Available online at www.sciencedirect.com

SCIENCE DIRECT®

Research Policy 33 (2004) 127–145

research policy

www.elsevier.com/locate/econbase

Networks of inventors and the role of academia: an exploration of Italian patent data[☆]

Margherita Balconi[a], Stefano Breschi[c], Francesco Lissoni[b,c,*]

[a] Università degli studi di Pavia, Pavia, Italy
[b] Università degli studi di Brescia, Brescia, Italy
[c] CESPRI-Università Bocconi, via Sarfatti 25, 20136 Milano, Italy

Received 7 June 2002; received in revised form 3 June 2003; accepted 9 June 2003

Abstract

This paper proposes a quantitative analysis of social distance between Open Science and Proprietary Technology. A few general properties of social networks within both realms are discussed, as they emerge from the new economics of science and recent applied work on "small worlds". A new data-set on patent inventors is explored, in order to show that social networks within Proprietary Technology are much more fragmented than Open Science ones, except for science-based technologies. Two propositions are then put forward on the "open" behaviour expected from *academic inventors*, namely university scientists getting involved in Proprietary Technology networks by signing patents. Both propositions are confirmed by data, which show academic inventors to be more central and better connected than non-academic ones. The database and methodology produced for this paper are suggested to be relevant for the more general debate on the role of geographical and cognitive distance in university–industry technology transfer.

JEL classification: O31; O34

Keywords: Patents; University–industry linkages; Social networks; Academic inventors

1. Introduction

University–industry knowledge transfer is nowadays a key research subject both in economics and management studies, as well as a top entry in the science and technology policy agenda of a number of developed and developing countries.

"Distance" between the two realms of academic and industrial research has been increasingly called in to explain whether the former may, or may not, benefit

☆ Early versions of this paper were presented at the Third Proximity Congress on New Growth and Territories (Paris, 13–14 December 2001), at the DRUID Winter PhD Conference (Aalborg, 17–19 January 2002) at the workshop on "Science as an Institution: The Institutions of Science" (Siena, 25–26 January 2002), at the conference "Rethinking Science Policy: Analytical Frameworks for Evidence-Based Policy" (SPRU-University of Sussex, 21–23 March 2002), at the NBER Summer Institute on "R&D, Strategy and Organizations" (Cambridge, MA, 23 July 2002), and at the workshop on "Innovation in Europe. Empirical Studies on Innovation Surveys and Economic Performance" (Rome, 28 January 2003). All of the discussants provided us with helpful remarks. Daniele Archibugi, Scott Stern and an anonymous referee provided decisive comments. The responsibility for any mistake or omission remains ours. The research benefited from MIUR grants 9913444547_004 and MM13563585_001.

* Corresponding author. Tel.: +39-02-5836-3376; fax: +39-02-5836-3399.
E-mail address: lissoni@ing.unibs.it (F. Lissoni).

0048-7333/$ – see front matter © 2003 Elsevier B.V. All rights reserved.
doi:10.1016/S0048-7333(03)00108-2

the latter. Two concepts have attracted most of the attention: *geographical* and *cognitive* distance.

Within the geographical realm, it is usually suggested that both scientific and technical knowledge are largely “tacit” and “non-codifiable”, and require distance-sensitive transmission means such as frequent face-to-face clarifying discussions and on-site demonstrations (Feldman, 1999).

As for cognitive distance, patent citations have been exploited to measure the impact of university patents and scientific publications for innovations in industry, and differences in the relevance of different research fields (Jaffe, 1989; Tijssen, 2001). Data from innovation surveys have provided useful additional evidence on the impact of other academic activities, such as meetings and informal contacts with university researchers (Mansfield, 1995).

These remarks suggest that both geographical and cognitive distance matter in so far as they contribute to reduce a more fundamental kind of distance between the academic and industrial realms, namely *social distance*. The exchange of tacit knowledge between university and corporate researchers requires the two social groups to share some acquaintances and/or a few codes of behaviour in terms of reciprocity and fairness (both in case of market transactions and in case of free sharing). Similarly, academic researchers' mobility to and from industrial labs (either in the position of employees or entrepreneurs) requires a web of personal contacts for exchanging information on job and financing opportunities, and again some codes of behaviour that do not punish such mobility by portraying it as free-riding.

While case studies on the theme of social distance abound, large-scale quantitative research on the same subject is more of a rare breed, limited as it is by highly demanding data requirements. The present paper summarizes the early results of a research program that aims at producing and exploiting a large data set for Italy, with information on individual inventors' location, activity, and social ties. To date, the chief output of that program is the EPO-INV data-set on the social ties of Italian inventors, as measured by their participation to patents registered at the European Patent Office, from 1978 to 2000. A nested data-set, named EPO-INV-DOC, identifies those inventors who in 2000 were employed as full and associate professors or researchers by Italian universities.

In Section 2, we discuss our choice of individuals as the key observational units. We first recall the theoretical debate on the role assigned by the ‘New Economics of Science’ to social networks as knowledge diffusion vehicles. Then we illustrate how the EPO-INV database can serve the purpose of exploring the expected general properties of those networks.

In Section 3, we introduce the EPO-INV-DOC database and notion of “academic inventor”, which help moving the measurement of universities' contribution to patenting away from the institutional to the individual level. The move may be of crucial importance for studying countries such as Italy, where universities are not organized to manage Intellectual Property Rights.

In Section 4 we provide a few exploratory statistics on both the EPO-INV and the EPO-INV-DOC databases, which help identifying the structure of the Italian social network of inventors, and the role played by academic inventors.

In Section 5 we conclude by sketching our future research plans.

2. The new economics of science and the role of social networks

2.1. Describing social networks in S&T: the new economics of science

Recent changes in the economic and sociological conceptualisation of scientific knowledge have forced researchers in the economics of innovation to question, if not to abandon, the treatment of scientific knowledge as a public good, as derived by textbook economics.

Re-thinking of the issue ranges from relatively timid attempts to re-qualify university research advancements as a *local* public good (as in the geographical literature surveyed by Breschi and Lissoni, 2001a, b), to the outright refusal to consider scientific knowledge anything different from a private good (Callon, 1994).

A sort of intermediate position is taken by the self-styled “New Economics of Science”, pioneered by Dasgupta and David (1994). Authors in this tradition share with economic historians such as Rosenberg (1976, 1982) and sociologists of science as Callon (1994) the view that science and technology do not differ in terms of contents or enquiry procedures: both scientific and technological knowledge are described as durable and indivisible (nonrival) goods. At the same time, though, the New Economics of Science places special emphasis on the assumption that science and technology differ in terms of their appropriability (excludability) regime.

This assumption reminds closely of contemporary theorizing of so-called impure public goods (e.g. local goods and club goods). Theories in this field derive the appropriability regime of different goods not from any qualitative feature of the goods themselves, but from explicit social arrangements (Cornes and Sandler, 1996; pp. 9–10).

In particular, Dasgupta and David counterpoise "Proprietary Technology" and "Open Science" as the result of two opposite incentive structures. The former is approximately identified with the result of privately sponsored industrial research. Intermediate research results, instruments, and methods will be shared with other researchers, in order to get feedbacks and gain credit for future help, but not outside some organizational boundaries defined by the research sponsors. Communication with researchers from rival companies will be monitored and restricted, codification efforts (such as those leading to the publication of research papers) will be delayed as long as possible.[1]

By contrast, the incentive structure of "Open Science" is modelled upon Merton's (1957) sociological account of the function of disclosure norms and publications in forging the career path of academic scientists. The New Economics of Science depicts the community of scientists as composed by many small groups, linked both by career schemes requiring scientists to move across groups, albeit occasionally, and by some degree of across-group legitimization mechanism for individuals' research contributions.

Each group of academic scientists (or each set of tightly connected groups) belongs to a wide community of researchers of the same science field (an "epistemic community", as defined by Cowan et al. (2000) and Steinmueller (2000)) and contributes to expanding, codifying and securing the reliability of scientific knowledge by establishing mutually recognized research and test procedures, as well as communication codes for both written and oral exchanges. Within each community, codified knowledge is a public good. In turn, links among different groups are as many as it is necessary to spread information on the reputation of individual researchers, both in terms of capabilities and adherence to the behavioural codes of "Open Science".

