



Paper to be presented at the DRUID 2011

on

INNOVATION, STRATEGY, and STRUCTURE -  
Organizations, Institutions, Systems and Regions

at

Copenhagen Business School, Denmark, June 15-17, 2011

## **Aggregates, Bridges or Isolates? Investigating the Social Networks of Academic Inventors**

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### **Abstract**

We analyse the acquaintances of a sample of academic inventors and their paired controls to investigate the contribution of social capital to the generation of inventive ideas. Prior to patenting, inventors have larger networks and participate in more cliques than their colleagues who do not invent. They are also more central within their respective networks, and they are more likely to act as bridges between otherwise sparse communities. Over time, both inventors and non-inventors extend their networks outward to reach distant nodes. Inventors do not isolate or close their networks after they patent.

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We analyse the acquaintances of a sample of academic inventors and their paired controls to investigate the contribution of social capital to the generation of inventive ideas. Prior to patenting, inventors have larger networks and participate in more cliques than their colleagues who do not invent. They are also more central within their respective networks, and they are more likely to act as bridges between otherwise sparse communities. Over time, both inventors and non-inventors extend their networks outward to reach distant nodes. Inventors do not isolate or close their networks after they patent.

***Keywords:*** *Academic Patenting; Social Network Effect; Technology Transfer*

## 1. Introduction

In recent years, academic patenting has been the subject of extensive scholarly investigation. Empirical analyses conducted on both sides of the Atlantic have consistently indicated that academic scientists who are active as inventors of patented technologies exhibit superior publication patterns compared to their colleagues who are not active in patenting. The scholarly literature has suggested several hypotheses to explain this observation. In this paper, we test one hypothesis: that the observed differences in the publication patterns of inventors and non-inventors in academia are explained (at least in part) by the social networks in which these two groups of individuals work and from which they draw their information and knowledge sets. Preliminary evidence has suggested that academic inventors have more co-authorships with researchers working in industry (Azoulay et al., 2009) and larger networks (Meyer, 2000, 2006) than non-inventors. Furthermore, there are hints of structural differences between the co-inventor networks of academics and those of non-academics (Balconi et al., 2004). Consistent with this evidence, their superior accomplishments in science may in principle depend on the greater ability of their social networks to convey useful information and knowledge. Their superior publication record may also depend on their ability to achieve a more favourable position within their network of relationships. In the first case, we should observe larger networks, more frequent (denser) interactions and/or participation within more cliques at the same time. In the second case, keeping the size of the network constant, we should observe that inventors are more likely to act as bridges across communities that would otherwise be disconnected, implying a greater centrality in networks. The hypothesis is that these comparative advantages brought by their social networks may allow them to better direct their research efforts toward aims that are richer in scope, minimise the risk of dead-ends, and/or help them envisage methodological solutions developed in distant fields.

To begin to distinguish between these hypotheses, we investigate the structure and features of ego-networks and the positions of individuals within their respective networks. Our results

confirm that the social networks of inventors differ from those of non-inventors. In particular, inventors have larger networks and participate in more cliques than their colleagues who have not invented. Second, inventors are found to be more central in their respective networks than non-inventors.

We also investigate whether these differences in network structure and position are individual-specific and fixed, or if they change over time. By including the time dimension, we ask whether the circumstance of being inventive contributes to alterations in the network and the inventor's position within it. Empirically, answering this question requires addressing the issue that networks of co-authors are strongly affected by time-varying confounding factors. Typically, as for all scientific indicators, the most relevant of these confounding factors is the life-cycle (or career age) effect. Productivity tends to grow (more than linearly) throughout most of a scientist's career but generally declines in the last years (Levin and Stephan, 1991). Therefore, when comparing scientific achievements before and after a specific year (e.g., the year of the invention), there is a general tendency to register growth. Problems arise in determining to what extent this tendency is to be attributed to merely the effects of time rather than to the event of interest. The methodology that we employ in this paper is suited to treating this problem of spurious correlation. We control for the life-cycle dependence and other confounding factors by assessing differences in network characteristics and positions across matched pairs of scientists with similar confounding factors.

Our results indicate that academic inventors have larger networks than non-inventors before they begin to invent, and they provide no evidence that the inventive activity is the antecedent of further increases in network size. Indeed, over time, both inventors and non-inventors extend their networks towards sparser nodes (with lower density). Inventors are more central in their networks than non-inventors before they begin to invent. However, non-inventors do catch up over the years.

The hypotheses that underlie this paper are grounded on the theories of socially constructed knowledge and on the power of weak ties. Networks channel the knowledge and information that each scientist receives and recombines into their research work. The accomplishments of a scientist

are hence affected by the power of their network to convey rich information. Networks that are larger in size, keeping all other things constant, convey more ideas to exploit, more complementary knowledge to make research successful and a larger group of supporters of one's own ideas. Networks with sparser nodes and fewer redundant links (less dense), keeping all other things constant, are more likely to convey newer (non-redundant), and hence more useful, information.

The empirical analyses presented in this paper are based on a sample of Italian scientists who were inventors of one or more patents assigned to their academic institutions together with a matched pair sample of comparable scientists that never patented an invention, regardless of the assignee type. For each group of people, we perform a first-level social network analysis based on co-authorships (direct co-authors) and compute information about the structure of the network and about the positions of the egos (the individuals upon which the network is centred) within their respective networks.

The evidence presented in this work contributes to the debate on the inventive activities of academia in several respects. First, to the best of the authors' knowledge, it is the only comprehensive account of the social capital effect on the inventive activities of scholars. The importance of the social capital dimension as a driver of academic inventions has been suggested in many descriptive scholarly works. These works portray academic inventors as a breed of highly connected individuals who are gatekeepers of information from and across different fragmented communities (Allen, 1977; Etzkowitz, 1983; Murray, 2004). Prior to this work, only Meyer (2000; 2006) has looked at the networks of scientists in the field of nanoscience and nanotechnology and found that academic inventors have networks of co-authors that are larger than those of non-inventors. However, he offers only a visual inspection of the networks of academic-inventors and does not investigate the positions of the egos within their networks or compare these networks with those of non-inventors.

Second, the analysis offered herein investigates the potential impact of inventions on the network's structure and the ego's position within the network by comparing pre and post-event

measures. This comparison allows us to speculate on whether the social capital effect should be thought of as an antecedent or as a consequence of the inventive activity. More precisely, we check if the event of patenting precedes changes in the network's structure and ego positions by comparing the indicators before and after the inventive event.

Third, the latter part of the analysis is also relevant to uncovering any potentially undesirable effects of academic patenting. In principle, closer proximity to the exploitation realm may alter the role of academic inventors within their scientific community, making them more secluded and distant from their non-patenting peers. For example, they may become more prone to relying on closer and more independent relational sets, ultimately diminishing the overall social returns of their scientific discovery.

