Mobility and Social Networks: Localised Knowledge Spillovers Revisited

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Paper prepared for the Workshop
"Empirical Economics of Innovation and Patenting"
Centre for European Economic Research (ZEW)
Mannheim, March 14th-15th 2003

This research has been supported by a grant provided by the Italian Ministry for Research and University (MIUR). Financial support from Fondazione Cariplo is also gratefully acknowledged. We wish to thank Jim Moody, whose SPAN programme and SAS macros helped us at a crucial stage of data processing. Seminar participants at Cespri (Milan), UQAM University (Montreal) and Max-Planck Gesellschaft (Jena) have provided useful comments and suggestions. We are of course responsible for any remaining errors.

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Abstract

The paper provides a reassessment of arguments and tests in support of the existence and magnitude of localized knowledge spillovers proposed by Jaffe, Trajtenberg and Henderson (1993). We use information in patents to control for the mobility of inventors across companies and space, as well as for the network ties that such mobility helps establishing. Our results indicate that localisation effects tend to vanish where citing and cited patents are not linked to each other by any network relationship. On the contrary, knowledge flows, as evidenced by patent citations, are strongly localized to the extent that labour mobility and network ties also are. We interpret these results as evidence that geography is not a sufficient condition for accessing a local pool of knowledge, but it requires active participation in a network of knowledge exchanges. Moreover, hiring workers from competitors and other firms seems to be a key means to access such a network.

JEL Codes: O31, J60

1. Introduction

In the past few years, very few buzzwords have resonated, through economists', geographers', and policy-makers' ears alike, more than "LKS".

LKS stands for "Localized Knowledge Spillover", an effective micro-founded, policy-oriented rewording of Marshall's classic metaphor on the secrets of industry being in the air. By invoking the existence of LKSs, supporters of public plans for R&D funding can reassure taxpayers that it will be the local community to reap most of the benefits of those plans. The recipients of public funds (whether incentive-driven new private R&D facilities, or local universities) will in fact produce some knowledge externalities. Any new knowledge of that kind, however, will comprise a vast amount of skills, intuitions, and best practices, whose transmission will require face-to-face contacts and lengthy explanations. As a result, only local companies will manage to access that body of knowledge through frequent interaction with its sources, so that the ultimate result of the policy plan can be reassuringly defined as the creation of a *local* public good.

Strong scientific support to such a thesis, and indeed a major diffusion drive to the LKS acronym, has come from an engaging and extremely successful econometric research programme, aimed at using patents, innovation counts, and patent citations as useful indicators of the existence and geographical reach of knowledge externalities (for a survey: Feldman, 1999; for a few key collected essays: Jaffe and Trajtenberg, 2002).

This paper aims at contributing to that research programme, by adding both new data (namely, data on Italian patents) and new measurable variables, such as *social proximity* between inventors, and inventors' *mobility* across firms.

To do so, we first sum up the main features of the LKS research programme, and place particular emphasis on the discussion of a statistical exercise first proposed by Jaffe, Trajtenberg and Henderson (JTH) in 1993 (section 2). We then describe our data and measurement techniques (section 3), and replicate that exercise, by adding our new variables and commenting the results (section 4). In section 5, we conclude by setting out our plans for further empirical research.

2. The LKS research programme

Although pioneered in its present form by Jaffe (1989), the LKS research programme is possibly the last legacy from professor Zvi Griliches' long-time efforts to produce reliable methodologies for the estimation of the relationship between R&D and economic growth.

In order to test models of endogenous growth, those methodologies had to measure effectively the extent of knowledge externalities, which in a production-function frame had to take the form of R&D spillovers across firms and/or from universities and public labs to firms. By regressing growth in per-capita income or total factor productivity against public and private R&D expenditures, professor Griliches reached the conclusion that knowledge spillovers existed and mattered a lot, but also that, in the absence of better data and improved econometric techniques, his own and many others' studies could not prove anything more than "back-of-the-envelope" calculations (Griliches, 1992).

The main challenge consisted in disentangling "pecuniary externalities" and "pure spillovers". The first ones are described as "R&D intensive inputs […] purchased at less than their full 'quality' price"[1] (we notice immediately that location advantages may well explain the extent of the discount). The second ones are "ideas borrowed by research teams"[2] of one firm from the research results of another one.

By citing Jaffe's early work (1986, 1988), prof. Griliches pointed out that a promising approach consisted in measuring separately the knowledge stock (e.g. the cumulated R&D) of individual companies or universities (or, at a more aggregate level, industries), and then weighing the influence of that stock on other companies' knowledge output, as measured, for example, by patents.

Weights had to be inversely related to the "distance" between "sending" and "receiving" agents. Griliches (1992) mainly thought of "technological distance" measures, such as differences in the technological base of firms and industries.

Jaffe (1989) coupled to technological differences a few measures for geographical distance. The basic intuition behind that addition was the need to recognize the "tacit" nature of knowledge, that is the need of frequent interaction between "sender" and "receiver" of the

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1 Griliches, 1992; p. 36.
2 Griliches, 1992; p. 36.

spillover, in the form of face-to-face contacts between people working for the former and people working for the latter.

Soon geographical distance took centre stage, possibly because of the renewed interest into economic geography spurred by the success of Paul Krugman's "Geography and Trade" lectures (Krugman, 1991). Jaffe's results, strengthened by similar, and similarly successful exercises by Acs, Audretsch and Feldman[3], were extremely timely in both confirming the geographic dimension of a key economic activity such as innovation, and in challenging Krugman's provocative assessment of "Marshallian externalities of the third kind" (read: knowledge spillovers) as both non-measurable and hardly conceivable as localized, and therefore irrelevant to the economic analysis of industrial localization.

The definitive piece of work in dismantling Krugman's contempt, and in popularizing LKS even among the most econometric-phobic sects of POGs ("plain old geographers", as in David's 1999), came two years later, by Jaffe, Trajtenberg, and Henderson (1993; from now on JTH). They worked out an imaginative "controlled experiment", specifically designed to test for the localization of knowledge spillovers, as measured by patent citations.

Quite differently from previous, Griliches-style work, here patents are used outside any "production function" frame; nor any R&D statistics are used, so that no strong assumption on the way knowledge affects innovation (and from here, growth) is put forward. Still, a few assumptions on the way knowledge "tacitness" may affect geography are retained from earlier work.

We now turn to describe the experiment, and discuss critically those assumptions.

2.1 The JTH experiment: design and technicalities

The JTH's experiment tests whether knowledge spillovers are indeed localized, and the extent of that localisation. To do so, a sample of patents applied for within a relatively short span of time is taken[4]. Then, all citations of those patents by successive ones are considered, with the exclusion of self-citations, i.e. those citations running between two patents assigned to the same company.

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[3] Key papers: Acs, Audretsch and Feldman (1992); Audretsch and Feldman (1996); Feldman and Florida (1994). More citations in Feldman (1999).