Do the "Open Science" and the "Proprietary Technology" realms ever get in touch? How do they reconcile their different systems of incentives and social structures? Dasgupta and David discuss a few possibilities. The one they attach most importance to (both historically and quantitatively) is advanced education: doctoral students trade their willingness to provide free or cheap research assistantship for learning, and most of them will then pursue a career as industrial researchers.

In addition, academic scientists can occasionally turn into industrial researchers, and vice versa, depending upon the origin (public versus private) of the research funds, and the possibility (for industrial researchers) to spend some time working in close contact with a university or a public research centre. Mobility of researchers to and from universities, public labs, and corporate labs can produce similar contamination effects.

It has to be noticed that university–industry direct exchanges (as opposed to education) push researchers to adjust their behaviour to the incentive structure of the contingent research program (both in terms of adherence to the research objectives and publication rules; see David, Mowery and Steinmueller, 1994). For example, industrial researchers for large corporate labs, more often involved in basic research along with universities and public labs, will find it easier to publish; they will also find it more rewarding, since they entertain hopes of further cooperation in the future (see data on scientific publications collected by Cockburn and Henderson, 1998). At the opposite end, as shown by Zucker et al. (1998), star scientists from disciplinary fields prone to commercial exploitation trade their knowledge assets on a market basis.[2]

[1] In addition, as suggested by Nelson (1959), industrial researchers will not be let free to pursue their own research interests, as long as this threatens to deviate them from their assigned objectives: this can result in a bias towards applied, as opposed to basic research.

[2] See also Mansfield's (1995) evidence on the choice of the research objectives by small versus large universities; and Cohen et al. (1998) on the trade-off between R&D productivity (in terms of viable innovation) and the publication record of university-industry research centres in the US.

2.2. Measuring social networks in Proprietary Technology: the EPO-INV database

In order to map social groups in Science and Technology we need data on information exchanges between researchers, both within individual companies and academic research groups, and across them.

As long as we regard team-working experiences as a key mean for knowledge exchange, co-authorship of scientific papers is the ideal quantitative indicator to investigate social networks of academic scientists, and indeed there is a long tradition of exploiting them to that purpose (e.g. Melin and Persson, 1996).

The most recent research efforts within this line of enquiry draw extensively from graph theory, as it may be applied to social network analysis. They describe the social structure created by Open Science rules as a "small world", i.e. a "distinctive combination of high clustering with short characteristic path length" (Watts and Strogatz, 1998). Each researcher has a number of links which suffice to involve him deeply in a local network of collaboration (his research group), and a few researchers have as many links with members of other research groups as it is necessary to connect most, if not all, the epistemic community. News spread fast, as well as chances to engage in research partnerships apt to allow for knowledge exchanges.

What about Proprietary Technology? How to measure social networks there? And which properties will those networks exhibit, especially at the boundary with "Open Science", i.e. when industry–university cooperation occurs?

When asked these questions, the New Economics of Science reveals many dark zones. It produces many fewer clear-cut statements than it manages to derive from its re-visitation of Mertonian sociology. Nor it points out clearly to a data source comparable to scientific paper co-authorship. David et al. (1999) seem to admit this weakness openly, when they call for more serious theoretical and measurement efforts, in order to overcome the abuse of the "network metaphor" in their field.

On the theoretical side one needs to outline the expected properties of the social network of industrial researchers, at the very least by counterposition to what we already know about scientists' networks. We try to do so in Section 2.3.

As for the empirical tools, we propose here to make use of another traditional indicator, namely patent applications, albeit in a way which mimics closely the use of co-authorship data from scientific publications. More precisely, we suggest that when it comes to measuring social distance, patent data can be extremely useful, as many inventions are the outcome of teamwork, so that the related patent documents list more than one inventor.[3] We assume that inventors listed on the same patent know each other, and have possibly exchanged crucial scientific or technical information.

These considerations led us to set up a biographical data-set, based upon all patent applications at the European Patent Office from 1978 (its opening year[4]) to the first semester of 1999, which listed at least one Italian inventor (the nationality being suggested by the inventor's address). The resulting EPO-INV database contains information on 30243 inventors (name, surname, address) and 38868 patent applications (technological classification code, name and address of the applicant or grantee, application year).[5]

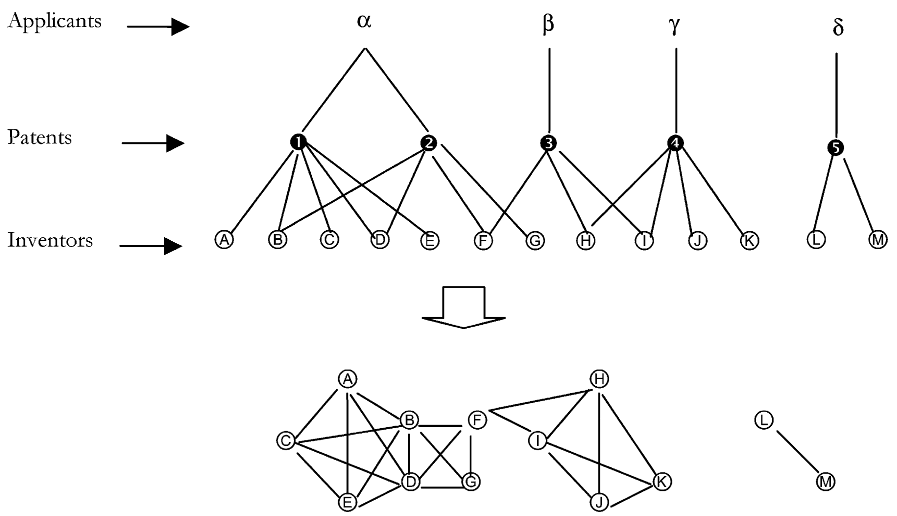
The EPO-INV data set permits to reconstruct the network of collaborative relationships linking Italian inventors.

The following hypothetical example illustrates the main idea (see Fig. 1). Let us suppose we face five patent applications (1–5), coming from four different applicants (α, β, γ, δ). Applicant α is responsible of two applications (1, 2), while applicants β, γ and δ one each. Patents have been produced by thirteen distinct inventors (A–M). So, for example, patent 1, ap-

[3] Patent documents report not only the names and addresses of the applicants, but also those of the inventors. These can be effectively combined with other sources of biographical information.

[4] Indeed, patent applications for 1978 are just a handful, and it is not until the 1980s that we can get a substantial flow of applications each year. This is due to the time which occurred to EPO in order to improve its reputation and build up the necessary organizational competencies.

[5] 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 first round of e-mailing and phones calls helped identifying "mobile inventors", i.e. individuals with identical name and surname, but different addresses. A second round of similar investigations is still under way, this time based upon careful checking of the applicants' names, and use of corporate addresses instead of personal ones (footnote 5). This implies that future editions of the data-set may contain a lower number of inventors (and a higher number of patents per inventor).



Top: Bipartite 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

Fig. 1. Bipartite graph of patents and inventors.

plied for by company α, has been produced by a team comprising inventors A–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 Fig. 1. Repeating the same exercise for each team of inventors, we end up with a map representing the network of linkages among all inventors.[6]

[6] 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 Fig. 1). Please note that the position of nodes and the length of lines in the graph do not have any specific meaning. For this and the following technical terms from social network analysis: Wasserman and Faust (1994).

Using the graph just described, we can derive various measures of "connectedness" among inventors. 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*. The geodesic distance is defined as the minimum number of steps (or, more formally, "edges") that separate two distinct inventors in the network. In Fig. 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.
(ii) 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.[7] In Fig. 1, for example, inventors A–K belong to the same component, whereas inventors L and M belong to a different component. A pair of inventors belonging to two distinct components are separated by a geodesic distance equal to infinity (i.e. there is no path connecting them).