Incidentally, our results are also useful because they help to separate team size effects from network effects. Prior works have taken team size (given by the average number of co-authors) into account, and found that inventors generally work in larger groups than non-inventors. Here, we distinguish between individuals that work repeatedly with a large team and individuals that cooperate with many diverse co-authors in different studies.

The paper is organised as follows. In the next section (§2), we develop the hypotheses that will drive the empirical investigation. In Section §3, we describe the research design, the dataset and the measures of social networks used in the analysis. In Section §4, we describe the matching procedure used to create the paired samples. Section §5 presents the empirical analysis and discusses the results. We conclude by highlighting the contributions of our paper and some open questions for future research in Section §6.

## **2. Academic Patenting and Social Network Effects**

### **2.1 Explaining the Research Accomplishments of Academic Inventors**

We have learned from recent works on academic patenting that inventors represent a small share of the population of academics. Even in the subfields in which patenting is relatively common, like biotech and chemistry, academic inventors never seem to exceed 10-15% of the scholars (Agrawal and Henderson, 2002; Lissoni et al., 2008). Several works have also consistently shown that the most productive and accomplished individuals in science are overrepresented within the sample of academic inventors (Fabrizio and Di Minin, 2008; Stephan et al. 2007). Furthermore, when data are analysed on longitudinal timespans, patents seem to be preceded by a flurry of publications (Azoulay et al., 2007; Calderini et al., 2007) and tend to boost productivity in the years immediately after patenting (Azoulay et al., 2009; Breschi et al., 2008; Calderini et al., 2009).

The fact that a few productive authors in science are disproportionately responsible for a large share of the publications has been well-documented since the early '60s (Derek de Solla Price, 1963; Allison and Stewart, 1974). Still, it is at first counterintuitive that an even smaller proportion of scholars seems to be capable of simultaneously producing advances in the scientific understanding of principles and phenomena and new technologies suitable for industrial application.

This circumstance has raised a question about what capabilities form the basis of academic patenting and if there are common drivers that explain the success of a scientist in the academic and industrial worlds. Although in the traditional view of science as a speculative activity, scientific inquiry and practical application are seen as antonyms, at a closer look, several considerations suggest that this vision is oversimplified and obscures the true nature of research. Scholars have suggested multiple potential explanations for the positive correlation between publications and patents.

First, there are areas of investigation (the so-called “Pasteur’s Quadrant”) in which fundamental understanding and practical applications can be pursued at the same time and other areas of investigation in which this is not the case (Stokes, 1997). In the first case, the pursuit of scientific and technological goals can be combined, and the two activities can generate positive

feedback for one another. This happened, for instance, in the early years of biotechnology when many eminent scientists became famous for their technological advances while maintaining a leading position in science (see, for instance, Zucker et al., 1998; Davies, 2001; Feldman et al., 2005). A first possible explanation for the correlation between scientific and technical achievements is therefore that we are observing areas in which the trade-off is less severe.

Second, success in research often requires the solution of technical problems that constrain scientific investigation. Scholars who study the creativity of scientists maintain that the rate-limiting factor for progress in science is not the pace at which new ideas come to researchers but the pace at which those ideas can be transformed into feasible operations on the bench (Holmes, 2004). Since a large proportion of the inventions that academic scientists produce relate to improved research technologies, the event of producing a patent precedes success in research (Franzoni, 2009).

Third, successful scientists are often described as individuals who are entrepreneurial by nature (Allen, 1977; Etzkowitz, 1983). Success in science requires extensive organisational skills as well as the capacity to raise funds to support a line of research. This is especially true in recent years, as evidenced by the steadily increasing sizes of research teams (Adams et al., 2005; Wuchty et al., 2007) and the enlarged budgets needed to equip fully functional research labs (Ehrenberg et al., 2006). A successful scientist needs to be skilled at envisioning funding opportunities, establishing collaborations, brokering research scope and uncovering market needs. These abilities are also likely to underlie success in developing technologies for the market (Murray, 2004; Franzoni and Lissoni, 2009).

## **2.2 The effect of social capital on inventive activities**

In this paper, we offer and investigate another explanation for why scientific and market achievements are correlated. This explanation is grounded on the theory of socially constructed knowledge and hypothesises that a larger and richer social network is the basis for superior performance by scientists in both research and inventive accomplishments.

Extensive studies on Social Capital and Network Theory have emphasised the relevance of the social network dimension in the creation and diffusion of knowledge (Coleman, 1988; Freeman, 1991; Auhja, 2000). The importance of social capital depends on the circumstance that knowledge is only partially codifiable and remains largely tacit and bound to individuals (Nelson and Winter, 1982).

This highlights the importance of direct face-to-face (or somehow socially-channelled) interactions to enable the generation of novel ideas in research. When scientists cooperate and work in teams, they recombine their knowledge and bring forth novel ideas, solutions and insights. Teamwork enables a faster pace of progress because it is not constrained by the speed of individual learning. Furthermore, the recombination of a team's knowledge generates more chances to produce creative results than the recombination of a single individual's knowledge, because the contribution of each person is different. Scholars who work on creativity in science have proposed a theory of chance and creativity, called Chance Combination Theory, which helps us to explicate this issue (Simonton, 2004). According to this theory, creativity results from the ability of the scientist to associate and combine pieces of knowledge and information in ways that are both novel (never tried before) and useful (Simonton, 2004). The probability of a successful combination is tiny and cannot be foreseen in advance, but it increases with the number of times that novel combinations are tried. If we consider people to be repositories of idiosyncratic and tacit knowledge, and co-authorship as the link through which knowledge travels from one individual to another, the number of unique combinations that each individual can make increases with the pool of knowledge that she can access and hence with the size of her network (Perry-Smith and Shalley, 2003). Several studies have confirmed this idea, for example, by finding positive correlations between the size of a research team and various indicators of the quantity and quality of its publications (De Beaver and Rosen, 1979; Kretschmer, 2004; Defazio et al., 2009).

A second argument suggesting a positive correlation between a scientist's social capital and her productivity relates to the internal approach to the world of science, which was extensively

explored by Robert K. Merton and colleagues (see for instance Merton, 1957; Hagstrom, 1965). Scientific theories and findings, especially new and disruptive ones, spread out and become affirmed when they are known, discussed and agreed upon by the scholarly community. Hence, numerous and frequent relationships with a large community of colleagues favour the acceptance of a scholar's work (Allen, 1977), while isolation reduces the probability of success.

Both of these arguments – that social capital supports the generation of new ideas, as well as their spread and acceptance – lead us to expect a positive correlation between social capital and success in both scientific research and inventive activities. In social network analysis, this leads to the expectation that individuals who perform better in scientific research and technological development alike should be found in larger proportions among those who belong to larger networks and among those who participate in many different cliques<sup>1</sup> at the same time.