[4] JTH selected two samples, one for 1975 and another for 1985, in order to check for changes in the geographical reach of spillovers due to changes in the patent contents, as a result of changes in patent rules and applicants' attitudes

To the extent that those citations are not imposed by patent examiners, they are taken as representative of some form of knowledge spillover from the inventors' team behind the cited patent to the team behind the citing one[5]. Moreover, to the extent that knowledge spillovers are geographically localised, citations should come disproportionately from the same geographical area as the cited patent.

However, this simple test would tell us little about the localisation of knowledge spillovers, unless one controls for the pre-existing geographic concentration of innovative activities. In other words, one might find that a disproportionate share of citations come from the same area as the cited patent simply because the *production* of technological innovations (i.e. patents) happens to be agglomerated in that area. The *production* of innovations, in turn, may be spatially agglomerated for a number of reasons, which have nothing to do with the access to the local knowledge pool and may be more properly categorised as "pecuniary" externalities (e.g. availability of skilled labour and specialised inputs, the infrastructure endowment of cities and regions, etc.).

The most important innovation of the JTH paper was to develop a methodology, which allows one to separate the effects of 'pure' knowledge spillovers from the impact of other agglomeration forces. Specifically, JTH built a *control* sample of patents in the following way. Each citing patent was matched to a randomly drawn patent, which had the same technology class and application date as its matched citing patent, *but did not cite* the same originating patent[6].

[5] Current patent applications cite older ones in order to define what is called "prior art" and, by contrast with the their own contents, the extent of their novelty claim. Some citations may be inserted in the application by the inventors themselves, thus witnessing they benefited from some of the knowledge content of the cited patent. Many other citations, however, are added by patent examiners and/or the applicant's patent consultants, for legal reasons. This type of citations have hardly anything to do with knowledge flows from the inventors of the cited patents to those of the citing one: much more likely, they reflect some duplication of the research efforts the inventors were unaware of. Duty of candour imposes USPO applicants to list all of the previous patents they are aware of, which can be considered prior art. EPO rules are much less strict in this sense, so that we expect the percentage of citations coming from examiners and consultants to be higher. Thus, our EPO data should be a poorer proxy of "true" knowledge flows than JTH's USPO ones. Notice, however, that a high percentage of examiner-imposed citation should in principle dilute the localization effect.

[6] Patent offices classify applications according to very detailed codes, which should mirror the patent technological contents. JTH's data fall under the US Classification (USC) system. Ours under the IPC (International Patent Classification) system. JTH matched patents according to the first three out of the nine digits of the USC. For a criticism of this choice, see Thompson and Fox-Kean (2002). Notice also that JTH's data come from USPO, the US Patent Office where the first-to-invent rule applies: patents are applied for by inventors, who then assign them to their employer or whatever company they produced the invention for. In first-to-file systems such as the one followed by EPO, the European Patent Office, companies apply directly

Finally, cited, citing, and control patents were assigned to a geographical entity (local area, state, country), according to the address of the inventor (if only one is credited on the patent document) or one of the many different addresses that may appear on patents credited to a team of inventors[7].

JTH's experiment consisted then in comparing the frequency with which citing and cited patents match geographically, with the frequency with which control and cited patents match geographically. If the former turns out to be significantly greater than the latter, this should interpreted as evidence of localisation effects (i.e. spillovers) *over and above* the agglomeration effects arising from other sources. More specifically, the JTH exercise consisted in comparing "the probability of a patent matching the originating patent by geographic area, *conditional* on its citing the originating patent, with the probability of a match *not conditioned on the existence of a citation link*. This noncitation-conditioned probability gives a baseline or reference value against which to compare the proportions of citations that match" (JTH, 1993, p. 581). The evidence reported by JTH shows indeed that citations are highly localised. Citing patents are up to two times more likely than the control patents to come from the same state, and up to six times more likely to come from the same metropolitan area.

2.2 Problems of interpretation and the need for further controls

JTH's interpretation of their own results as evidence of the existence of pure spillovers hides quite a naïve portrait of the channels along which knowledge externalities flow. Basically, one should believe that knowledge externalities are the result of oral communications. Although no thorough discussion can be found in JTH, nor in any other econometric work on LKS, many scattered remarks point in this direction (for a discussion and a few quotes, see Breschi and Lissoni, 2001).

Within the original production-function frame that started the LKS research programme, the naivety of the description comes as a logical necessity: any input-embodied knowledge (whether the input is labour, or some good or service) is traded consciously between the two sides of the market; as long as it is not entirely paid for, some externality may exist, but

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for patents in their names, and simply list the inventors' names to oblige to the legal duty of making clear who, eventually, will be entitled to the so-called "equo premio".

[7] JTH's rules in this case are quite complicated. Two full paragraphs of their article are devoted to their explanation, at page 585. States are the US ones, while country is registered as US vs. non-US. Local areas are identified by Metropolitan Areas, either taken from statistical classification or adjusted by JTH to the purposes of their paper.

of a pecuniary kind. Pure spillovers can take place only within the realm of trade-unrelated personal communication, or through reverse engineering of some kind (i.e., reverse engineering both of manufactured goods and of technical documents, such as patents).

As soon as "tacitness" is called in, to explain why distance matters, reverse engineering exits the scene: studying thoroughly a piece of machinery or a patent is not enough to understand how it works, unless the original inventors adds some explanation and/or practical demonstration.

But why should that inventor accept to pass on information deliberately, without being paid for? How can we make sure that short distances convey pure spillovers and not, once again, pecuniary ones?

Social obligations are the answer. This is best seen when discussing knowledge flows from universities to firms: treating those flows as pure spillovers sounds reasonable, since university researchers obey to the principles of "Open Science" and dedicate themselves to the production of public goods. They have the duty to communicate and discuss widely and freely their results and discoveries. It is not by chance that LKS literature devotes special attention to externalities from local universities.

Community of practitioners may also have some obligations of this kind. As described by von Hippel (1987), industrial researchers and engineers working for different companies within the same technological niche may be willing to provide their colleagues with free advice, with their employers tolerating this practice as long as it provides some returns in terms of access to information.

At a closer look, however, one realizes that community of scientists or practitioners exchange "tacit" knowledge even from a long spatial distance, that is, they are not necessarily concentrated in space. Meeting a few times a year, at conferences and workshops, may be enough for two scientists to get mutual understanding, and start exchanging files, references, and any other piece of information. As made clear by Cowan, David and Foray (2000), the knowledge exchanged in that way is still "tacit", to the extent that both oral and written messages make use of a language and some basic concepts whose meaning is highly context-specific and would take a long time to explain to outsiders. Scientists and industrial researchers engaged in this kind of exchanges are producing knowledge which we can portrait as a *club* good (Cornes and Sandler, 1996).

Spatial closeness thus disappears as a necessary condition for setting up a club of this kind: *Fairchildren* may all be located in Silicon Valley, but communities of open source software developers are scattered worldwide.

Nor spatial closeness is a sufficient condition: no multinational can hope to set up a branch plant within an Italian industrial district with the hope of being admitted to the tight web of personal relationships that convey the local knowledge.