(iii) Some inventors stand out for the number of links they exhibit: they have not just signed a high number of patents, but have also worked along with a large number of co-inventors (that is in large teams, on with many different teams). We expect these inventors to be chief researchers in large R&D departments, or senior academic researchers with a long tradition of consultancy to or joint research with industrial firms. For example, in Fig. 1, inventor B has worked with no less than six co-inventors, signing two patents (1 and 2) both of them produced by relatively large teams (six and four people, respectively). In her absence, the overall connectedness of the component she belongs to would be much lower, that is distances between inventors would be higher. Social network analysis refers to this property as high "degree centrality".

(iv) Some inventors may have a particularly important role in connecting different components. They can be either by "mobile" inventors, that is industrial researchers moving across firms, or, once again, academic researchers whose ties with industry are not limited to just one company. For example, in Fig. 1, inventor F worked for both company α and β, thus connecting the sub-component listing inventors from A to G with the sub-component listing inventors H–K. In her absence the component "A–K" would be split in two. Social network analysis refers to this property as high "betweenness centrality".

Summing up, the EPO-INV data-set allows for a description of the network of Italian inventors which makes use of most of the standard tools of social network analysis, and extends them to a very large size population.

2.3. Social networks within Proprietary Technology: expected general properties

Original work from Dasgupta and David suggests that private companies are most likely to discourage their employees to exchange "proprietary knowledge" with colleagues from other rival organizations. If the companies' grip on their intellectual assets were indeed so tight, we would expect low mobility of industrial researchers across firms: company loyalty would be highly valued, and efforts to avoid knowledge spillovers would result in long internal career paths. Similarly, resort to independent inventors or research organizations ought to be limited.

Under these extreme conditions we would expect the networks of industrial researchers to be quite different from the "small worlds" of scientists.

As shown by Newman (2000, 2001) "small world" properties translate into the emergence, within a network of scientists from the same discipline, of a "giant component" connecting most of the nodes, with only a few outsiders marginalized in a number of much smaller, peripheral components. All scientists within the main (giant) component are reachable through short paths, i.e. they are close to each other in terms of geodesic distances, despite the size of the component.[8]

On the contrary, we expect networks of industrial inventors to be composed of many more disconnected "network components" than any comparable populations of scientists, with no component reaching a giant size; nor we expect very low geodesic distances between inventors, unless the component which hosts them is very small.

Finally, we observe that the new economics of knowledge, with its insistence on "openness" and codification of knowledge (or the lack of them) as a function of the researchers' rewards structure, has been confronted by a number of authors stressing the existence of "technological regimes". Regimes are better seen, for the purpose of this paper, as a set of exogenous constraints, which differ across technological and scientific fields, and make the latter more or

[7] More precisely, a component of a graph is a subset of nodes, for which one can find a path between all pairs of nodes within the subset, but no paths towards the nodes outside. In our specific context, a node must be interpreted as an individual scientist/inventor.

[8] More properties are discussed by Watts and Strogatz (1998).

less resistant to codification efforts, regardless of the rewards attached to those efforts by universities or private companies (Malerba and Orsenigo, 1996; see also the rankings produced by Breschi et al., 2000).

Dasgupta and David (1994) tries to take in this criticism by suggesting that codification costs exist and researchers can somehow measure them, thus agreeing (within their own epistemic community, but also in the wider community of practitioners) on whether the effort is worth doing. These costs can admittedly differ across technological fields.[9] It follows that the structure of inventor networks should differ across technical fields, depending upon the degree (costs) of knowledge codifiability. In particular, most science-based fields should be less distant from "small world" properties than the other fields.

3. Spotting "academic inventors" in Italy: the EPO-INV-DOC database

Patenting by universities is all but one among many channels for transferring academic research to industrial applications. Nevertheless, the boom of university patenting in the United States since the Bayh-Dole Act of 1980 has turned the subject into the hottest topic for most of the empirical researchers in the economics of science. The results of their enquiries suggest that a few peculiarities of the US institutions and history have to be taken into account before imitating their methodology.

In particular, Mowery and Sampat (2001a, b) show convincingly that many US state and private universities have a long tradition in patenting, much older than the Bayh-Dole Act. In particular, they point at the important role played by the Research Corporation, a no-profit organization dating back to the 1920s, in spreading IPR awareness and management experience across a large number of university technology transfer offices. To date, we are not aware of a similar historical development in Europe, with the only exception of Britain.[10] That is to say, no continental European counterparts to the Research Corporation ever existed, nor one can find the kind of IPR awareness the Research Corporation contributed to create. In fact, official statistics on patents held by universities in continental Europe compare poorly with data for the US and the UK.

But before concluding that the latter do not contribute to (patented) industrial innovation, as it is often done, one should first check which other IPR arrangements have been in place in European academic circles, which may call for different statistical proxies.

Italian universities, for example, have only recently started moving away from a passive attitude towards IPR-related technology transfer. Despite being regarded by the law as the natural owners of all the IPRs concerning their employees' inventions,[11] Italian universities have traditionally made no effort to take advantage of this, and left patenting entirely to individual professors' initiative. As a matter of fact, IPRs over inventions derived from sponsored research programmes were left entirely to the sponsors, either private (such as many chemical and pharmaceutical companies, or ST Microelectronics, the largest European semiconductor company) or public ones (the most important being the National Research Council (CNR) and the National Agency for Energy and the Environment (ENEA)). As for inventions stemming out from generic funds from MIUR (the Ministry of University and Research), they were often left with no IPR protection, unless individual professors took the initiative of pushing their administrative offices to apply for patenting, most often meeting high resistance and no success at all. A few professors escaped

[9] Cowan and Jonard (2000) come back to the point, and specify the cost structure of codification activities as composed of both a fixed part (creation of models, languages, and aggregation of an epistemic community around them) and a variable part (which has to do with refining those models and languages, as well as increasing the size of the epistemic community using them).

[10] In 1948, the British government set up the National Research Development Corporation (NRDC) to commercialise British publicly funded research. After being merged with the National Enterprise Board (NEB) in 1975, this organization, now renamed as British Technology Group (BTG), was finally privatized in 1992. Many thanks to Aldo Geuna for pointing out the role of BTG to us.

[11] Until 2001, these matters were regulated by the Italian patent law, which dates back to 1939. A recent amendment by the current government shifted all IPRs over academic research output to individual researchers, but has been met with scepticism and will be changed significantly in the near future, if not withdrawn. As a consequence, future developments of these matters are surrounded by high uncertainty.

bureaucracy by applying themselves for patents, although the legitimacy of this practice is doubtful.

As a consequence, we expect patents based upon academic research not to belong to universities but either to individual professors or, more often, to their research sponsors. When looking for "university patents" we are then forced to look closely at the list of inventors' names attached to patent applications, searching for clues leading to academic researchers. The EPO-INV-DOC data-set was explicitly created to take into account the specificities of these Italian "do-it-yourself" institutional arrangements.

The EPO-INV-DOC database focuses on the contribution to patenting by what we call "academic inventors", namely university researchers and professors whose name appears on one or more patents, no matter whether these patents were applied for by their own employers. As such, the database is a subset of EPO-INV, which we obtained by crossing the latter with the complete list of academic staff of science and engineering departments in year 2000 (27844 full professors, associate professors, or researchers). By doing so, we came out with a list of 919 "academic inventors" and 1475 patents.[12]

As for academic scientists' contribution to industrial research, we expect those scientists to be able to maintain their independence from private sponsors, both in terms of having the chance, in their career, to work for more than one or just a few sponsors, and in terms of retaining their ability to carry on "open research". We expect those differences to show in our network analysis, as given further.

PROP1. Academic inventors holding patents are more central than non-academic ones with the same number of patents. In particular, this should show up when considering betweenness centrality, as long as academic inventors provide a bridge between academic and non-academic communities, or across non-academic communities (i.e. groups of industrial researchers) otherwise not linked by any joint research effort.

[12] A dedicated round of phone calls and e-mailing allowed to check for namesakes. Only individuals who answered to our questions were included. Patents in the EPO-INV-DOC data-set are those which include at least one university researcher in their list of inventors.

As a consequence of PROP1 we also expect the following.

PROP2. Network components hosting academic scientists are larger and possibly better connected than other components.