This leads us to formulate the following hypotheses:

*Hp.1: All other things being equal, patenting activity is associated with a larger network size in the pre-invention phase.*

*Hp.2: All other things being equal, patenting activity is associated with a higher number of cliques in the pre-invention phase.*

As we learn from social network scholars, the links between individuals that are remotely bound to one another and do not belong to the same community of references are more likely to carry novel information to an individual. Conversely, when individuals continue to interact with the same group of people, chances are higher that they will receive the same information several times (Burt, 1997). Redundant transmission of information is less relevant and exhausts creative power. The ability of weak ties to bring novel, non-redundant information has been extensively

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<sup>1</sup> For a comprehensive definition of clique, see paragraph 3.3.

investigated and documented (Granovetter, 1983; Nahapiet and Ghoshal, 1998). Scholars assessing the impact of collaboration and networks have stressed the dual effect of the intensity of exchanges. While cohesion generally supports productivity and trust, very densely-knit groups cause information to travel in circular paths and increase the number of non-informative exchanges (Uzzi et al., 2007). Excess cohesion may even reduce creativity by limiting the openness of the field to new ideas, reducing variety and paving the way to conformism (Nahapiet and Ghoshal, 1998; McFadyen and Cannella, 2004). In contrast, loosely coupled and distant ties are a more powerful vehicle for information and are the antecedent of creative combinations. By linking two or more individuals that have very diverse endowments of information, the chances of non-duplicative exchanges of knowledge increase, and this has a beneficial effect on creative capabilities (Perry-Smith and Shelley, 2003; Uzzi and Spiro, 2005). We maintained before that people with a larger network have, in principle, a larger pool of knowledge to draw combinations from. Here, we are saying that these combinations are potentially richer if they come from more distant communities and sparser networks. This will be our next hypothesis.

*H<sub>p</sub>.3: All other things being equal, patenting activity is associated with a lower network density in the pre-invention phase.*

Sparser and less densely-knit networks bring together individuals who are repositories of very diverse pieces of knowledge. In these networks, a few nodes typically serve as bridges in connecting loosely coupled individuals. These nodes perform a key role in the overall system and, as a consequence, gain a higher status (Langlois, 1977; Burt, 1997). In social network analysis, individuals that act as bridges by connecting otherwise secluded nodes are accounted for by means of the Freeman betweenness centrality. These people should exhibit a comparative advantage over less central individuals. In this paper, we are interested in knowing whether or not the position of a scholar in their respective network is associated with their inventive behaviour. Hence, we

formulate the following hypothesis:

*H<sub>p</sub>.4: All other things being equal, patenting activity is associated with a higher betweenness centrality of the scientist in the pre-invention phase.*

### **2.3 The impact of inventive activities on social capital**

A final issue we want to explore in our analysis relates to the participation of academic inventors in networks and communities in the post-invention period. A very rich debate has flourished in the last decade about the positive and negative implications of favouring the patenting activities of academic scholars. A summary of this extensive debate would exceed the scope of this paper<sup>2</sup>. Here, we limit our discussion to recalling that isolation in secluded communities and areas of scientific inquiry has been reported among the potential risks associated with strongly market-oriented research activity performed by academic scientists. This may occur if the scientist substantially changes her community of co-authors and/or her community of reference because she aims to become a successful inventor of industrial applications.

In this paper, we contribute to this debate by investigating the connections and social capital of academic inventors in the five years that followed their invention. To do so, we analyse the structure of the social network and the position of the scientist in her network during the post-invention period. To put the results into perspective, on one side, we look at comparable indicators computed from the network of the author in the pre-invention phase. From the other side, we look at comparable indicators computed from the networks of a matched colleague that we had paired as a control.

If academic inventors in search of success in the industrial world are more prone to isolate themselves from the academic community to devote more time to technological development and market partnerships, then the following hypotheses should be supported by the data.

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<sup>2</sup> See for example Siegel and Wright (2007) for a review.

*Hp.5 All other things being equal, patenting activity is associated with a higher network density in the post-invention phase.*

*Hp.6 All other things being equal, patenting activity is associated with a decreased betweenness centrality of the scientist in the post-invention phase.*

### **3. Research design**

#### **3.1 Data**

Studies on the communities of scientists often highlight profound international differences in the scientific labour markets as well as differences among academic institutions operating in the same country (Bonaccorsi and Daraio, 2007). To control for the effects of such institutional differences in this paper, we focus on one single country, Italy, with a homogeneous university system and homogeneous training, hiring and promotion practices. The dataset used in our analysis includes all publications authored by a sample of 110 scientists (evenly split among inventors and non-inventors) and their 32,415 co-authors from 1987 to 2006. Publication data were retrieved using ISI Web of Science and extensively checked to avoid mistakes during the name matching procedure.

Academic inventors were identified using the Patiris database, which includes all patent applications by Italian universities filed nationally and abroad, both directly or as extensions of patents filed elsewhere (see [www.patiris.unibo.it](http://www.patiris.unibo.it) for details). This database includes all of the inventors appearing in patents filed by a university or national research agency based in Italy. It does not include, however, all Italian academic inventors, as many academic inventors have filed patents with companies or under their own name, given the academic privilege that was in force during most of the timespan considered (Balconi et al., 2004). We will keep this in mind when

interpreting the results.

To remove disciplinary differences, we focused exclusively on the field of Chemistry<sup>3</sup>. This restricts the sample to 59 inventors. Of these, 9 are serial inventors: 9 of them were inventors of three patents or more and 3 of them of five patents or more.

Matched pairs of non-inventors were drawn from data collected by Baldini (2004) and were based on the answers to a questionnaire that was sent to a sample of Italian academic scholars working in the same fields as the inventors listed in the Patiris database. For the purpose of our study, we selected all respondents in the Chemistry field who declared that they had never filed a patent. Given the structure of the questions, we can tell with considerable certainty that these scholars had never filed a patent with their institution, with other organisations or on their own. This gave us a sample of 85 non-inventors in the field of Chemistry that we used as the sample from which we drew our matched pairs.