This is not to say that personal acquaintances and face-to-face contacts do not matter: on the contrary, members of a social network who know each other personally exchange more information and help, and do it more frequently; those with many acquaintances send and receive more messages; and peripheral members, who are in touch with very few network members are reached by news later than central actors, and meet more difficulties to understand and appreciate them. Above all, peripheral members who would like to be introduced to some network member they have never met or interacted with, have to ask around a lot before finding who can help them in that direction (who knows whom).

This means that, when thinking of knowledge as a club good, we can distinguish both between club members and outsiders, and between members at different **social distances** from each other. Spillovers from an active club member will reach distant fellow members with some delay or imprecision, and will possibly never reach outsiders.

It remains true, however, that many social networks dedicated to the production of knowledge as a club good are geographically bounded, since spatial proximity may help the network members to communicate more effectively and patrol each other's behaviour (compliance with the social norms of inward openness and outward secrecy).

We conclude that co-localization (spatial proximity) is used by JTH as a proxy for what social network analysis calls *social proximity*. To the extent that many networks are concentrated in space, co-localization would appear as a significant determinant of access to spillovers.

If this is true, by replacing co-localization with direct measurers of social proximity, we would diminish the importance of geography as an explanatory variable of spillovers: the latter would be localized (in the physical space) if and only if a significant proportion of social networks are also localized in space.

Proposing a measure of social proximity and showing its usefulness is the first contribution of this paper to refining the JHT analysis. As explained with more details in the next section, we assume that inventors who worked together on the same patent know each other well enough to be willing to exchange information in future, and to tolerate to see that information passed on to somebody else the receiver knows personally. That is, the clubs of researchers and technologists we consider relevant for our analysis are described as *social network of inventors*. To the extent that these networks include members from more than one company, we expect some knowledge to circulate freely among the various companies, the extent of which will be measured by patent citations across firms.[8]

The second contribution of our paper to improving the JHT analysis consists in showing how many patent citations come from "mobile inventors", and how this result casts a few doubts on the capability of citations to represent "pure" knowledge spillover. This criticism comes from the observation that, for social networks of inventors to span across different firms, some inventors must move across companies. Two inventors currently employed by different companies may be supposed to know each other only if they previously worked together in the same company, or at most in a joint venture between their current employers. This is also a reasonable guess on how socializing among professionals actually occurs: industrial researchers who met only at conferences, and have no personal acquaintances in common, can hardly exchange sensitive information, or be willing to waste time to help each other. The opposite holds for two former colleagues, one of which may also introduce the other to his new ones.

Here comes in a conceptual problem. Any inventor who moves from one company to another one brings along some technical knowledge. To the extent that he can appropriate it, any pure spillover disappears, and only pecuniary externalities survive. In other words, by hiring an inventor, the new employer gets access to the specific knowledge embodied in the inventor and to the social capital of contacts he brings with him. If the inventor is able to fully appropriate the value of his knowledge and social capital, the externality is fully internalised. Moreover, even if the inventor cannot fully appropriate the value of his knowl-

[8] One could argue that previous common working experiences are quite a narrow criterion to define personal acquaintances However, as we made clear above by recalling von Hippel's and Cowan et al.'s work, it is only acquaintances among practitioners that matter: the receiver of the knowledge flow may be up to task of understanding it, which is not the case with acquaintances that have nothing to do with professional life. Notice also that since we measure flows with heavy technical contents, pure exchanges of broadly conceived new technical ideas (such as those that may take place between a scientist or technologist and an entrepreneur with no technical background) do not matter.

edge, only a pecuniary externality is likely to arise, i.e. the new employer gets access to a fundamental knowledge input at a price lower than its full quality price.

Patent citations allow us to control for this possibility, or at least for its likelihood. Besides *company* self-citations (one company's patent cites a patent from the same company, as in JTH) we can check for *personal* self-citations (one inventor's patent cites a patent from the same inventor, although the two patents belong to different companies).

A high rate of personal self-citations makes the interpretation of any JTH-style experiment quite fuzzy. To the extent that a mobile inventor keep in touch with his former employers (i.e. leaves some colleagues behind, who he still considers members of his social network) personal self-citations may signal a pure spillover. But if firms can access to the club good only by recruiting a network member, the latter's wage will reflect the value of the service he provides to his new employer. This is true for all network members: the network as a whole regards knowledge as a public (club) good, but one whose returns from sale are totally appropriated by the network as a whole. Rules of behaviour by the network members amount to nothing more than barter of knowledge assets, aimed at sharing those returns as fairly as possible.

Notice that labour mobility is quite likely to be limited in space, with classical explanations being sunk costs for relocation and aversion to the risk of unemployment.

Notice also that even JTH concede that under a few circumstances the validity of citations as indicators of knowledge spillovers is doubtful. They suggest that

> "… a firm [may get] a patent on an invention and then contracts with another firm to make some part of it, or a machine necessary to make it, or any other aspect of the downstream development. It is possible that such a contractor might later get a patent on a related technology. To the extent that the flow of rents between these parties is governed by a complete contract, there could conceivably be no externality running from the original inventor to the contractor. If we now add to this hypothetical contract the assumption that such contracted development is relatively likely to be localised, *we have the potential for the observed localisation of citations to be greater than the true localisation of knowledge spillovers*"[9]

[9] Jaffe, Trajtenberg and Henderson (1993), p. 583-4; italics added

What we are saying here is that complete contracts may also govern the recruitment of inventors, and the related access to knowledge as a club good. While JTH suggests that their own doubts refer to a very special case, which does not invalidate the overall meaning of patent citations, we put forward the suggestion that our doubts refer on the contrary to a very common case.

Summing up, we will show that localized spillovers from our data set are localized, and then control for social proximity among inventors. After proving the importance of that control, we will move on to show how much of that proximity is due to labour mobility.

3. Data selection, and the measurement of mobility and social distance

Our methodology for selecting the three samples of patents follows rather closely the one developed by JTH (1993).[10] For this study we have selected three cohorts of "originating" patents, consisting respectively of 1987, 1988 and 1989 patent applications. In each cohort we included all patent applications by Italian firms and institutions to the European Patent Office (EPO), which received at least one subsequent citation by the end of 1996.[11] The 1987 originating cohort contains 699 patents that had received a total of 1631 citations by the end of 1996. The 1988 originating cohort contains 843 patents that had received a total of 1784 citations by the end of 1996. The 1989 originating cohort contains 779 patents that had received a total of 1615 citations by the end of 1996.

For each cohort of "originating" patents, we eliminated all applications that either received citations only from foreign organisations, or whose applicant was an Italian organisation, *but did not* report any Italian inventor.[12] It must be pointed out that the choice of excluding citations from foreign companies implies that our study investigates the extent of intra-national localisation of patent citations, and it is unable to say anything about the extent of international localisation. This choice has been mainly dictated by data constraints, as the

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[10] Recently, Thompson and Fox-Kean (2002) have criticised the selection process proposed by JTH. Their main argument is that the level of technology aggregation adopted by JTH to match citing and control patents is likely to induce spurious localisation effects. Although the results are surely interesting, we will stick to the original JTH basic methodology, in order to allow easier comparisons of results.