In addition, we expect the contribution of academic inventors to differ across technological fields. As shown by a number of case studies and by some more general evidence produced by Henderson et al. (1998) and Mowery et al. (2001), the patenting boom of US universities has been largely due to opportunities in the biotech field (whose role is even more striking when statistics are referred to licensing revenues and not just patent counts). This leads us back to the general properties of networks of inventors (Section 2.3): besides "ease of codifiability" (an inherent property of knowledge) it is the presence of academic inventors that may explain why the structure of those networks differ across technologies.

4. Networks of inventors in Italy

4.1. General properties

The general properties of the Italian network of inventors are summed up in Table 1, both for the overall network and for a few nested networks, each of them built by considering only the patents belonging to specific patent families (or technological "fields"), such as chemicals, consumer goods, electronics, instruments, mechanical engineering, and process engineering.[13]

We first notice that, as expected, networks in all fields are highly fragmented, showing no less than 600 components per field (excluding isolated inventors, i.e. inventors who never entered any team of inventors), with peaks of almost 1000 and 1500 components in the two fields dealing with Engineering patents. However, the relative size of the various components differ widely across technological fields.

The variance of the component size is extremely high in the chemical field, where the largest

[13] These fields cover all IPC codes, as used by EPO in 1999. They are the result of an aggregation of a finer classification discussed at length in Breschi et al. (2003).

Table 1
Networks of Italian inventors, by technological field, 1978–1999

	All technological fields	Chemicals	Consumer goods	Electronics	Instruments	Mechanical engineering	Process engineering
Number of inventors	30243	6454	4616	4479	4189	8646	5867
Academic inventors	919	549	21	101	179	64	123
Number of patents	38873	6606	5825	5164	4002	11095	6177
Number of edges[a]	31621	13219	2032	4835	3418	4536	4781
Number of isolates[b]	10601	894	2598	1184	1435	4128	2101
Number of components[c]	4074	629	686	684	768	1405	979
Density (×100)[d]	0.0069	0.0634	0.0197	0.0482	0.0389	0.0121	0.0277
Largest component							
Diameter[e]	40	19	8	16	8	26	22
Size[f]	6390	3301	112	885	105	267	381
	(21.1)	(51.1)	(2.4)	(19.8)	(2.5)	(3.1)	(6.5)
	[32.5]	[59.4]	[5.6]	[26.9]	[3.8]	[5.9]	[10.1]
2nd largest component							
Size[f]	203	60	75	77	55	87	227
	(0.7)	(0.9)	(1.6)	(1.7)	(1.3)	(1.0)	(3.9)
	[1.0]	[1.1]	[3.7]	[2.3]	[2.0]	[1.9]	[6.0]
Size ratio 2nd/largest	3/100	2/100	2/3	9/100	1/2	1/3	3/5

Sources: EPO-INV database (CESPRI-Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).
[a] Number of links connecting inventors.
[b] Number of inventors with no co-inventors.
[c] Excluding isolates.
[d] Ratio (×100) between the total number of edges and the maximum possible number of edges.
[e] The diameter of a connected (sub)graph is the length of the largest geodesic (i.e. distance) between any pair of nodes.
[f] Size = number of inventors in the component. In brackets: size as a percent of total number of inventors. In square brackets: as above, excl. isolates.

component gathers almost 60% of the non-isolated inventors, and it is followed by a second component which is 50 times smaller. It seems we are facing the emergence of a giant component of the same kind envisaged by Newman (2000) in small worlds.[14]

In electronics, the size of the largest component drops to 27% of the overall network (excl. isolates), while the second largest component is only 10 times smaller. In all the other fields, the largest component never goes beyond 10% of the network, and it is barely twice as big as the second largest.

The overall connectedness of the network also varies across technologies. The density of the network is the highest in chemicals, followed by electronics and instruments: this suggests that the possibility for two inventors in the chemical field to get in touch through a chain of personal acquaintances is much higher than in other fields, despite the much wider size of the network they are embedded in. This is because each inventor in the chemical field has been working with many more other inventors than it usually happens in other fields.

The diameter of the largest component (i.e. the length of the largest geodesic distance between any pair of nodes) provides a rough indication of how effective the network is in connecting pairs of inventors in the component.[15] Such diameter measures only 19 in the chemical field, compared to more than 20

[14] In particular, the largest component we get for the Chemical field is as big as the giant component that Newman identifies in the medical sciences, but much smaller than the giant components in a number of subdisciplines all related to physics. Newman suggests that the smaller size of the giant component in medical sciences may be explained by the higher disciplinary heterogeneity of the bibliographical data-set he drew the data from, as compared to data-set for physics. The same line of reasoning applies even more forcefully to our data, where technological fields are defined very broadly.

[15] A more precise indicator of the efficiency in communication paths would be the average distance among all pairs of nodes in the component.

in the two engineering fields, whose largest component is far smaller. Even shorter diameters, such as those in the consumer goods or instruments, appear to be extremely long when compared to the overall size of the component (second-last row in the table). Electronics is, once again, the only field whose connectedness is comparable to what we find in chemicals.

Overall, with the exception of chemicals (and, to a more limited extent, electronics), networks of industrial inventors are much more fragmented than it is usually found for networks of scientists. At the same time, the exceptions we find are positively related to the importance of scientific inputs to commercial technologies, which suggests that codifiability increases both size and connectedness of networks.

4.2. Academic inventors in Italy: fields of activity and IPR ownership

As shown in Table 2, academic inventors play a key role in chemical technologies, and contribute significantly to innovation in electronics, instruments, and industrial engineering.[16] Notice the outstanding contribution of academic inventors to drugs and, above all, biotechnology, which is in line with the US evidence we reported in Section 3: respectively, these two fields owe more than 19% and almost 30% of their patents to teams of inventors which included at least one academic inventor (last column of Table 2). Outside chemical technologies, only environmental technologies (within process engineering) stand out as a field which owes a consistent part of its patents to academic inventors.

As to the owners of patent applications listing at least one academic inventor, CNR, MIUR, and ENEA hold less that 13% of the total, with individual universities altogether reaching barely a 6% share. Property of the other patents is spread over almost 500 Italian applicants (mostly business companies, but also individual inventors[17] and a few no profit organisations) and a still indeterminate number of foreign applicants.[18] Among Italian applicants, some provisional calculation indicate that only six applicants reach a share of patents from academic inventors larger than 2%, with the ENI Group (petrochemicals) and ST microelectronics (semiconductors) standing out with more than 5%.

Overall, foreign applicants hold almost 11% of patents by Italian inventors (excluding individual inventors). Table 3 shows that in chemical technologies (especially drugs and biotech) and in a few fields within electronics academic inventors' patents are more likely than other inventors' to be held by foreign applicants, which we interpret as one more sign of the quality of academic inventors' contribution. Patents for instruments, organic chemistry and process engineering for basic chemistry are the main exceptions, possibly due to the strength of Italian companies in both fields.

The scientific disciplines which, according to the MIUR classification, broadly identify the fields of expertise of the Italian academic staff are:

- physics, geology/earth sciences, agricultural sciences, and civil engineering, with less than 1% of their staff having ever been involved in patenting;
- medical research (which includes genetics, and microbiology) and biology (includes biochemistry, and pharmacology) with respectively 1.7 and 3.2% of professors being also "academic inventors";
- industrial engineering (i.e. mechanical, chemical, and electrical engineering) and information sciences (i.e. electronics, computer sciences, telecommunications) with percentages over 5%;
- chemistry (which includes biotechnology, and pharmaceuticals), with 9.4% of staff being "academic inventors".

Digging further into the MIUR classification leads us to uncover the fact that "inventing for patenting" is

[16] Notice that when using data from 1978 to 2000, as in Table 1, we certainly underestimate the academic inventors' relevance, since we end up missing all patents due to retired academic inventors (and we will anyway miss all patents due to PhD students, post-doctoral fellows and non-teaching staff). However, we have not yet defined the proper criteria for selecting the right time interval.

[17] Individual inventors are inventors who apply for patents on their own name, without handing over their IPRs to any business company or organisation. Their patents are easily identified by the applicant's and the inventor's names being the same.