### 3.2 Matching procedure

We adopted a pair matching procedure starting with 59 academic inventors and 85 academic scholars in the same discipline that did not hold inventions. Methodologically, we performed an event analysis. We regarded the event of becoming an inventor as a “treatment” and held the non-inventors as “untreated” individuals to serve as controls. The observable pre-treatment differences were accounted for by looking at a set of exogenous demographics (age, gender, geographic location) and at a set of exogenous personal variables (has a PhD, PhD obtained in Italy vs. abroad, subfield of Chemistry to which the scientist belongs). We calculated an individual propensity score by means of a probit estimate performed on all 144 individuals given the two sets of covariates<sup>4</sup>. The propensity score assigns a predicted probability of being an inventor to each individual, as affected only by the exogenous covariates. Having calculated the dependency of the individual's

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<sup>3</sup> All Italian professors are affiliated [with](#) a unique subfield within the classification of the Italian Ministry of University and Research. The list of classes and the professors affiliated [with them](#) is publicly available at the following URL: <http://www.miur.it/UserFiles/116.htm>

<sup>4</sup> Omitted for brevity, but available upon request to the authors.

propensity to patent on all factors except our variables of interest, we then wanted to associate each actual inventor to her closest peer in terms of patent propensity. To do so, we chose to adopt a one-to-one nearest-neighbour matching procedure without replacement. Under a reasonably strict Caliper (Cochran and Rubin, 1973) of .70, we dropped four individuals from the group of academic inventors because no good match was available for them. We were left with 55 inventors and 55 controls. The matching had a mean difference probability of 19.52% (Std. Dev .24), indicating a satisfactory matching Caliper of .67.

### 3.3 Construction of the ego-networks

We begin with two sets of egos, each composed of 55 scientists. Ego-network data require three elements to be determined: the egos, in our case the 110 academic inventors and controls; the alters, in our case all the individuals with which one of the egos (either an inventor or a control) co-authored their papers within a certain time window; and finally, a measure of ego-alter relationships, in our case the co-publication frequency (i.e., the number of articles co-authored by any pair of one ego and one alter) (Wasserman and Faust, 1994:42, Scott, 2000).

Alters were identified by retrieving the scientific publications of all egos listed in the ISI Web of Science database within a moving window of 11 years between 1987 and 2006. This time window varies for each individual and is centred on the year of patent priority for each inventor and the same year for the inventor's matched control. Inventors start to be observed five years before the invention<sup>5</sup> and are observed for five years after the invention, which gives an 11-year window of observation. Controls are observed over the same time window of their paired inventor.

Name matching is a huge endeavour in most publication- or patent-based research, and ISI Web of Science provides only last names and first and middle initials. To make sure that a last name and first initial were consistently the same person, we controlled for homonyms and common

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<sup>5</sup> This is the patent priority year. Please note that in Italy, as well as within the European Patent Office countries, the inventors are required to file a patent application before disclosing the invention in any form. This results in quick patent filing. Patent filing and priority hence give a close and fairly good approximation of the [timing of an](#) invention.

names. Additionally, for each individual in our sample we checked affiliation data, publication subject and consistency between the time of publication and the age of the scientist. However, while these checks could be performed on the focal sample of inventors and non-inventors (egos), we could not run the same checks on all of their co-authors (alters) due to a lack of knowledge of the attributes of those individuals. This methodological choice raises the caveat that our analysis will produce unbiased results only to the extent that common name biases and mistakes apply randomly to both the alters of the inventor and to those of their controls. Fortunately, this circumstance is likely to be satisfied. To avoid name bias when building inventors' and non-inventors' publication networks, our study includes publications for all of the 110 focal scientists (egos) and their co-authors (alters), but it does not extend to the co-authors of the alters.

Our final dataset is composed of the following two subsets: 2,899 scientific articles written between 1987 and 2006 by the 55 academic inventors plus their 17,853 co-authors (alters); and 2,406 scientific articles written between 1987 and 2006 by the matched academic professors plus their 14,562 co-authors (alters).

We build on these two subsets to derive indicators of collaboration within the scientific community for our two populations of inventors and controls. We do so by generating affiliation matrices from the ego-networks, one for the inventors and one for the controls. The matrix includes all co-author relations for all the scientists and all of their co-authors. The event linking any pair of authors is a joint publication. Algebraically, the affiliation matrix is valued and symmetric. The values in the cells along the main diagonal represent the total number of publications made by any of the authors in that row and column during the time window from 1987-2006. Values off of the diagonal represent the total number of publications jointly authored by each pair of individuals in the respective row and column.

### **3.4 Descriptive statistics**

Table 1 gives an account of the characteristics of the egos split between the two samples of

inventors and non-inventors. Around 24% of the scientists sampled are between 35 and 45 years old, and consistent with studies on age and productivity, this age class exhibits the peak of productivity. In agreement with the country-level age distribution of university professors, 46% are rather senior (55 years old or older). The majority of the scientists sampled (over 50%) work in the north of the country, around 20% work in the south, and the remaining 30% are based in central Italy. This distribution is again consistent with the geographical distribution of universities in the country. About one-third of the scientists have a PhD, while the majority have a second-level university degree. Again, this is consistent with the age profile when considering that PhD programs were first introduced in Italy in 1984 and full training abroad was quite unusual in the seventies.

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### **3.5 Ego-networks indicators**

We characterise individual networks by four properties: *size*, *density*, *betweenness centrality* and *cliques*. First, a network's size grows with the total number of individuals directly related to each other without the mediating role of the relevant ego. Accordingly, we compute the *size* indicator to assess the dimension of the community to which a scientist belongs. Second, a network's *density* relates to the intensity of the relationship linking the authors based on the frequency of their interactions. Since overall density is affected by network size, we compute a standardised measure of density – the relative network density - instead of an absolute density (Friedkin, 1981).

Third, *betweenness centrality* measures are used to characterise the position of an ego within its own network and to assess the strength with which the individual acts as an intermediary in the circulation of information (Freeman, 1979; Borgatti, 2005). Centrality increases when the individual is a necessary link connecting two pairs of nodes from a larger network (Borgatti and

Everett, 2006). Technically, information centrality indexes are based on the geodesic distance between actors and measure the shortest path connecting a pair of actors (Wasserman & Faust, 1994). The more an individual lies between others on their geodesics, the greater their importance in keeping the nodes in contact. We normalise the betweenness indicator by dividing simple betweenness by its maximum value.

Finally, investigating the division of scientists into groups and sub-structures may have important implications for the social dynamics of scientific communities. When at least two scientists co-author a piece of research they form a group or “*clique*”. Individuals within the group are tied to each other and tend to access a common pool of information, resources and social support. Our approach to studying cliques seeks to assess the features of the groups that a scientist takes part in during their career. At the most general level, a clique is a sub-set of a network in which the actors are more closely and intensely tied to one another than they are to other members of the network. This is a useful and commonly accepted way of thinking, because sometimes more complex social structures evolve or emerge from very simple ones (Scott, 2000). Formally, a clique at level  $c$  in a valued graph is defined as a sub-graph in which the ties between all pairs of actors have a value of  $c$  or greater and there is no other actor outside the clique with ties of strength  $c$  or greater to all actors in the clique. In line with Wasserman and Faust (1994: 279), we choose a clique level equal to 3.