[11] Patent applications made by individual inventors were excluded from the sample.

[12] The nationality of inventors has been derived by the address reported in patent documents. It is worth pointing out that the share of patent applications by Italian organisations made exclusively by non-Italian inventors is negligible (around 2% for each cohort of originating patents). On the other hand, the share of originating patents receiving citations *only* from foreign organisations is high (around 60% for each cohort of originating patents).

inclusion of citations coming from foreign organisations would have implied the construction of the whole network of inventors (see below). At the same time, given that the basic intuition behind the notion of localised knowledge spillovers is that the strength of spillovers should fade with distance, our choice should not have any effect upon the results.

For each originating patent, we then took all patents that subsequently cited them as prior art. For the construction of the citing sample, we considered only patent applications made before 1996 inclusive. Moreover, since we are interested in knowledge spillovers, we removed all observations in which citing and originating patents have the same applicant (i.e. self-citations).

Finally, from each citing patent we took the primary classification code at the 4-IPC-digit level and used this to construct a sample of "control" patents. Specifically, for each citing patent we identified all patents in the same patent class with the same application year. We then chose from that set a control patent whose application date was as close as possible to that of the citing patent, and that did not cite the same originating patent. The resulting data set therefore consists of all "originating" patents, for which there is a matching of citing and control patents. In turn, each citing patent is paired with a specific control patent within the same technological class and the with (approximately) the same application date. The final sample consists of 366 originating patents, which have received 483 citations from other Italian organisations.

3.1 Geographic assignment of patents

A major problem in measuring the frequency of matching by geographic area between cited and citing (control) patents relates to the way patents are assigned to locations. Patent documents report the town/city and postal address of each inventor. However, the problem is that patents can have multiple inventors. Therefore, the location of patents in geographic space cannot be resolved in a unequivocal way. In case of multiple inventors, JTH assigned each patent to the country/state in which pluralities of inventors resided, with ties assigned arbitrarily. Here, we take a slightly different approach and argue that two patents match geographically to the extent that they share *at least* one inventor's location in common.

3.2 Linkages: mobility and "social" distance

The major novelty of our study consists in improving the methodology described above with the purpose of assessing the relative importance of pre-existing "linkages" among patents on the probability of a geographical match. By reporting the names, surnames, address and company affiliation of each inventor, patent documents allow us to measure at least one type of such "linkages", namely those arising from the participation in a common "team" of inventors. Moreover, as the composition of teams changes among patents and over time, exploring the composition of teams and their evolution permits to reconstruct the network of collaborative relationships linking inventors (and, through them, patents).

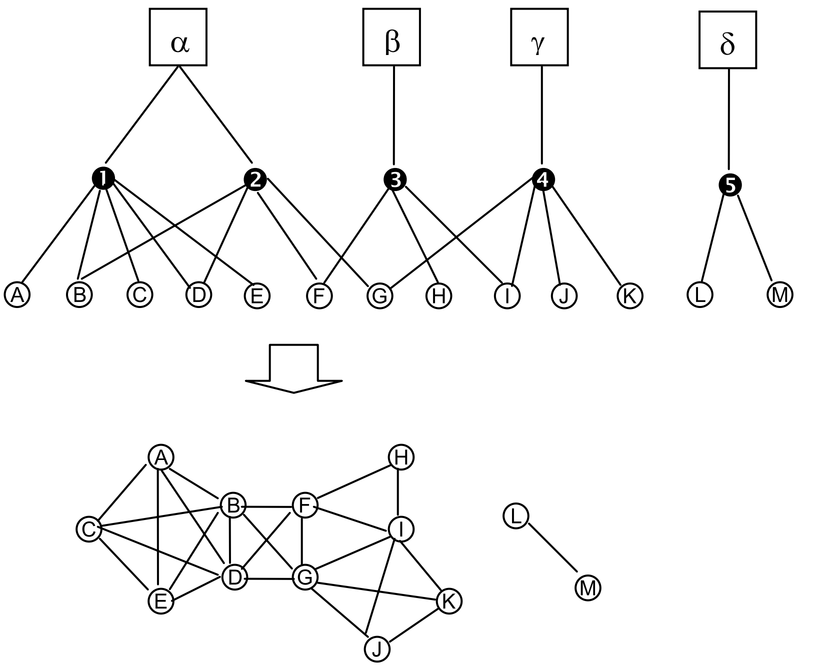
The following hypothetical example illustrates the main idea (see Figure 1). Let suppose to have five patent applications (1 to 5) and four applicants (α, β, γ, δ). Applicant α made two applications (1,2), while applicants β, γ and δ one each. Patents have been produced by thirteen distinct inventors (A to M). So, for example, patent 1 applied for by company α has been produced by a team comprising inventors A, B, C, D and E. A reasonable assumption to make at this point is that, due to the collaboration in a common research project, the five inventors are "linked" to each other by some kind of knowledge relation. The existence of such a linkage can be graphically represented by drawing an undirected arrow between each pair of inventors, as in the bottom part of Figure 1. Repeating the same exercise for each team of inventors, we end up with a map representing the network of linkages among all inventors.[13]

Using the graph just described, we can derive measures of "connectedness" among pairs of patents. In order to see how, we have first to make some observations:

i) one can measure the "distance" among pairs of inventors in the network, by calculating the so-called *geodesic distance*.

[13] In the language of graph theory, the top part of the figure reports the affiliation network of patents, applicants and inventors. An affiliation network is a network in which actors (e.g. inventors) are joined together by common membership to groups of some kind (e.g. patents). Affiliation networks can be represented as a graph consisting of two kinds of vertices, one representing the actors (e.g. inventors) and the other the groups (e.g. patents). In order to analyse the patterns of relations among actors, however, affiliation networks are often represented simply as unipartite (or one-mode) graphs of actors joined by undirected edges- two inventors who participated in the same patent, in our case, being connected by an edge (see bottom part of Figure 1). Please note that the position of nodes and the length of lines in the graph do not have any specific meaning.

Figure 1. Bipartite graph of patents and inventors



***Top*: Tripartite graph of applicants (α,β, γ, δ), patents(1 to 5) and inventors (A to M), with lines linking each patent to the respective inventors and applicants.**
***Bottom*: the one-mode projection of the same network onto just inventors.**

The geodesic distance is defined as the minimum number of edges that separate two distinct inventors in the network[14]. In Figure 1, for example, inventors A and C have geodesic distance equal to 1, whereas inventors A and H have distance 3. This means that the linkage between them is mediated by two other actors (i.e. B and F). In other terms, even though inventor A does not know directly inventor H, she *knows who* (inventor B) knows who (inventor F) knows directly inventor H.

i) Inventors may belong to the same component or they may be located in disconnected components. A component of a graph can be defined as a subset of the entire graph, such that all nodes included in the subset are connected through some path. In Figure 1, for example, inventors A to K belong to the same component, whereas inventors L and M belong to a different component. A pair of inventors belonging to

[14] For this and the following technical terms from social network analysis: Wasserman and Faust (1994)

two distinct components have distance equal to infinity (i.e. there is no path connecting them).

ii) Some inventors have an extraordinarily important role in connecting different components. We call them "mobile" inventors. For example, in Figure 1, inventor F worked for both company α and β, thus connecting the team of inventors (B,D) with the team of inventors (H,I). Similarly, inventor G worked both for company α and γ, thus connecting the team (B,D,F) with the team (I,J,K).