[18] Identifying foreign applicants requires accessing as many datasets as the number of countries where the property of patents of Italian inventors is officially registered. This requires an effort we have not yet been able to undertake.

Table 2
Weight of academic inventors' patents on total patenting activity by Italian inventors, by technological field; 1978–1999

Technology fields	Professors[a]	Professors/inventors[b]	Academic patents/total patents	
			Weighted[c]	Unweighted[d]
Chemicals	549	8.5	7.0	12.2
Drugs	155	12.2	13.9	19.5
Biotechnology	113	12.4	12.5	28.4
Organic chemistry	255	9.4	6.1	12.1
Consumer goods	21	0.5	0.4	0.5
Electronics	101	2.3	2.4	3.5
Audiovisual technologies	11	2.1	3.1	4.9
Telecommunications	36	2.6	3.3	5.6
Computer sciences	25	3.5	3.1	5.2
Semiconductors	16	3.2	1.7	2.2
Instruments	179	4.3	4.3	6.3
Medical technologies	74	5.4	4.7	6.6
Optics	22	3.0	2.9	4.4
Control technologies	86	4.0	4.6	6.8
Mechanical engineering	64	0.7	0.5	0.6
Process engineering	123	2.1	2.0	2.3
Basic chemistry	33	3.9	2.9	4.9
Chemical engineering	31	3.0	3.1	3.6
Surfaces	25	3.6	3.8	4.9
Environmental technologies	36	6.7	6.5	8.1
All fields	919	3.0	3.0	3.8

Sources: EPO-INV database (CESPRI-Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

[a] Number of professors enrolled by Italian Universities and Polytechnics at 31 October 2000, appearing as inventors of patent applications registered at the European Patent Office between 1978 and 1999.

[b] Ratio (×100) between the number of academic inventors and the total number of Italian inventors of patent applications registered at the European Patent Office between 1978 and 1999.

[c] Ratio (×100) between the total number of times academic inventors were listed as inventors of patents registered at the European Patent Office between 1978 and 1999 and the total number of times any Italian inventor was listed in patent application documents in the same period of time.

[d] Ratio (×100) between the total number of patent applications containing at least one academic inventor and the total number of patents by Italian inventors registered at the European Patent Office between 1978 and 1999. *The above indicators are reported for six major technological fields. Technology subfields where the contribution of academic inventors is particularly important are also reported. For classification criteria see Breschi et al. (2003).

an important part of academic researchers' activity in a number of disciplines.

Table 4 reports the disciplinary fields with the highest percentages of professors found out to be academic inventors: all of them turn out to be chemical- and biochemical-related disciplinary niches, plus two broad fields such as electronics and organic chemistry.[19]

The EPO-INV-DOC database thus catches only a portion of academic scientists' direct contribution of commercial inventions (others portions having to do

[19] In scientific disciplines whose boundaries are, for administrative reasons, extermely narrow, half of the professors are academic inventors, as in "mechanical bioengineering" and "chemical bioengineering", which together host nine academic inventors over 18 professors and researcher. Similar cases are those of "chemistry and biotechnology of fermentation", "nuclear measures and instruments" and "terrestrial vechicle manufacturing technology". Academic inventors are no less than 10% of professors and researchers of "biophysics", "chemical engineering" and "applied physical chemistry", although their absolute number is less than five per discipline.

Table 3
Distribution of academic patents by applicants' nationality and technological field; 1978–1999

Technology fields	Patent applications with academic inventors[a]			Other patent applications[b]		
	N	Nationality of applicant		N	Nationality of applicant	
		Italian (%)	Foreign (%)		Italian (%)	Foreign (%)
Chemicals	805	74.8	19.3	5800	80.1	15.8
Drugs	207	58.5	29.0	855	71.6	19.9
Biotechnology	122	65.6	29.5	307	77.5	20.2
Organic chemistry	318	85.8	11.9	2309	85.7	13.4
Consumer goods	28	71.6	0.0	5797	70.5	8.1
Electronics	180	77.8	17.2	4984	83.7	9.7
Audiovisual technologies	25	80.0	20.0	488	84.6	5.3
Telecommunications	65	70.8	24.6	1094	85.6	11.0
Semiconductors	13	53.8	38.5	569	95.1	4.2
Instruments	254	66.9	14.2	3748	63.3	18.6
Medical technologies	101	50.5	16.8	1392	49.1	23.7
Optics	33	78.8	18.2	716	60.5	30.3
Mechanical engineering	67	74.6	6.0	11028	78.4	6.3
Process engineering	141	74.5	17.0	6036	72.8	13.6
Basic chemistry	34	70.6	23.5	655	50.5	43.4
Chemical engineering	32	71.9	15.6	858	74.9	9.3
Surfaces	26	76.9	19.2	506	65.8	25.3
Environmental technologies	31	77.4	6.5	352	69.3	8.0
All fields	1475	73.8	16.9	37393	75.7	10.9

The table reports results for six major technological fields. Moreover, technology subfields where the contribution of academic inventors is particularly important are also reported. Note that for each category the sum by row may be less than 100% since the share of individual inventors (not reported) may be positive. *Sources*: EPO-INV database (CESPRI-Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

[a] Patents registered at the European Patent Office between 1978 and 1999 with at least one academic inventor.

[b] Patents registered at the European Patent Office between 1978 and 1999 by Italian non-academic inventors.

Table 4
Weight of academic inventors on total University professors; selected disciplines, 1978–1999

	Number of academic inventors	Academic inventors/all professors (%)
Industrial and materials chemistry	12	37.5
Industrial and technology chemistry	19	33.3
Industrial chemistry of polymers	37	25.2
Applied technological pharmacology	30	18.0
Science and technology of materials	24	14.9
Telecommunications	29	13.9
Molecular biology	16	13.4
Electronics	39	13.4
Pharmaceutical chemistry	54	12.1
Chemical plants	11	10.7
Organic chemistry	68	10.6
Chemistry	19	10.1

Note: Only disciplines with at least 20 professors/researchers, and no less than 10% of academic are reported. *Sources*: EPO-INV database (CESPRI-Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

Table 5
Average number of patents per inventor, 1978–1999

	Academic inventors	Other inventors
Chemicals*	2.20 (2.65) ($n = 549$)	2.73 (4.32) ($n = 5905$)
Consumer goods	1.48 (0.75) ($n = 21$)	1.66 (2.61) ($n = 4595$)
Electronics	2.30 (3.53) ($n = 101$)	2.16 (3.29) ($n = 4378$)
Instruments	1.66 (1.67) ($n = 179$)	1.63 (2.28) ($n = 4009$)
Mechanical engineering*	1.23 (0.58) ($n = 64$)	1.80 (2.62) ($n = 8582$)
Process engineering	1.64 (1.10) ($n = 123$)	1.75 (2.53) ($n = 5744$)
All technology fields	2.23 (2.74) ($n = 919$)	2.22 (3.63) ($n = 29321$)

Notes: Standard deviations and total number of inventors among brackets. *Sources*: EPO-INV database (CESPRI-Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

* *t*-Test on mean differences is 0.95 significant.

with inventions and innovations escaping patenting), but certainly a relevant one, both in terms of quantity and quality. Moreover, as we will see below, it provides important information in terms of inventors' social activities.

Finally, we observe that the "patent productivity" of academic inventors hardly differs from average. As shown in Table 5, the average number of *patents per inventor* increases very little when moving from academic to other inventors, while chemicals and mechanical engineering are the only fields with statistically significant differences.

Plots of the overall distributions of patents per inventor (not reported here, but available on request) confirm the absence of significant differences. They also suggest that the distribution of patents per inventor recalls similar highly-skewed distributions of scientific papers, irrespective to the inventors' affiliation to a university or a business company: very few inventors sign a high number of patents, while most inventors sign just one.

4.3. *Academic inventors in social networks for Proprietary Technology*

According to proposition PROP1 and PROP2 we expect academic inventors to be central and to contribute significantly to the overall size and connectivity of social networks for Proprietary Technology.