Substantively, in our case, a clique is a unique set of co-authors that jointly sign a paper. The total number of cliques is the number of different combinations of scientists with which the ego co-authors her articles during the observed timespan. A clique of level 3 would imply that any author in the clique has co-authored at least three papers with all other authors in the clique. Inventors and non-inventors are compared on the basis of the number of cliques to which they belong and their size (i.e., the number of actors included in the clique).

### **3.6 Indicators of scientific performance**

For each publication, we retrieved the *article's citations* obtained year after year during the observation period (11 years centred on the invention year). Second, focusing on the journal in which the articles were published, we retrieved two measures of their qualitative features: the *Journal Impact Factor*, published in the ISI Journal Citation Reports in 2007, and the *Journal Level of Basicness*, published by the consulting firm IpIQ on behalf of the NSF. The former indicator expresses the journal article's short-term (2-years) average citations, and the latter expresses a ranking from 1 to 4 of the basicness of the journal, where 1 means very applied and 4 means very basic research (see Narin et al., 1978 and IpIQ, 2005). The use of journal-based indicators as a proxy of article characteristics brings several advantages and disadvantages that have been extensively discussed in the scientometrics literature (for instance, see Garfield, 2000; Glanzel and Moed, 2002)<sup>6</sup>.

A summary of all variable construction and general references is available in the appendix.

## 4. Empirical Analysis

### 4.1 Preliminary results: productivity, impact and basicness

We start our analysis by comparing the scientific productivity of the paired samples of inventors and controls. We do so cross-sectionally, by pooling together all scientific articles that appeared during the 11-year observation period.

We want to test the null hypothesis that the mean differences of the observed variables between each sample equal zero. As explained before, the paired samples are meant to remove the effects of confounding variables on the values of the observation variables.

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<sup>6</sup> Among the known disadvantages is the fact that citations of articles are highly skewed in all journals, while a unique journal indicator levels off any differences. Nonetheless, this measure is commonly used, because citations received by a single article cannot in general be used to compare articles of different ages due to the non-linear distribution of citations over time (Glanzel and Moed, 2002). Another known problem relates to using an indicator computed for a journal in a given year and applying it to all articles from the same journals in several other years. Although imprecise, this technique is also considered preferable to varying Impact Factor, Level, etc. by year, at least in reasonably short time lags. This is because 1) yearly variations mostly capture changes in the size of the journals or in the coverage of ISI, and because 2) for the Science Citation Index (unlike for the Social Science Citation Index or the Art and Humanities Index), the ranking of the journals does not vary substantially over time (Garfield, 2000).

In this and in all subsequent comparisons, we take the following approach: for normally or log-normally distributed paired differences, a simple T-test was performed under the null hypothesis of zero mean difference. For variables that did not pass the Shapiro-Wilk Test of normality or log-normality, we tested the null hypothesis that the sum of paired differences obeyed a normal distribution with the mean equal to the variance by running a one-way Kolmogorov-Smirnov Test. This is equivalent to testing whether the values of the variables in the two samples have a similar distribution. Table 2 reports the average values taken by the sample variables and the results of the paired samples test. The stars identify statistically significant differences in either the T-test or the Kolmogorov-Smirnov Test, as appropriate.

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The paired sample accounts for the unobserved heterogeneity between inventors and controls, at least under the assumption that confounding factors are captured by the set of observable covariates used to compute the propensity score matching.

Our comparisons across the whole time window show no strong statistically significant differences in the scientific accomplishments of the two samples. In terms of total publications, inventors on average published nearly 53 papers over eleven years, while controls published 44 papers on average. Although notable, this difference was measured in the presence of strong variance, which makes the two-tailed test statistically unreliable. The one-tailed test under the null hypothesis that the inventors have more publications than controls is 90% significant. Although the inventors tend to be slightly more productive, we find no statistically significant differences in the qualitative features of the articles published. Inventors and controls show comparable numbers of citations received by their papers measured either by the average citations received per paper (13.53 vs. 12.53) or by the average Impact Factor of the journal, (2.22 vs. 2.1). Similarly, the level of basicness of content published by the journals in which the articles appeared is comparable (2.9 vs.

2.8) across both groups.

In this preliminary look at the data, we are also interested in spotting potential differences in the patterns of co-authorships of the two groups. The total number of co-authors of all papers, compared by means of a Kolmogorov-Smirnov Test across the whole timespan, indicates that inventors tend to work in larger teams than controls (324 vs. 264), but there is considerable variance in the samples, and this difference is not statistically significant. The average number of co-authors per paper is also approximately the same in both groups (6.12 for the inventors and 5.67 for the controls). Overall, when pooling the data irrespective of time, we observe that inventors tend to have higher values of all of the indicators, although none of these differences is significant in statistical terms.

Next, we compare the scientific performance of the two groups before and after the focal year. The latter is, for each pair of individuals, the year in which the inventor filed the patent (the patent priority year). Our aim is to see whether the research accomplishments of the two groups of individuals are comparable before and after the event and to identify any change that occurred over the time immediately preceding or following the event. The patent year was not taken into account, and we compare two periods of five years each. Table 3 reports the mean differences of the publication-related variables calculated before the patenting event separately for the inventors and for the controls. Table 4 reports the results of the between- and within-group differences along with the results of the tests of equality of means and distributions. The between-group tests compare the inventors to the non-inventors in paired samples. We run the between-group test first over the 5 years preceding the patent priority year (Column 1) and then over the 5 years following the patent priority year (Column 2). The within-group tests compare the values of the variables five years after the patent priority to those registered five years before the patent priority. We run the within-group test separately for the inventors (Column 3) and for the non-inventors (Column 4).

As stated before, we should be aware that most of the indicators of scientific performance tend to grow over time, consistent with the life cycle effect (the scientists in our sample are on

average 53 and hence experience monotonic growth on average). For both the inventors and the controls, the increase in the total number of articles published is statistically significant.

We further observe that the average impact factor remains statistically unchanged in both samples. The level of basicness indicators of both samples increases over time but is not statistically significant for the inventors due to large variability.

The decrease in total citations is obvious given the construction of the indicator (younger publications had less time to accumulate citations), whereas we register an upsurge in the average number of citations received per paper. Both groups exhibit increasing numbers of citations, but the inventors show a much larger increase. The citations per paper of the inventors change from being lower than that of the non-inventors on average to being higher. The papers published by the inventors received a mean of 2.22 more citations per article than those of the non-inventors in the five years following the invention, while they were slightly less cited before the invention. This increase appears surprising, especially as it is also associated with a statistically significant rise in the average level of basicness of the journals in which the inventors published compared to the non-inventors. The average Impact Factor of the journals in which the articles appeared remains comparable in both the inventor and non-inventor samples. This evidence seems to confirm that the patent event did not hinder scientific activities, because no evidence indicates that the scientific production of the inventors was reduced in quantity, impact, basicness or citations received. Our data suggest that inventors in the five years after the patent perform better (or no worse) in all respects and catch up to the non-inventors on the only indicator –the level of basicness- in which they seemed to have a comparative disadvantage. This evidence is consistent with the findings of similar analyses (Azoulay et al, 2009; Calderini et al., 2009).