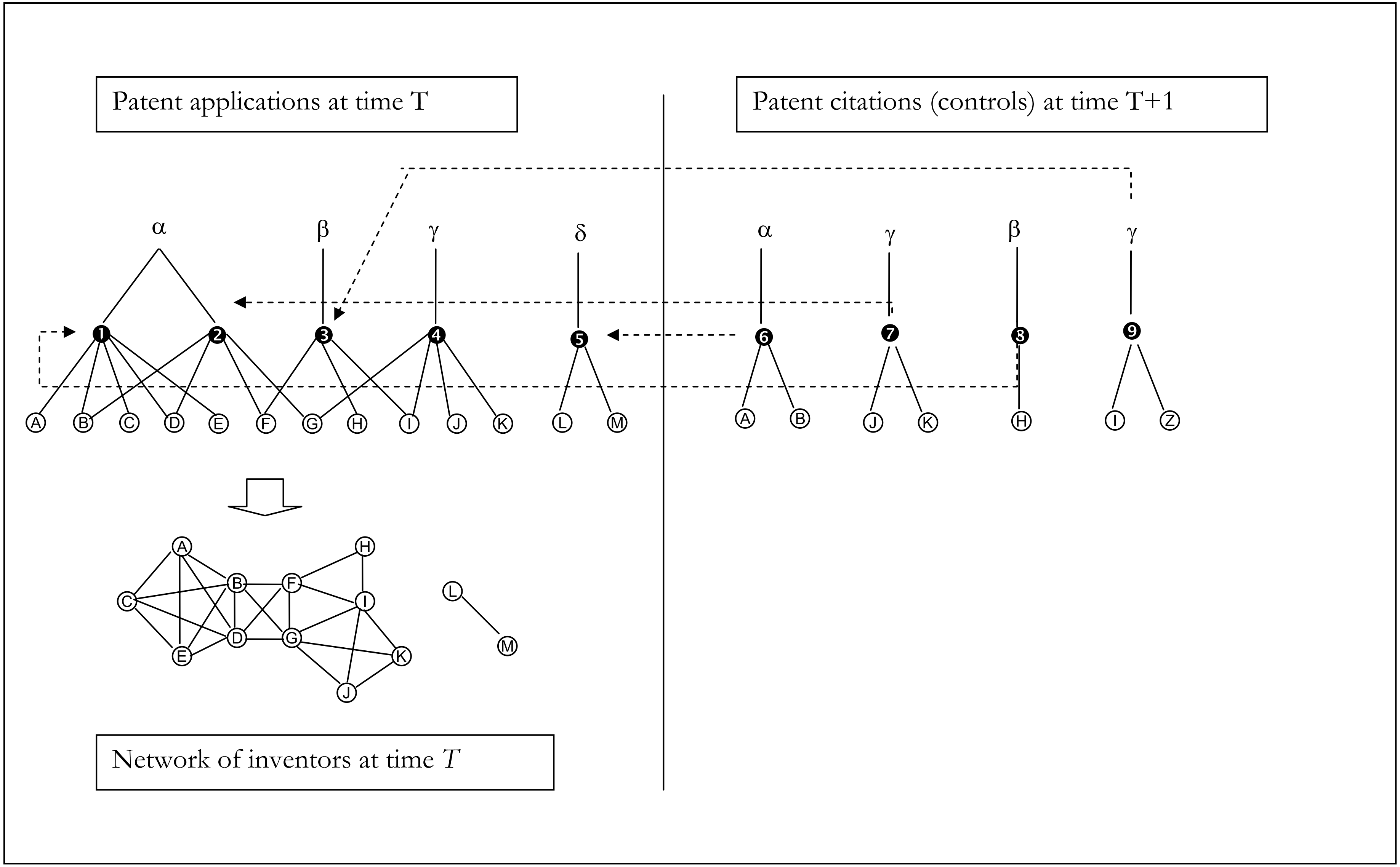
The next question is how using information derived from the network of inventors in order to ascertain the existence of a "linkage" between citing (control) and cited patents, besides the link arising from the citation (non-citation) itself. This is again illustrated by the previous example. Let us include now in the picture a patent document citing a previous patent and not being a self-citation. Four sub-cases can arise (Figure 2):

1) There is no linkage between citing and cited patents. This is the case of patent 6 citing patent 5. Inventors of patent 6 (A,B) were not previously connected to the inventors of patent 5 (L,M). They belonged to different components and their distance was equal to infinity.

2) There is a *direct* linkage between citing and cited patents. This is the case of patent 7 citing patent 2. Inventors of patent 7 (J,K) know personally one of the inventors of patent 2, namely inventor G, , through previous collaboration on patent 4. At time T, they belong to the same connected component. Note that the geodesic distance between either J or K and G is equal to 1. On the other hand, the distance between either J or K and the 'other' inventors of patent 2 (B,D,F) is equal to 2.

3) There is an *indirect* linkage between citing and cited patents. This is the case of patent 8 citing patent 1. Inventor of patent 8 (H) was not directly linked to any of the inventors of patent 1 (A,B,C,D,E). However, she was indirectly linked to them through collaboration with F on patent 3. In other words, inventor H knows somebody (F) who knows inventors of patent 1. The geodesic distance between H and any of the inventors of patent 1 is therefore equal to 2.

Figure 2. Mobility and network linkages between citing and cited patents (Dotted arrows indicates the existence of a citation link between two patents)



4) There is a <u>*perfect* linkage between citing and cited patents</u>, when at least one inventor appears in both patents. This is the case of patent 9 citing patent 3. One of the inventors of patent 9 (I,Z) also appears in the team of inventors of patent 3 (I,F,H). The geodesic distance between I and herself is, by definition, equal to 0. Note that the pair patent 9 – patent 3 is not a self-citation, as the applicants of the two patents are different, and it should therefore be included in the sample of originating patents. The linkage between citing and cited patents arises in this case from the *mobility* of one inventor (I) from company β to company γ.

Using information from the pre-existing network of collaboration among inventors, we can derive a measure of whether and to what extent citing (control) and cited patents are connected by linkages other than the citation itself. Absent any linkage among the inventors of the two patents, we can say that the latter are not connected. On the other hand, whenever a linkage (direct, indirect, perfect) exists among the two patents, we can say that they are connected.

