0.351*	–							
6	0.640	0.695*	−0.299*	−0.240*	−0.290*	–						
7	−0.009	−0.109	0.695	−0.022	−0.006	−0.092	–					
8	−0.013	0.624	−0.023	−0.037	−0.076	0.163*	−0.347*	–				
9	−0.004	−0.016	−0.015	0.113*	−0.124*	0.3035	−0.049	0.282*	–			
10	−0.368*	−0.309*	0.375*	−0.143*	−0.147*	−0.125*	−0.043	0.090	0.139*	–		
11	−0.088	−0.194*	0.141*	0.280	−0.042	−0.169*	−0.027	0.122*	−0.122*	−0.162*	–	
12	−0.116*	−0.032	0.153	−0.029	0.422	−0.070	−0.061	0.236	−0.014	−0.033	0.783	–
13	−0.019	0.217	−0.045	0.231	0.001	0.119	−0.010	−0.068	0.134	−0.045	0.255	0.356*

* $p < 0.5$

Legenda

Variables	Legenda
1	Average number of patents (cited firm)
2	Average number of citations received (cited firm)
3	Average number of citations received (cited firm)—Dummy 1
4	Average number of citations received (cited firm)—Dummy 2
5	Average number of citations received (cited firm)—Dummy 3
6	Average number of citations received (cited firm)—Dummy 4
7	Average number of patents (citing firm)
8	Average number of citations made by citing firm patents
9	Average number of patents (inventor)
10	Technological distance
11	Domestic mobility
12	Geographical match
13	Mobility

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