An interesting highlight from these comparisons relates to team size, which we will further analyse in the social network analysis that follows. For now, we observe that the team size, as expressed by the number of co-authors signing the same article, increases in both groups in the aggregate. This evidence can be explained by the general trend toward expanding research teams in

recent years (Adams et al., 2005; Wuchty et al., 2007). The team sizes of the inventors increase more markedly than those of the non-inventors, although the differences between the two groups remain statistically insignificant. After patenting, the average team sizes of the two groups start to diverge more markedly. Although this divergence remains statistically insignificant, the inventors significantly increase their mean team size by an average of two co-authors per paper five years after patenting compared to five years prior to patenting.

Overall, this evidence leads us to conclude that, after patenting, the inventors published more with a larger number of co-authors per article. The papers that they published exhibit no decline in quality as expressed by average citations and journal impact factor. On the contrary, they catch up in terms of the level of basicness of the journals in which they publish compared to the controls and reverse the previously existing disparity.

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#### **4.2 Preliminary evidence: Time-invariant Analysis of Social Network and Ego Positions**

This preliminary evidence of changes in the team size confirms the relevance of inquiring in greater detail about the network and relational effects that may be associated with the event of patenting. Knowing the sheer number of co-authors per paper can only provide information about the size of the team that worked on each single paper and does not describe the network and community effects of a smaller or larger team. For example, we would be incapable of appreciating the web of linkages of an author who has many different co-authors but works with few of them on each paper. Similarly, when we observe large teams, we do not know whether it is the same group of people that works together on repeated papers or if we are observing a larger web of connections.

We start this part of the analysis by looking at the ego-networks and the position of the ego within their network during the entire 11-year window. In the next subsection, we will perform the

analysis only in the years preceding and following the invention and provide an answer to our research hypotheses. Comparisons of the time-invariant statistics of the paired samples of inventors and controls are reported in Table 5. We observe that the network size, i.e., the number of different nodes connected to each ego, is greater for the inventors than the non-inventors, despite there being a large variance among individuals that makes the mean difference statistically insignificant. Conversely, the network density is approximately the same in both groups, presenting no differences in the strength or level of redundancy of the links between the nodes of each group.

However, there are some sizable differences between the two groups that are observable from the cross-sectional comparison. First, inventors on average take part in larger cliques than their colleagues that do not invent. For the inventors, the average number of authors per clique is 6.73, as opposed to 6.24 authors per clique for the controls. Second, the inventors are more central in their networks of relationships than the non-inventors, as expressed by a larger normalised betweenness centrality. This indicator captures the geodesic distance between each pair of nodes in the network and gives a measure of the position of the ego that captures how important she is in enabling the connections among other people. The rationale is that individuals who are required for the connection between two nodes score higher in their level of betweenness centrality when compared to those individuals who represent redundant connections. A high betweenness centrality indicates that the ego is the bridge that brings together otherwise disconnected individuals. We observe that inventors are more central i.e., they are more likely to play a bridging role among nodes than non-inventors (Wasserman and Faust, 1994:188; Borgatti, 2005).

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#### **4.3 Social capital and ego position before patenting**

In Tables 6 and 7, we perform within- and between-group comparisons of the network characteristics and network positions of inventors and non-inventors in the pre-invention and post-invention phases. Table 7 reports the results of between- and within-group tests before and after the

event.

The results of the within-group comparisons (columns 3 and 4) indicate that both inventors and non-inventors increase their network sizes over time. This means that the growth of the teamwork discussed in the preliminary analysis is (at least in part) due to a broader pool of connections and social capital. This is confirmed by the statistics on the average number of cliques. Recall that a clique is a unique set of co-authors that jointly sign a paper, and the total number of cliques is the number of different combinations of scientists with which the ego co-authors her articles during the time frame. We observe that both groups participate in more cliques as time passes. This increase is sizable: inventors go from participating in 16.6 to 23.7 different cliques during the years of observation and non-inventors go from participating in 14.7 to 20 different cliques over the same years. In both time frames, the inventors participate in more cliques than non-inventors, and the difference is statistically relevant.

We now come to the measures of social capital computed for inventors and non-inventors in the five years before the patent priority (Table 6 Column 1, 2. Table 7, Column 1). In principle, given that European law forces inventors to deposit a patent prior to publishing the invention, we can state with considerable certainty that we are observing the period of time that precedes the formation of the inventive idea. During this time span, we observe that the inventors rely on larger networks than the non-inventors. The computed measure of network size for the inventors is statistically larger than that for the non-inventors. This is consistent with our Hp.1 that predicted a positive association between the broadness of the connections expressed by the network size and the inventive activity of a scientist.

This result is further substantiated by the data on cliques, which also confirm our Hp.2. Prior to patenting inventors participate in 2.28 more cliques than non-inventors on average, and these cliques are not substantially larger than those of the controls. Hence, we can conclude that inventors enjoy larger social capital than non-inventors before they begin to invent. This broader social capital is constructed by means of participation in many different groups at the same time rather

than in larger groups.

This evidence does not prove clear causality between the reach of a social network and the capacity to invent. Nonetheless, the association of the two is a meaningful observation that may underlie the invention process.

Consistent with this result and with our Hp.3, we observe that the densities of the networks of the inventors are not higher than those of the non-inventors prior to patenting. The normalised betweenness centrality is greater for the inventors than for the non-inventors. This establishes that inventors serve more as bridges between otherwise distant communities than their colleagues that did not invent and supports our Hp.4. The evidence is consistent with a world in which academic inventors arbitrage across the boundaries of relatively disconnected communities, such as those of industry and academia. Again, even though the evidence does not prove that this positioning is the cause of their inventive activity, it is interesting to note that inventors are disproportionately represented among individuals that have a wider spectrum of connections in sparser networks during the time preceding the invention.

#### **4.4 Social capital and ego position after patenting**

We now come to assessing the social capital and network position of the inventors in the period that follows the patent disclosure. Our aim is to inquire whether the event of patenting is associated with substantial alterations in the acquaintances of the inventors in the scholarly community, with a specific focus on looking for any evidence of increased separation of secluded networks.

As stated before, we know that all scientific performance is strongly dependent on life and career effects (Levin and Stephan, 1991). Furthermore, a general trend of increasing cooperation in science has been documented in recent years (Adams et al., 2005; Wuchty et al., 2007). Hence, comparing measures derived from scientific outcomes (articles published, citations, co-authorship) in a certain period against similar measures derived from scientific outcomes at a later period can be

misleading and result in spurious correlations. To avoid this pitfall, in this paper we compare the indicators calculated in different time periods against those of a paired sample of scientists studied in the same time periods under the assumption that life cycles approximately follow a common pattern over the career of a scientist.