3.3 Constructing the network of inventors

To implement the ideas described above, we have constructed a biographical dataset, based upon all patent applications at the EPO from 1978 (its opening year) to 1999, which listed at least one Italian inventor (the nationality being suggested by the inventor's address). The resulting database contains information on 30,170 inventors (name, surname, address) and 38,868 patent applications (technology classification code, name and address of the applicant or grantee, application date and year). The number of inventors results after checking raw data for misspelling of Italian personal and city names, use of initials, and loss of second names. A round of e-mailing and phone calls helped identifying "mobile inventors", i.e. individuals with identical name and surname, but different postal addresses (and, possibly, different company affiliations)[15].

[15] Inventors listed with the same name and surname (and different postal address) are identified as the same person when all or most of their patents belong to the same company: if this attribution sounds doubtful, further attempts of personal contacts have been made.

Table 1 – Evolution of the one-mode network of Italian inventors (1978-95)

Year	Number of inventors	Number of edges [(a)]	Number of components of size ≥ 2 [(b)]	Average size of components [(c)]	Size of largest component [(d)]
1978-1986	6670	5203	1084	3.7 (8.0)	164
1978-1987	8058	6534	1287	3.8 (20.3)	723
1978-1988	9554	7912	1487	3.9 (26.9)	1032
1978-1989	11117	9557	1661	4.1 (33.4)	1359
1978-1990	12951	11474	1878	4.2 (43.7)	1885
1978-1991	14613	13294	2100	4.3 (48.1)	2194
1978-1992	16412	15421	2329	4.4 (52.6)	2504
1978-1993	18048	17514	2508	4.5 (58.0)	2858
1978-1994	19725	19437	2731	4.6 (61.7)	3166
1978-1995	21526	21593	2969	4.6 (64.8)	3449

[(a)] Total number of edges in the one-mode network of inventors
[(b)] Number of components including at least two connected inventors
[(c)] Average number of inventors in components with at least two inventors (standard deviation)
[(d)] Number of inventors in the most numerous component

Using the data set just described, we have constructed the affiliation network of patents, applicants and inventors, as well as the one-mode projection of the same network onto just inventors, for each year from 1986 to 1995. Table 1 reports some descriptive statistics for the resulting one-mode network of inventors. The network size grows as new inventors start patenting. At the same time, the average number of inventors in each component also grows, as previously disconnected teams are joined by some 'mobile' inventors. Notably, also the absolute (and relative) size of the largest component grows steadily over time.

As explained above, we can derive measures of "linkage" between citing (control) and cited patents using information provided by the inventors' network. Specifically, for each pair of citing-cited patents at time T (e.g. a patent issued in 1995 citing a patent issued in 1987), we constructed the network of inventors at time T-1 (e.g. in 1994) and calculated the following measures of "linkage":

i) *Connectedness*: the variable takes value 1 if some of the inventors of citing and cited patents are in the same component at time T-1 (i.e. there is a path connecting at least two of them); the variable takes value 0 in case the inventors belong to disconnected components.

ii) *Distance*: the variable measures the shortest distance between the team of inventors of the citing and the cited patent. The variable may take values comprised between 0 and infinity. The distance between citing and cited patents is 0 when at least one inventor is reported in both. The distance takes a positive and finite value when the two patents do not share any inventor in common, but some of the inventors of citing and cited patents are in the same component at time T-1. Finally, the distance between the two patents is infinite when none of the inventors in the two teams belong to the same component at time T-1.

The same variables are computed for each pair of control-cited patents. Table 2 reports the composition of the final sample of patents, as well as some summary statistics concerning the inventors included in it.

Table 2 – Sample of cited, citing and control patents: number of inventors and linkages

	N. of patents	N. of inventors	N. of inv. *per patent*	N. of pairs [(a)]	N. of connected patents		
					Total [(b)]	*Geodesic = 0* [(c)]	*Geodesic ≥ 1*[(c)]
Cited	366	572	1.8 (1.2)	-			
Citing	483	721	2.0 (1.4)	1789	132	*76*	*56*
Control	483	726	1.9 (1.2)	1927	99	*17*	*82*

(a) A patent made by three inventors citing a patent made by two inventors generate 6 possible pairs of inventors, The column reports the total number of pairs cited inventors – citing (control) inventors summed up over all patents in the sample.
(b) The column reports the absolute number of citing (control)-cited patents, whose inventors belong to the same connected component.
(c) The columns report the absolute number of citing (control) – cited patents, whose inventors have either 0 or a positive, but finite distance.

None but six of connected patents (both from the citing and the control sample) lists less than two inventors. This suggests that inventor mobility is a phenomenon hardly distinguishable from social networking: it is not isolated inventors who move across companies, but team workers, who meet and interact with different co-inventors when reaching the new company. As a result of this interaction, even personal self-citation (i.e. self citation at the inventor's level) witness some knowledge diffusion, in this case from the mobile inventors to new team mates

4. Results and comments

Table 3 reports the results of the JHT experiment, as run on our data. The first column reports the percentage of citing patents that are co-located with the cited ones, at the city, province or regional level[16]. The second column reports the same percentage for the control sample, and the third one the "odds ratio" of a positive association between the probability for a patent to be a citing *and* a co-located one. Odds ratio greater than one signal that the differences between the values in the first and second columns are significant, i.e. the existence of LKSs, according to the current interpretation of the JTH experiment.[17]

It appears immediately that our data replicate successfully the JTH fundamental result: the percentage of "co-located" citing patents is higher than expected, that is higher than the equivalent percentage for control patents. In the Odds Ratio terminology, the probability of co-location between a cited and a citing patent is much higher (OR>1) than the probability of co-location between the same cited patent and the "control" one.

Table 3 Co-location percentages, for citing and control patents

	Co-location percentages		
Co-location level	Citing *(n. of patents)*	Control *(n. of patents)*	Odds Ratio *(chi-square; df)*
City	25.1	17.4	1.6 *
	(121)	*(84)*	*(8.477; 1)*
Province	38.7	29.8	1.5 *
	(187)	*(144)*	*(8.498; 1)*
Region	53.8	40.6	1.7 *
	(260)	*(196)*	*(17.014; 1)*

* 99% significant ; † 95% significant; ‡90% significant

[16] Nomenclature of Statistical Territorial Units (NUTS) has been used here to define the spatial units of analysis. The city level corresponds to the so-called "comuni" (NUTS4), of which there are 8,100. Moreover, there are 95 provinces (NUTS3) and 20 regions (NUTS2).

[17] A more user-friendly comparison technique of values in the first two columns would consist in computing t-tests for the difference in the frequency of geographical matching between, respectively, citing-cited patents and control-cited patents. JTH follow this strategy. Using odds ratios, however, turns useful for more complex comparisons, as those we propose below. Formally, we define odds ratios from the following 2x2 table whose row labels list the origin of the patent from either the "citing" sample or the "control" one (the two samples have the same size: 483 observations); the column labes tell us about the co-location of each patent and the cited one it refers to. For example, the cell *p11* gives the probability of a patent being a citing one *and* being co-located with the cited patent.