We first examine degree centrality. Table 6 suggests that academic inventors are more central than non-academic ones. This is because the former have more ties than the latter, that is they have worked with and therefore know more fellow inventors. Average

Table 6
Degree centrality: average number of acquaintances per inventor

	Academic inventors		Other inventors	
	Including isolates	Excluding isolates	Including isolates	Excluding isolates
Chemicals[a]	4.36 (4.27) ($n = 549$)	4.88 (4.23) ($n = 490$)	4.07 (4.85) ($n = 5905$)	4.74 (4.92) ($n = 5070$)
Consumer goods[a]	1.71 (2.03) ($n = 21$)	2.77 (1.92) ($n = 13$)	0.88 (1.73) ($n = 4595$)	2.01 (2.15) ($n = 2005$)
Electronics[a,b]	3.36 (3.42) ($n = 101$)	3.77 (3.40) ($n = 90$)	2.13 (2.70) ($n = 4378$)	2.91 (2.78) ($n = 3205$)
Instruments[a]	2.07 (1.98) ($n = 180$)	2.68 (1.86) ($n = 139$)	1.61 (2.06) ($n = 4009$)	2.47 (2.09) ($n = 2615$)
Mechanical engineering[a,b]	1.84 (1.84) ($n = 64$)	2.62 (1.66) ($n = 45$)	1.04 (1.60) ($n = 8582$)	2.00 (1.72) ($n = 4473$)
Process engineering[a,b]	3.71 (2.69) ($n = 123$)	3.90 (2.62) ($n = 117$)	1.59 (2.11) ($n = 5744$)	2.50 (2.17) ($n = 3649$)
All technology fields[a,b]	3.91 (4.06) ($n = 919$)	4.51 (4.03) ($n = 798$)	2.03 (3.28) ($n = 29321$)	3.16 (3.63) ($n = 18842$)

Notes: For each category, the first column includes into the calculation of the average size the teams with only one inventor, while the second column excludes them. Standard deviations and total number of patents among brackets. *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

[a] *t*-Test on mean differences 0.99 significant, when including isolates (0.90 for chemicals; 0.975 for consumer goods).

[b] *t*-Test on mean differences 0.99 significant, when excluding isolates.

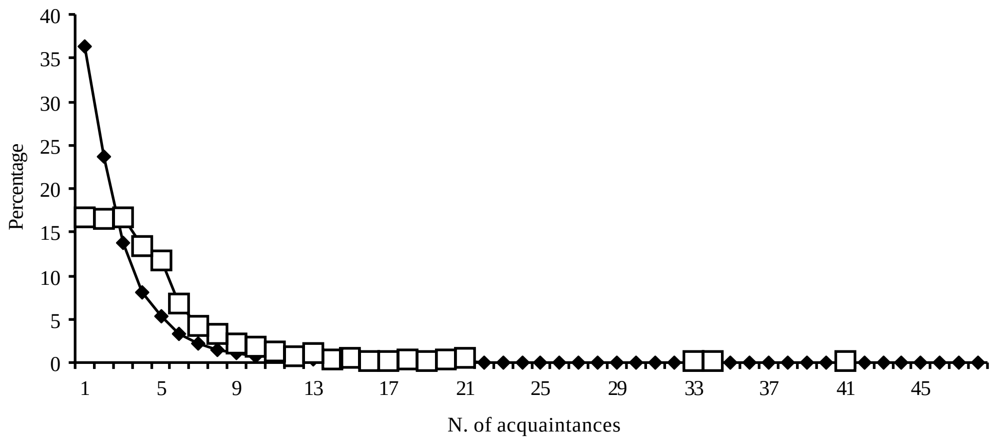


Fig. 2. Degree centrality: frequency distribution of number of acquaintances per inventor: (□) academic inventors; (◆) other inventors. *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

values are calculated first by including isolated inventors (whose degree centrality is null; first and third columns) and then by excluding them (second and fourth columns): differences between academics and "others" are always significant in the first case (although barely at 0.90 level for chemicals), and remain so in the second case, with the exception of chemicals, consumer goods, and instruments.

Fig. 2 illustrates the same result more in detail, although without distinguishing across technological classes. The figure plots the distribution of acquaintances per inventor, both for academics and non-academics. The pattern for the former is much less skewed than for the latter, which implies that academic professors are both less likely than other inventors to be isolates, and also tend to entertain more social contacts. Contrarily to other inventors, academics are as likely to have two or three acquaintances as they are to have just one; besides, academic inventors are more likely than non-academic ones to have from 4 to 10 acquaintances.

As for more than 10 acquaintances, non-academic ones show higher frequencies, but this is a very rare occurrence. Therefore, when comparing the average degree centrality of academic and non-academic inventors, it is not the "highly connected" people (i.e. inventors with very many acquaintances) who make the difference, but non-isolates and "moderately connected" ones.

Three attitudes of academic inventors help explaining the latter's propensity to entertain wider social circles. First, academic inventors have a tendency to work within larger teams than non-academic ones. Second, they also have a tendency to work for a larger number of applicants. Last, academic inventors keep producing patents for longer than non-academic ones (which we also take as an indication that their involvement in commercial invention is not occasional). As for the sheer number of patents per inventor, this plays no role since academic inventors hold no advantage (see again Table 5 in the previous section).

4.3.1. Team size and the role of applicants

Table 7 shows that patents signed by at least one academic inventors were produced by larger teams. The result holds for all technological fields when the average team size is calculated by including isolated inventors (one-man teams) and even when isolates are excluded.

Fig. 3 sums up effectively the same finding for all technological fields. It plots the frequency of patents according to the size of teams producing them, ranging from one inventor (isolates) to 13 and more. It shows that isolates are much more frequent among non-academic inventors; teams of 2–7 occur more frequently when at least one academic inventor is involved; and teams made of more than 10 inventors always involve at least one academic inventor. When

Table 7
Average team size per patent

	Academic teams[a]		Non-academic teams [b]	
	Including single inventor teams	Excluding single inventor teams	Including single inventor teams	Excluding single inventor teams
Chemicals[c]	3.29 (1.75) (n = 805)	3.73 (1.56) (n = 675)	2.53 (1.48) (n = 5800)	3.22 (1.28) (n = 4000)
Consumer goods[c]	2.04 (1.73) (n = 28)	3.23 (1.96) (n = 13)	1.31 (0.66) (n = 5797)	2.36 (0.70) (n = 1323)
Electronics[c]	2.87 (1.38) (n = 180)	3.22 (1.22) (n = 152)	1.84 (1.03) (n = 4984)	2.63 (0.87) (n = 2568)
Instruments[c]	2.33 (1.23) (n = 254)	2.89 (1.04) (n = 178)	1.67 (0.98) (n = 3748)	2.60 (0.90) (n = 1565)
Mechanical engineering[c]	2.36 (1.55) (n = 67)	3.17 (1.45) (n = 42)	1.39 (0.71) (n = 11028)	2.35 (0.68) (n = 3189)
Process engineering[c]	3.28 (1.51) (n = 141)	3.56 (1.37) (n = 126)	1.62 (0.94) (n = 6036)	2.61 (0.85) (n = 2318)
All technology fields[c]	3.00 (1.64) (n = 1475)	3.49 (1.46) (n = 1186)	1.68 (1.04) (n = 37393)	2.69 (1.01) (n = 14963)

Sources: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

[a] Average number of inventors in teams containing at least one academic inventor.

[b] Average number of inventors in teams containing no academic inventors.

[c] For each category, the first column includes into the calculation of the average size the teams with only one inventor, while the second column excludes them. Standard deviations and total number of patents among brackets. *All* mean differences are 0.99 significant (t-test), both when including and when excluding single inventor teams.

interpreting the plot, however, the reader should bear in mind that the largest teams can be found in chemicals (compare rows in Table 7), which is also the technological field wherein academic inventors are most active, and where the difference between academic and non-academic teams is lower.

Table 8 shows that, for every possible date of entry in our data set (i.e. the year when they signed their first patent) academic inventors have been more persistent than non-academic ones, going on with signing patents for a longer time: for each entry period, academic inventors are relatively more concentrated in higher duration spells (grey cells in the table). Such persistence gives them more chances to enter more teams, and to widen their own personal social network.