First, we notice that the network sizes of both the inventors and the controls increase over the years, and even though the inventors experience a larger increase in magnitude, the differences between the network sizes of inventors and controls do not become statistically significant due to large variance. Nonetheless, inventors continue, as before, to participate in substantially more cliques than their corresponding non-inventors, and their cliques are also larger on average than those of the non-inventors. This preliminary evidence suggests that the inventors do not substantially reduce their acquaintances within the community of co-authors, and they continue to show a greater propensity to link different research teams than the controls.

Next, we consider the bridging role played by the inventors. Overall, the density of the networks, i.e., the frequency of redundant links that connect the network of co-authors, diminishes over time for both the inventors and the controls. This observation, coupled with the evidence of participation in more cliques, shows that scientists have a common tendency to extend their cooperation and work with different groups of people as they age. From the results reported in Column 2 of Table 7, we can appreciate that this tendency is even stronger in magnitude for the inventors, who pass from having denser to having sparser networks than their controls. Hence, contrary to our  $H_{p.5}$ , inventors present an even stronger decrease in their network density in the post-patenting period than their non-inventing counterparts.

Finally, we observe that the betweenness centrality of the inventors decreases in the five years after the invention, while that of the non-inventors increases. In the post-patenting period, the controls increase their centrality within their networks, while inventors become less central. The difference in the betweenness centrality values of the inventors and the non-inventors changes from being positive to being negative, although the difference is still statistically insignificant. Overall,

we see no clear confirmation of our H<sub>p.6</sub> regarding a sizable reduction of the bridging role, although the trend does point in this direction. Our results may be consistent with a scenario in which inventors, after serving as bridges to initially separated communities, maintain frequent interaction with their co-authors and further extend their cooperation. Nonetheless, they partially lose their bridging role as these communities slowly become less separated from one another.

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## 5. Conclusions

Scholars investigating academic patenting have observed that inventors exhibit superior scientific accomplishments compared to non-inventors in cross-sectional analyses both before and after the invention, and they have proposed several possible explanations for these findings. In this paper, we have proposed and empirically investigated one further explanation that relates to the network structure and social capital of academic inventors.

We hypothesised that the inventive activity of scientists was associated with a larger, more variegated and more informative network structure in which they are involved and with a central position in the network of reference that lets them act as a bridge between otherwise distant communities. We found support for these hypotheses by looking at the network structures of a sample of Italian academic scientists in the field of chemistry and at their positions within the networks. Their networks were built based on the names of the co-authors listed in a large sample of their scientific publications collected in the 11 years centred around the patent priority year.

To cope with the effects of life-cycle and selection, our research strategy was to assemble a paired sample of scientists comparable to the inventors but who have never obtained a patent. Comparability across the samples was achieved by means of a one-to-one pair-matching strategy

based on the estimation of a propensity score. The latter was made to depend only on predetermined and exogenous variables. The sample we used offers multiple advantages, including being geographically confined and disciplinarily homogeneous.

Although in this paper we are only capable of highlighting correlations rather than identifying precise causal links, we did find support for our hypotheses that inventive activities are associated with a broader network and participation in many different cliques in the pre-invention phase. The networks of the inventors are also less tightly knit and are therefore more capable of conveying richer (non-redundant) information sets. Academic inventors are more likely to play a bridging role in their communities prior to patenting than the non-inventors, although over time the non-inventors reduce this disparity.

We also searched for evidence that the inventors became more secluded from their respective communities after patenting, but this hypothesis was not confirmed. Quite the opposite, we saw that in the years after patenting, inventors keep extending their networks and participating in more cliques, and these networks do not become closer or more densely knit.

## **6. Limitations and Avenues for Future Research**

Our work suffers from several limitations. First, we observe only inventors of patents assigned to their respective universities of affiliation. We are aware from previous studies (Balconi et al., 2004) that this is not the prevailing invention strategy in Italy, and we cannot rule out the possibility that academic inventors of patents owned by private firms may show different publication behaviours or social network structures. More generally, as is often the case in social network analysis, accurate sampling at the individual level might not necessarily lead to stronger external validity with respect to the network results. This is particularly true when, as in our case, one looks at longitudinal data. While we followed all of the standard procedures normally used in these cases and normalised all indexes and defined comparable network structures over the different time intervals, some problems with the computation of the different indexes may still remain. This

reasoning also led us to explicitly rely on a limited number of indicators that have been proven to be less sensitive to computational problems.

Name matching is a huge endeavour in most publication- and patent-based research, and the ISI Web of Science provides only the last name and first and middle initials. To ensure that a last name and first initial were consistently the same person, we controlled for homonyms and common names. Additionally, we checked affiliation data, publication subject and overlap between times of publication and age of the scientist for each individual in our sample. However, while these checks could be performed on the focal sample of inventors and non-inventors (egos), we could not run the same checks for all of their co-authors (alters) due to a lack of knowledge of the attributes of those individuals. Consequently, our results are reliable only under the critical assumption that name-matching biases apply randomly to both the inventor and control samples.

Finally, our social network analysis looks at the first circle of the ego's acquaintances. It includes publications for all of the 110 focal scientists (egos) and their co-authors (alters), but it excludes co-authors' publications. This means that we look at the ego's friends, but we do not consider the friends of friends, or the friends of friends of friends, etc. We do not deny that the second and third circles of acquaintances may still contribute to the information at the ego's disposal. However, we do not take these connections into account in this work.

Despite these shortcomings, we believe that our paper offers a unique and original contribution to the debate about the characteristics and behaviour of academic inventors. Future work should extend our comparative analyses to include multivariate modelling of social network structure in the immediacy of the inventing event. It should also extend the investigation to more scientific disciplines and to different institutional environments.