	Co-located? Yes	Co-located? No	Total
Citing patent	*p11*	*p12*	*p11*+*p12*=50
Control patent	*p21*	*p22*	*p21*+*p22*=50
Total	*p11*+*p21*=21.2	*p12*+*p22*=78.8	∑*pij*=100

The odds ratio for each table is then; OR = $p11p22/p12p21$

Odds ratios greater than one suggest a positive association between two probabilities, in our case the probability for a patent to come from the citing sample, and the probability of being co-located to the patent it cites.

Tables 4 and 5 show the same kind of calculations, after controlling for social links among the inventors. For each pair of patents (whether citing-cited or control-cited) we check their "connectedness" value, and proceed to calculate again the co-location percentages for citing and control patents (table 4).

We then move on to calculate different sets of "citation and co-location" Odds Ratios for connected and non-connected pairs of patents. We then test homogeneity between the two sets of Odds Ratios by calculating Breslow-Day statistics.

Finally, we apply Mantel-Haenszel methods to:

- performing a "nonzero correlation" test, which tells us whether some association between "citation" and "co-location" survives to the adjustment for connectedness;
- calculating the lower-bound 95% confidence limit of so-called "common odds ratios": for any positive association between citation and co-location to be significant this value must be higher than one.

Table 4 Co-location percentages, citing vs. control patents, adjusted for connectedness

	Non-connected		Connected	
Co-location level	Citing *(n. of patents)*	Control *(n. of patents)*	Citing *(n. of patents)*	Control *(n. of patents)*
City	8.8 *(31)*	10.4 *(40)*	68.2 *(90)*	44.4 *(44)*
Province	22.2 *(78)*	22.4 *(86)*	82.6 *(109)*	58.6 *(58)*
Region	41.0 *(144)*	33.3 *(128)*	87.9 *(116)*	68.7 *(68)*

Size of samples after adjusting for connectedness: Non-connected: 351 (citing) + 384 (control)
Connected : 132 (citing) + 99 (control)

We first notice from table 4 that co-location percentages for non-connected patents, whether from the citing or control sample, are much lower both of those for the aggregate sample (see table 3) and of those for connected patents. The highest co-location for non-connected patents come from analysis at the regional level of the citing sample, and it is just 41 per cent, less than the minimum value for connected patents (44.4 per cent, from city-level analysis of the control sample). This clearly suggests connectedness to bear great influence on any result one can get from the spatial analysis of patent citations.

Table 4 also suggests that, in absence of any social connection with cited patents, citing and control patents bear no differences in terms of co-location at the city and province level (at the city level, control patents are indeed slightly more located than citing ones). Some difference may possibly survive at the regional level. On the contrary, when social connection is present, JTH's results survive at all levels.

These suggestions are confirmed by Odds Ratio analysis in table 5. "Citation and co-location" Odds Ratios are always higher for connected patents than for non-connected ones, as confirmed by the Breslow-Day test (differences between Odds Ratios for the two sub-samples are always non homogenous). The same test and a look at the data, however, confirms those differences to be slightly less significant at the regional level, compared to smaller geographical aggregates. Notice also that Odds Ratios for connected patents are much higher than those calculated for all patents, while the opposite holds for non-connected patents. Again, social connection is a pre-requisite for JTH's results to survive, and indeed be strengthened.

Table 5 Odds ratios for "citation *and* co-location", for connected vs non-connected patents

	Odds Ratio *(chi-square; df)*				
Co-location level	Non-Connected	Connected	Breslow-Day: Chi-sq./ df	Non-zero corr: Chi-sq. / df	Common OR 95%: confidence limit
City	0.8 *(0.528; 1)*	2.7 * *(13.086; 1)*	9.930 / 1 *	3.707 / 1 ‡	0.991
Province	0.9 *(0.003; 1)*	3.3 * *(16.255; 1)*	12.066 / 1 *	4.065 / 1 †	1.006
Region	1.4 † *(4.655; 1)*	3.3 * *(12.857; 1)*	5.387 / 1 †	11.980 / 1 *	1.228

* 99% significant ; † 95% significant; ‡90% significant

Nonzero correlation tests suggest the overall association between citation and co-location to be weakened by the inclusion of controls for connectedness, with the usual exception of regional level analysis. Similarly, the 95% lower bound limit for Odds Ratios include value one for analysis at the city level, and barely excludes it for the province level.

As suggested in section 3, however, "connectedness" hides two fundamentally different varieties of social links: those directly generated by the mobility of inventors, which reduces the geodesic distance between two connected patents to zero, and those due to indirect links between the teams of inventors, such that the distance is finite, but never less than one (in particular, see table 2 and related comments).

In order to test the effects of these two varieties of social links, we run a series of logit regressions of the same kind one can find in JTH[18]. Only patents from the citing sample are considered, with the binary variable *"co-location"* (yes/no) as the dependent one. Explanatory variables are just three. The first one refers to connectedness, and distinguishes between connectedness from *"mobility"* and *"know-who"* connectedness, due to direct or indirect social links between inventors from the two patents' teams, but no overlapping between the two; no connectedness take the zero (baseline) value. The second one controls for the co-location of technological activities, and makes use once again of information from the control sample: for each citing patent, it takes value one if the related control patent is co-located with the cited one, and zero otherwise (*control co-location*). Finally, we also control for the likelihood of patent connection by technological field, that is we control whether the control and cited patents are linked by mobility or know-who connections, or are not connected at all (*control mobility* and *control know-who*)

We run backward-inclusion regressions for main effects only, starting with the inclusion of all the explanatory variables. One regression is run for each geographical level. When it comes to regional analysis we added a dummy variable for *Lombardy*, that is for the possibility that at least one of the inventor of the cited patent points to Lombardy, the largest and most innovative region of Italy, where more than 50 percent of the inventors come from. Besides improving the estimates, this dummy is expected to cast light on the different results we got in tables 4 and 5 for analysis at the regional level, as opposed to city- and province-level analysis.

Tables 6 reports the results of the regressions, in terms of parameter estimation. Table 7 calculate the Odds Ratios one can derive from those parameters.

The importance of controlling for the localization of technological activities is confirmed: the co-location of control patents bears always a positive influence (table 6) and the odds that citations will be co-localized along with control patents are always greater than one (table 7).

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[18] Jaffe, Trajtenberg and Henderson (1993), table IV, p. 593

Table 6 Co-location probability for citing patents: logit estimates *(Chi-Sq. in brackets)*

	City	Province	Region
Intercept	-2,55	-1,62	-0,92
	(149,43)	*(101,99)*	*(31,48)*
Connection:			
Know-who	1,61	1,61	1,42
	(21,71)	*(26,43)*	*(18,21)*
Mobility	4,70	5,58	4,75
	(100,27)	*(30,00)*	*(21,86)*
Control co-location	1,17	1,19	0,61
	(11,65)	*(22,87)*	*(8,08)*
Control know-who	b.e.	b.e.	b.e.
Control mobility	b.e.	b.e.	b.e.
Lombardy	-	-	0,80
			(13,44)

b.e. = backward eliminated.
* All reported parameters are 99% significant.