Fig. 4 shows that most inventors in our data set have signed patents applied for always by the same applicant. However, the percentage of non-academic inventors having worked for only one applicant almost reaches 80%, while for academic inventors is well below 70%. As for inventors working for two or more

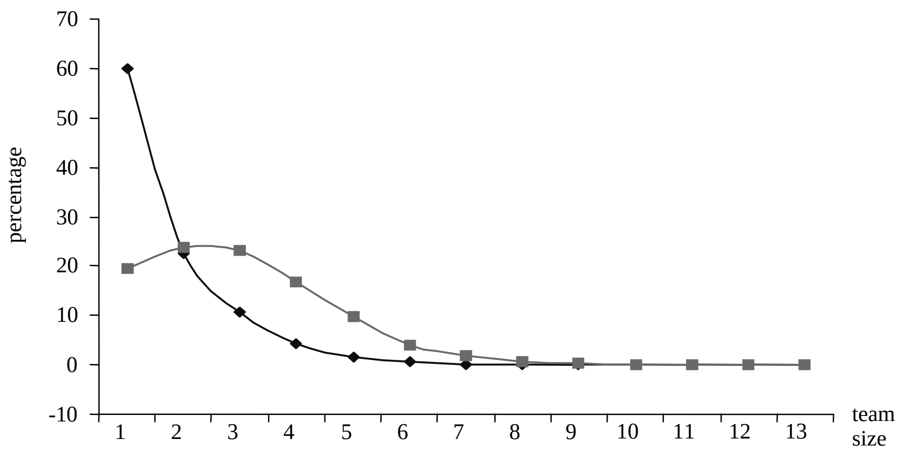


Fig. 3. Frequency distribution of patents according to the size of the inventing team. (■) Teams involving at least one academic inventor; (◆) other teams. *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

Table 8
Duration of inventors' activity in the network, by date of entry, 1978–1999 (all technologies)

Type	Entry[b]	Duration in years[a]					Total
		0	1–5	6–10	11–15	16–21	
Non-academic	0	100.0	0.0	0.0	0.0	0.0	447
Academic		100.0	0.0	0.0	0.0	0.0	10
Non-academic	1–5	84.2	15.8	0.0	0.0	0.0	9775
Academic		85.7	14.3	0.0	0.0	0.0	252
Non-academic	6–10	69.6	**22.4**	**8.0**	0.0	0.0	8339
Academic		63.7	**24.9**	**11.4**	0.0	0.0	289
Non-academic	11–15	62.6	18.6	**13.0**	**5.7**	0.0	6580
Academic		53.2	16.9	**22.4**	**7.6**	0.0	237
Non-academic	16–21	57.2	15.4	**11.0**	**11.2**	**5.2**	4134
Academic		45.8	13.7	**15.3**	**16.0**	**9.2**	131

*Bold values show where percentages are higher for academic inventors. *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

[a] Duration in years is the number of years elapsed between the date of entry into the network (i.e. first year of patent) and the date of the last patent signed by a given inventor. For an inventor with a single patent, the duration in the network is therefore equal to zero.

[b] The date of entry is calculated as the difference between 1999 (last year of our series) and the year of entry of each inventor into the network (i.e. year of the first patent).

applicants, academic inventors register higher percentages.

4.3.2. "Betweenness" centrality and connectedness

Data on degree centrality and its determinants provided so far clearly support PROP1. However, for the proposition to be fully confirmed, we ought to see also a high degree of "betweenness" centrality. Table 9 reports our calculations for a "betweenness" index based on counting how often a node (inventor) finds itself in 'between' a pair of nodes (inventors) along all the possible communication paths linking such two nodes,

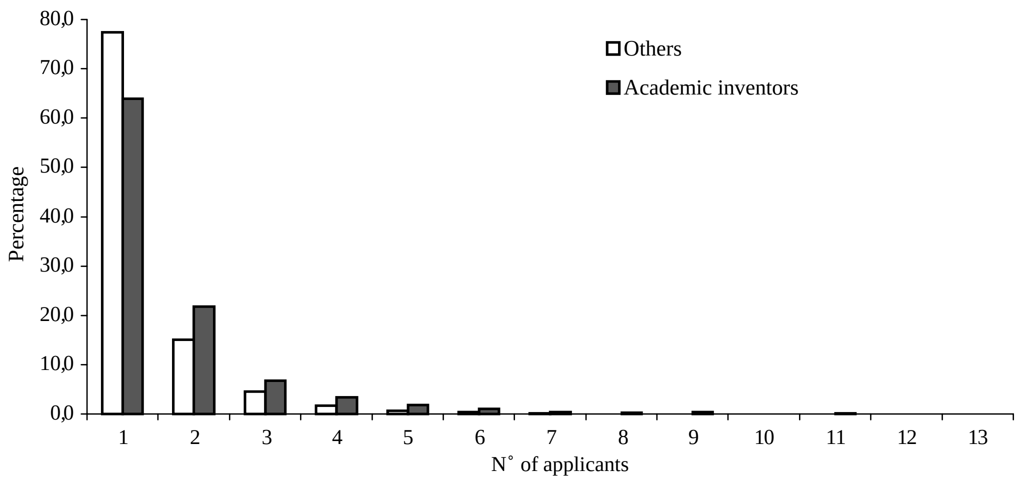


Fig. 4. Distribution of inventors by number of applicants for their patents; percent values, 1978–1999 (all tech.). Average values (tandard deviations): academic inventors = 1.67 (1.26); others = 1.35 (0.84). *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

Table 9
Distribution of inventors by betweenness centrality, giant component (all technologies); 1978–2000

Betweenness[a]	Academic inventors		Other inventors	
	Count	Percentage	Count	Percentage
0	188	57.1	3598	59.4
0–0.10	30	9.1	661	10.9
0.10–0.50	46	14.0	846	14.0
0.50–1	17	5.2	334	5.5
1–2	15	4.6	235	3.9
2–5	15	4.6	190	3.1
5–10	11	3.3	105	1.7
10–50	7	2.1	76	1.3
50–100	0	0.0	16	0.3
Total	329	100.0	6061	100.0

Sources: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).
[a] Betweenness index (×10,000).

Table 10
Distribution of inventors by size of connected components, all technologies; 1978–1999

Size of component	Other inventors	%	Academic inventors	%
6390 (1)	6061	20.7	329	35.8
203 (1)	195	0.7	8	0.9
51–200 (5)	422	1.4	16	1.7
26–50 (11)	379	1.3	3	0.3
11–25 (71)	1040	3.5	57	6.2
5–10 (376)	2257	7.7	162	17.6
4 (320)	1222	4.2	58	6.3
3 (855)	2494	8.5	71	7.7
2 (2434)	4775	16.3	93	10.1
1 (10601)	10479	35.7	122	13.3
Total	29324	100.0	919	100.0

Notes: Number of connected nodes (inventors) in the component. In brackets: number of components for each size category. *Sources*: EPO-INV database (Università L. Bocconi), EPO-INV-DOC database (Università di Pavia).

for all possible pairs. The index ranges between 0 (the inventor is absolutely marginal) and 100 (the inventor falls on all communication paths between all possible pairs of actors): marginal inventors will never be contacted, unless one needs their specific services; central ones, on the contrary, will be often asked to introduce other inventors to those willing to get acquainted with them. Calculations are provided only for the giant component (see Table 1), since comparisons across components of different size are not meaningful.

Table 9 shows that the percentage of absolutely marginal nodes among academic inventors is slightly smaller than the corresponding percentage for non-academic ones. The same holds for low values of the centrality index. Moving over unitary values, however, the percentages reverse, and academic inventors consistently show higher percentages of nodes with relatively high values. The only exception is provided by 16 (versus zero) extremely central non-academic inventors (index above 50, up to 100).

We therefore conclude that academic inventors are more likely than others to act as “inventor brokers”, that is to be frequently asked to set up teams, or to signal those who have the right competences to join existing teams. That is, academic inventors are more likely to be at the crossroads of individual relationships and knowledge exchanges.