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## Tables

**Table 1 - Descriptive Statistics of the Whole Sample (Obs. 110)**

<b>Variable</b>	<b>Mean: Inventors</b>	<b>Mean: Non- Inventors</b>
Year of Birth	1952 (9.48)	1950 (9.26)
Dummy age: 35-45	0.24 (0.43)	0.20 (0.40)
Dummy age: 46-55	0.29 (0.46)	0.29 (0.46)
Dummy age: 56-65	0.33 (0.47)	0.36 (0.49)
Dummy age: Over 65	0.15 (0.36)	0.15 (0.36)
Gender	0.78 (0.42)	0.89 (0.32)
Geographic Location: North	0.51 (0.51)	0.58 (0.50)
Geographic Location: Centre	0.33 (0.47)	0.20 (0.40)
Geographic Location: South	0.16 (0.37)	0.22 (0.42)
Phd	0.35 (0.48)	0.24 (0.43)
Phd in Italy	0.33 (0.47)	0.22 (0.42)
Phd Abroad	0.02 (0.14)	0.02 (0.14)

St. Err. in parentheses

**Table 2 - Publication-Related Indicators Over the Entire Observation Period**

<b>Variable</b>	<b>Inventors</b>	<b>Non-Inventors</b>	<b>Difference</b>
Total Publications	52.71 (35.35)	43.75 (30.21)	8.96 (6.05)
Total Number of Co-authors	324.45 (235.8)	264.69 (243.83)	+59.76 (340.32)
Average Num. of Co-authors per Paper	6.12 (1.64)	5.67 (1.24)	0.44 (0.27)
Total Citations Accumulated as of 2006	696.73 (646.95)	581.15 (564.41)	+115.58 (863.3)
Average Citations received by articles published as of 2006	13.53 (1.30)	12.33 (1.01)	+1.30 (10.47)
Average Impact Factor (log)	2.22 (0.77)	2.10 (0.88)	0.12 (0.15)
Average Level of Basicness	2.92 (0.72)	2.88 (0.85)	0.04 (0.13)

<sup>+</sup> Kolmogorov-Smirnov Test  
St. Err. in parentheses

**Table 3 - Pre- and Post-Patent Between- and Within-Group Differences**

Variable	5 years before patent		5 years after patent	
	Inventors	Non-Inventors	Inventors	Non-Inventors
Total Publications	20.55 (14.94)	17.29 (13.61)	27.25 (19.12)	22.27 (15.09)
Total Num. of Co-authors	119.20 (95.81)	101.36 (107.19)	177.13 (139.64)	138.00 (120.55)
Average Num. of Co-authors per Paper	5.40 (1.77)	5.11 (1.82)	7.40 (2.45)	6.90 (1.77)
Total Citations Accumulated as of 2006	358.82 (357.90)	298.21 (358.36)	252.71 (231.91)	230.05 (236.27)
Average Citations received by articles published as of 2006	6.92 (5.60)	7.31 (5.70)	19.21 (16.44)	16.98 (11.20)
Average Impact Factor (log)	2.09 (1.06)	1.91 (1.03)	2.32 (0.76)	2.28 (0.91)
Average Level	2.80 (0.87)	2.81 (1.06)	3.04 (0.76)	2.94 (0.75)

(Standard errors in parentheses)

**Table 4 - Differences and Significance**

Variable	Between Groups (Inv. vs. Non-inv.)		Within Groups (Before vs. After)	
	5 years before patent	5 years after patent	Inventors	Non- Inventors
Total Publications	3.25 (2.74)	4.98 (3.04)	6.71 (1.83)***	4.98 (1.24)***
Total Num. of Co-authors	+17.83 (20.55)	+39.12 (23.33)	ψ57.93 (14.74)***	36.64 (8.64)***
Average Num. of Co-authors per Paper	0.30 (0.30)	0.50 (0.40)	ψ2.00 (0.31)***	+0.33 (0.08)
Total Citations Accumulated as of 2006	+60.6 (70.85)	22.65 (41.03)	+106.11 (36.80)	ψ68.16 (42.48)***
Average Citations received by articles published as of 2006	+0.39 (1.01)***	+2.22 (2.50)**	ψ12.29 (1.84)**	ψ9.67 (1.15)***
Average Impact Factor (log)	0.18 (0.19)	0.04 (0.14)	0.23 (0.14)	+0.37 (0.12)
Average Level	+0.00 (0.14)	+0.10 (0.14)***	+0.24 (0.12)*	+0.13 (0.11)**

+ Kolmogorov-Smirnov Test

ψ Log-normal

\*\*\*p<.01 , \*\*p<.05 , \*p<.10

**Table 5 - Network Indicators Over the Entire Observation Period**

<b>Variable</b>	<b>Inventors</b>	<b>Non-Inventors</b>	<b>Diff.</b>
Size	115.93 (94.26)	95.42 (95.67)	20.51 (18.11)
Density	12.48 (9.70)	12.34 (8.77)	0.14 (1.76)
Cliques	45.95 (38.02)	34.15 (24.37)	13.49 (6.94)**
Average n° of Authors per Clique	6.73 (1.30)	6.24 (1.20)	$\psi$ 0.49 (0.24)**
Normalised Betweenness	1.82 (1.20)	1.29 (1.71)	0.53 (2.85)*

$\psi$  Log-normal

\*\*\*p<.001 , \*\*p<.05 , \*p<.10

St. Err. in parentheses

**Table 6 - Pre- and Post-Patent Between- and Within-Group Differences**

<b>Variable</b>	<b>5 years before patent</b>		<b>5 years after patent</b>	
	<b>Inventors</b>	<b>Non Inventors</b>	<b>Inventors</b>	<b>Non-Inventors</b>
Size	50.36 (46.03)	42.25 (46.72)	72.49 (57.87)	59.62 (58.13)
Density	25.31 (22.2)	24.2 (21.39)	18.4 (14.64)	19.27 (15.84)
Cliques	16.6 (14.11)	14.69 (15.06)	23.71 (18.73)	20.04 (15.99)
Average Num. of Authors per Clique	6.15 (1.56)	5.71 (1.65)	6.88 (1.52)	6.28 (1.48)
Normalised Betweenness	2.16 (3.17)	1.31 (2.00)	1.48 (1.97)	1.98 (2.31)

(St. Err. in parentheses)

**Table 7 - Differences and Significance**

Variable	Between Groups (Inv. vs. Non-inv.)		Within Groups (Before vs. After)	
	5 years before patent	5 years after patent	Inventors	Non- Inventors
Size	$\psi$ 3.39 (0.20)***	<sup>+</sup> 12.87 (10.55)	$\psi$ 22.12 (4.77)***	<sup>+</sup> 17.36 (3.87)*
Density	<sup>+</sup> 1.12 (4.42)	$\psi$ -0.87 (3.06)***	$\psi$ -6.92 (3.03)*	$\psi$ -4.93 (1.95)***
Cliques	$\psi$ 2.28 (0.18)***	$\psi$ 2.42 (0.19)***	7.11 (1.45)***	5.34 (1.34)***
Average Num. of Authors per Clique	<sup>+</sup> 0.44 (0.34)	0.60 (0.27)**	$\psi$ 0.73 (0.29)	$\psi$ 0.57 (0.22)
Normalised Betweenness	<sup>+</sup> 0.85 (0.54)*	-0.50 (0.44)	-0.67 (0.53)	0.67 (0.43)*

<sup>+</sup> Kolmogorov-Smirnov Test

$\psi$  Log-normal

\*\*\*p<.001 , \*\*p<.05 , \*p<.10