Table 7 Co-location probability for citing patents: Odds Ratios *(95% confidence lower bound in brackets)*

	City	Province	Region
Connection			
Know-who vs. No connection	5,02	5,01	4,12
	(2,55)	*(2,71)*	*(2,15)*
Mobility vs. " "	110,38	264,14	115,20
	(43,96)	*(35,93)*	*(15,75)*
Mobility vs. Know-who	21,99	52,73	27,94
	(7,95)	*(6,76)*	*(3,54)*
Control co-location	3,24	3,28	1,84
	(1,65)	*(2,02)*	*(1,21)*
Lombardy	-	-	2,22
			(1,45)

On the contrary, controlling for the social connection of technological activities is unnecessary. The social connection of control patents never affects significantly the co-location probability for citations and is eliminated in all of our backward exclusion regressions (table 6).

Social connection between cited and citing patent is clearly the most important determinant for co-location between the two. Parameters of the *mobility* and *know who* variables in table 6 are always positive and significant, and the odds ratios in table 7 rather impressive. Citing patents linked to cited ones by at least one inventor (i.e. mobility) are more than hundred times more likely to be co-located than non-connected ones: clearly, Italian inventors may move across firms, but do not like to re-settle in different regions, provinces or even cities.

Indirect (know-who) social connection between inventor teams also matter: citing patents connected to cited ones in this way are from four to five times more likely than non-connected ones to be co-located. However, indirect links bear much less influence than mobility of inventors: besides comparing the two sets of Odds Ratios, one can also calculate Odds Ratios for "mobility" vs. "know-who" connection, and notice that the former kind of connection makes co-location probability at least 20 times more likely than the other.

Finally, we notice that the persistence of regional effects in tables 4 to 5 is not due to any specific contribution of "unconnected" LKSs, but only to the peculiarity of the Italian innovation system, which is largely concentrated in Lombardy. The control variable for the location of cited patents in this region is positive and significant, so that citations directed to patents from Lombardy are two times more likely than others to be located in the same region.

5. Conclusions

This paper brought JTH's recommendation to use patent citations as "a paper trail" for tracking knowledge flows to its extreme consequences. Patents have been used to check for the mobility of inventors across companies and in space, as well as for the social ties that such mobility helps establishing.

By doing so, we have given further confirmation to the original intuition of those economists and sociologists that first stressed the tacit content of technological knowledge: knowledge always travel along with people who master it. If those people move away from where they originally learnt, researched, and delivered their inventions, knowledge will diffuse in space. Otherwise, access to it will remain constrained in bounded locations. That is, knowledge flows (whether pure spillovers or traded services) are localized to the extent that labour mobility also is.

Whether knowledge flows as measured by patent citation can represent "spillovers" or not remains a matter for further enquiries. However, the overwhelming weight of mobility-induced citations in our data casts some doubt on enthusiastic interpretation of JTH-linked results as evidence of LKSs. Our intuition is that mobile inventors are most likely to be scientific or technological "stars" whose wages or fees pay for the access they can provide to a valuable club good such as the knowledge stock mastered by them, and the inventors in their network. If it is so, either externalities may be fully internalised or just pecuniary externalities arise (stars can accept lower wages and fees to the extent that their employees and customers do not ask them to relocate), but no pure spillovers.

If confirmed, this interpretation bears great relevance for policy. It suggests that fashionable policies for attracting high-tech companies, private R&D facilities, and public R&D funds in cities and regions, which are lagging behind the technological frontier may be fatally flawed. Even if enough incentives would convince a few bright inventors to relocate, these would maintain their social ties with distant colleagues and fellow researchers, and find no reason to forge some new ones locally. Many more incentives would be then needed for helping local firms to recruit those bright inventors, and finally get access to the club good they can provide.

To confirm these conclusions, however, more empirical work is required. First, we will increase our sample sizes, to allow for a more secure scrutiny of our results on Italian data. Second, testing our hypothesis against USPO data, rather than EPO ones, could be more safe, due to the greater accuracy with which the US Patent Office checks the information provided by applicants on inventors. Finally, we ought to test our hypothesis on a larger, and less peripheral, innovation system than the Italian one: in this way, we could generalize our results.

While the first proposed extension will be a matter for further drafts of this paper, the others will require separate efforts for setting up new data sets.

References

Acs Z.J., Audretsch D.B, Feldman M.P. (1992), "Real effects of academic research: Comment", *American Economic Review* 82 (1), 363-367.

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

Audretsch D.B., Feldman M.P. (1996), "R&D spillovers and the geography of innovation and production", *American Economic Review* 86(3), 630-640

Breschi S., Lissoni F. (2001), "Knowledge Spillovers and Local Innovation Systems: A Critical Survey", *Industrial and Corporate Change*, vol. 10 n. 4, 975-1005.

Cornes R., Sandler T. (1996), *The theory of externalities, public goods and club goods*, Cambridge University Press, Cambridge MA.

David P.A. (1999), "Krugman's Economic Geography of Development. NEGs, POGs and Naked Models in Space", *International Regional Science Review* 22, 162-172

Feldman M.P. (1999), "The New Economics of Innovation, Spillovers and Agglomeration: A Review of Empirical Studies", *Economics of Innovation and New Technology* 8, pp.5-25.

Feldman M.P., Florida R. (1994), "The geographic sources of innovation: technological infrastructure and product innovation in the United States", *Annals of the Association of American Geographers* 84(2), 210-229.

Griliches Z. (1992), "The Search for R&D Spillovers", *Scandinavian Journal of Economics* 94, Supplement, 29-47.

Jaffe A.B. (1986) "Technological opportunity and spillovers from R&D: Evidence from firms' patents profits and market value", *American Economic Review* 76, 984-1001.

Jaffe A.B. (1988) "Demand and supply influences in R&D intensity and productivity growth", *Review of Economics and Statistics* LXX, 431-37.

Jaffe A.B. (1989), "Real effects of academic research", *American Economic Review* 79, 957-70.

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

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

Jaffe A.B., Trajtenberg M., Henderson R. (1993), "Geographic localisation of knowledge spillovers as evidenced by patent citations", *Quarterly Journal of Economics* 10, 577-598.

Krugman P. (1991), *Geography and Trade*, MIT Press, Cambridge MA.

Newman M.E.J. (2000), "Who is the best connected scientists? A study of scientific coauthorship networks", *SFI Working Paper* 00-12-64, Santa Fe.

Newman M.E.J. (2001), "The structure of scientific collaboration networks", *Proceedings of the National Academy of Science USA* 98, 404-409.

Thompson P., Fox-Kean M. (2002), "Can Patent Citations Identify Knowledge Spillovers?", http://www.andrew.cmu.edu/~pt/current/working_papers.html, Carnegie Mellon University

von Hippel E. (1987), "Cooperation Between Rivals: Informal Know-How Trading", *Research Policy* 16, 291-302.

Wasserman S., Faust C. (1994), *Social Network Analysis: Methods and Applications*, Cambridge University Press.

Zucker L.G., Darby M.R., Armstrong J. (1998), "Geographically localised knowledge: spillovers or markets?", *Economic Inquiry* 36(January), 65-86.