If this is true, we also expect PROP 2 to hold, that is we expect academic inventors to be more likely than others to belong to large components, since their own presence helps a component to attract more inventors and to grow. Table 10 seems to support this view.

The table classifies components according to their size, and reports the average probability for academic and non-academic inventors to join a given size category. We can see that academic inventors have a higher probability to join the largest component (first row of the table) and a lower probability to end up as isolates (last row). Academic inventors are also more likely to be found in components of intermediate size towards the upper end of the size distribution (second to seventh row, with the exception of fourth).

5. Conclusions

This paper reports the early steps of quite an ambitious research program, whose ultimate goal is assessing the role of geographical and knowledge proximity in technology transfer not just on the basis of a few assumptions on the nature of knowledge exchanges, but as a function of the social structure supporting them (see also Breschi and Lissoni, 2003).

The steps undertaken here are limited to the exploration of the social structure of Italian inventors, as it emerges from data on patent applications and co-invention relationships. In particular, we have explored whether the social positioning of academic inventors is by any means outstanding, as the new economics of science seems to suggest. Two propositions have been put forward. Taken together, they suggest that academic inventors may retain some of their “openness” when moving from the realm of Open Science to that of Proprietary Technology.

We also outlined the reasons why testing those propositions require large data sets on individual researchers, such as the EPO-INV and the EPO-INV-DOC databases.

Our empirical enquiry has just started, so that we could produce little more than descriptive statistics. While preliminary, the conclusions we reach are nevertheless promising.

- Networks of inventors, which we take as representative of social networks within Proprietary Technology, are highly fragmented, with the exception of technological fields wherein science plays an important role, such as chemical and, to a lesser extent, electronics.
- Academic inventors that enter the network are, on average, more central than non-academic inventors: academics exchange information with more people and across more organizations. Therefore; they play a key role in connecting individuals and network components.

However interesting, these conclusions are little more than a good start. First and foremost, we need to know more about non-academic inventors, whom by-and-large we have been dealing with as a sort of residual, thus ignoring their heterogeneity. At the very least, we ought to be able to distinguish between researchers from large corporate labs from other industrial researchers, something we can do only by checking the applicants’ names thoroughly.

Second, in order to know more about academic inventors’ attitudes towards patenting we need to proceed with interviews and questionnaire enquiries. They will help us checking the identity of the co-inventors of academics: are they university technicians, PhD students or retired professors (who have escaped our EPO-INV-DOC database)? Or are they not academics, such as researchers from the patent applicants’ labs?

More information on this point will help us refining the positive evaluation we have tentatively expressed when commenting the high centrality of academic inventors. Does centrality really signal a deep involvement in an applied research field, to which academic inventors contribute also by connecting people and introducing young researchers to the community of industrial researchers? Or does is merely reflect an opportunistic behaviour, by which university scientists sell some of their research ideas on an occasional basis, and rely either on colleagues or on the applicants’ employees to set up an improvised research team?

Finally, we need to produce data-sets for countries other than Italy, comparable with EPO-INV and EPO-INV-DOC. It is the only way to judge whether the amount of patents produced by Italian academic inventors is high enough to force a revision of the usually harsh judgements on Italian universities’ contribution to innovation, or it is a mere reflection of the original way we found to calculate university patents. The same question holds for Europe as a whole, when compared to the US: could re-classifying patents by inventor, rather than by applicant, lead to a more positive evaluation of university–industry links in Europe, one which takes into account the relative inexperience of European universities in handling IPRs?

Although demanding, these are research questions which we expect to answer in the near future, on the basis of the data and methodology presented here.

References

Breschi, S., Lissoni, F., 2001a. Knowledge spillovers and local innovation systems: a critical survey. Industrial and Corporate Change 10/4

Breschi, S., Lissoni, F., 2001b. Localised Knowledge spillovers vs. innovative milieux: knowledge ‘tacitness’ reconsidered. Papers in regional science 80/3.

Breschi, S., Lissoni, F., 2003. Mobility and social networks: localised knowledge spillovers revisited. In: Proceedings of the Workshop on Empirical Economics of Innovation and Patenting. Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim, 14–15 March.

Breschi, S., Lissoni, F., Malerba, F., 2003. The empirical assessement of firms’ technological coherence: data and methodology. In: Cantwell, J., Gambardella, A., Grandstand, O. (Eds.), The Economics and Management of Technological Diversification. Routledge.

Callon, M., 1994. Is science a public good? Science, technology, and human values 19 (4), 395–424.

Cockburn I.M., Henderson R.M., 1998. Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. Journal of Industrial Economics XLVI, 157–182.

Cohen, W.M., Florida, R., Randazzese, L., Walsh, J., 1998. Industry and the academy: uneasy partners in the cause of technological advance, In: Noll, R. (Ed.), Challenges to Research Universities. Brookings Institute, Washington, D.C.

Cornes, R., Sandler, T., 1996. The Theory of Externalities, Public Goods and Club Goods. Cambridge University Press, Cambridge, MA.

Cowan, R., David, P.A., Foray, D., 2000. The explicit economics of knowledge codification and tacitness. Industrial and Corporate Change 9, 211–254.

Cowan, R., Jonard, N., 2000. The dynamics of collective invention, MERIT WP # 00-018. Maastricht Economic Research Institute on Innovation and Technology, Maastricht University.

Dasgupta, P., David, P.A., 1994. Toward a new economics of science. Research Policy 23, 487–521.

David, P.A., Mowery, D., Steinmueller E., 1994. University-industry research collaborations: managing missions in conflict. In: Proceedings of the CEPR/AAAS conference on University Goals, Institutional Mechanisms, and the Industrial Transferability of Research. Stanford, March 18–20.

David, P.A., Foray D., Steinmueller, W.E., 1999. The research network and the new economics of science: from metaphors to organizational behaviours. In: Gambardella, A., Malerba, F. (Eds.), The Organization of Economic Innovation in Europe. Cambridge University Press, Cambridge, UK.

Feldman, M.P., 1999. The new economics of innovation, spillovers and agglomeration: a review of empirical studies. economics of innovation and new technology 8, 5–25.

Henderson, R., Jaffe, A.B., Trajtenberg, M., 1998. Universities as a source of commercial technology: a detailed analysis of university patenting 1965–1988. Review of Economics and Statistics 80 (1), 119–127.

Jaffe, A.B., 1989. Real effects of academic research. American Economic Review 79 (5), 957–970.

Malerba, F., Orsenigo, L., 1996. Schumpeterian patterns of innovation are technology-specific. Research Policy 25, 451–478.

Mansfield, E., 1995. Academic research underlying industrial innovations: sources, characteristics, and financing. Review of Economics and Statistics 77, 55–65.

Melin, G., Persson, O., 1996. Studying research collaborations using co-authorship. Scientometrics 36, 363–377.

Merton, R.K., 1957. Priorities in scientific discovery: a chapter in the sociology of science. American Sociological Review 22 (6), 635–659.

Mowery, D.C., Nelson, R.R., Sampat, B.N., Ziedonis, A.A., 2001. The growth of patenting and licensing by US universities: an assessment of the effects of the Bayh-Dole act of 1980. Research Policy 30, 99–119.

Mowery, D.C., Sampat, B.N., 2001a. Patenting and licensing unviersity inventions: lessons from the history of the research corporations. Industrial and Corporate Change 10/2, 317–355.

Mowery, D.C., Sampat, B.N., 2001b. University patents and patent policy debates in the USA, 1925–1980. Industrial and Corporate Change 10/3, 781–814.

Nelson, R., 1959. The simple economics of basic scientific research. Journal of Political Economy 67, 297–306.

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, pp. 404–409.

Steinmueller, E., 2000. Does information and communication technology facilitate ‘codification’ of knowledge?. Industrial and Corporate Change, forthcoming.

Tijssen, R.J.W., 2001. Global and domestic utilization of industrial relevant science: patent citation analysis of science-technology interactions and knowledge flows. Research Policy 30, 35–54.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of ‘small world’ networks. Nature 393, 440–442.

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