When does centrality matter? Scientific productivity and the moderating role of research specialization and cross-community ties

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Abstract

The present study addresses the ongoing debate concerning academic scientific productivity. Specifically, given the increasing number of collaborations in academia and the crucial role networks play in knowledge creation, we investigate the extent to which building social capital within the academic community represents a valuable resource for a scientist's knowledge-creation process. We measure the social capital in terms of structural position within the academic collaborative network. Furthermore, we analyse the extent to which an academic scientist's research specialization and ties that cross community boundaries act as moderators of the aforementioned relationship. Empirical results derived from an analysis of an Italian academic community from 2001 to 2008 suggest academic scientists that build social capital by occupying central positions in the community outperform their more isolated colleagues. However, scientific productivity declines beyond a certain threshold value of centrality, hence revealing the existence of an inverted U-shaped relationship. This relationship is negatively moderated by the extent to which an academic focuses research activities in few scientific knowledge domains, whereas it is positively moderated by the number of cross-community ties established.

Keywords: scientific performance, social capital, structural centrality, research specialization, cross-community ties

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Introduction

Scientific research outcomes differ enormously across work by academic scientists in terms of both productivity and impact on subsequent research. This finding was noted for the first time by Lotka (1926), who observed how a small minority of academics produce the vast share of published scientific works. Accordingly, the following questions naturally arise. Why do some scientists achieve superior scientific performance? Which factors lead some scientists to produce scientific outcomes that have a greater impact on subsequent research? These are important concerns that have increasingly attracted the attention of academic scholars, policy makers, and governors of research organisations. In fact, a better understanding of what drives academic scientists' productivity is essential for economic development because scientific research outcomes are a fundamental input for industrial R&D, technological and economic progress, and social welfare (e.g. Dasgupta & David, 1994; Henderson, Jaffe, & Trajtenberg, 1998; Mansfield, 1995; Narin, Hamilton, & Olivastro, 1997). Furthermore, revealing the dynamics underlying scientific knowledge production allows us to more precisely define rewards systems and career paths for individuals working in the science realm (Kelchtermans & Veugelers, 2010).

Previous research tried to disentangle the skewness characterising academic scientific productivity by focusing on individual demographics (e.g. Allison & Stewart, 1974; S. Cole, 1979; Fox, 1992; Lehman, 1953; Levin & Stephan, 1991), laboratory composition (e.g. Adams & Griliches, 1998; J. R. Cole & Cole, 1973; Crow & Bozeman, 1987; Williamson & Cable, 2003), 'Matthew effect' (Merton, 1968), and, more recently, university-industry relationships (e.g. Agrawal & Henderson, 2002; Azoulay, Ding, & Stuart, 2007;

Fabrizio & Di Minin, 2008). Nevertheless, these studies systematically neglected the role that collaborative networks across and within scientific communities play in shaping scientists' productivity (except for Balconi, Breschi, & Lissoni, 2004). In fact, social networks have been found inextricably linked to knowledge creation by influencing both search and recombination processes (e.g. McFadyen & Cannella, 2004; Tsai & Ghoshal, 1998). The increasing number of collaborations among scientists characterising the last decades further confirms the importance of these networks in determining the advancements in science (e.g. Katz & Martin, 1997). Scientists, therefore, are embedded in networks of collaborations where they exchange ideas, resources, and information to generate new knowledge (e.g. Barabási, 2005; Granovetter, 1973; Moody, 2004). The configuration of these networks, as well as the position an academic scientist occupies within them, may significantly affect performance in terms of both number and quality of scientific articles.

The social capital theory (e.g. Adler & Kwon, 2002; Granovetter, 1973; Nahapiet & Ghoshal, 1998) provides important clues on micro-social dynamics that may affect the relationship between a scientist's position within the scientific community and his or her productivity. In this regard, the present research aims at investigating how a scientist may better contribute to the scientific knowledge frontier by building social capital within the scientific community. Specifically, we expect academic scientists that build social capital as reflected by central structural positions—we adopt the Bonacich's (1987) centrality measure—to exhibit higher levels of scientific productivity because they are in a better situation for recombining, accessing, and diffusing knowledge (Dasgupta & David, 1994; Freeman, 1979). However, we also expect to observe diminishing returns from this action since considerable resources are required to maintain social capital (Adler & Kwon, 2002; Nahapiet & Ghoshal, 1998). Furthermore, we advance the extant literature by providing a contingent perspective on the relationship between social capital and scientific productivity;

We explore the moderating effect of academics' research specialization and cross-community ties. Both the moderating effects are expected to interact with the costs and benefits of social capital.

We developed a set of hypotheses that we empirically tested on the Italian community of tenured academic scientists listed in the disciplinary affiliation 'ING-IND/35 Ingegneria Economico-Gestionale' between 2001 and 2008. The sample is composed of 203 academic scientists who published 484 scientific articles during the observation period.

Findings confirmed that social capital, in the form of structural centrality, affected an academic scientist's productivity but in a curvilinear fashion. In addition, the scientist's degree of research specialization and number of cross community ties had negative and positive moderation effects on the shape of the 'social capital-scientific productivity' curve, respectively.

The remainder of the paper is organised as follows. The next section develops our main predictions. We then describe the research setting, data, variables, and estimation method as well as the tests of our hypotheses. Finally, we discuss the results.

Theory and Hypotheses

Scientific research outcomes are the antecedents of technological progress and represent an essential input for industrial innovation (e.g. Dasgupta & David, 1994; Henderson et al., 1998; Mansfield, 1995; Narin et al., 1997). However, as discussed, their distribution across the work of academic scientists is extremely skewed since just a small minority produces the vast share of published scientific works (Lotka, 1926). Thus, scholars have paid great attention to investigating the main dynamics underlying scientific knowledge creation by adopting different perspectives of analysis. First, past research found that academics' performance is partially explained by individual characteristics, such as age (S. Cole, 1979; Lehman, 1953), academic position (Fox, 1992), and scientific disciplines (Levin

& Stephan, 1991). For instance, Allison and Stewart (1974) showed that a scientist's productivity, resources, and esteem increase as their career age increases due to a process of accumulative advantage. In fact, according to the 'Matthew effect', the more productive scientists enhance their productivity over time thanks to increasing returns on reputation and visibility (Merton, 1968). Second, performance has been found to be related to the composition of the laboratory, such as average age and research productivity of colleagues (Williamson & Cable, 2003), prestige of the university department (J. R. Cole & Cole, 1973), size (Adams & Griliches, 1998), and funding structure (Crow & Bozeman, 1987). Finally, a recent stream of literature highlights how entrepreneurial activity represents a source of new research questions for academics. Specifically, those scientists strongly linked to industry and involved in patenting activity (e.g. Agrawal & Henderson, 2002; Azoulay et al., 2007) publish more and better quality papers than their colleagues. Agrawal and Henderson (2002) analysed the patents developed at the Massachusetts Institute of Technology and found that patent volume is positively correlated with research impact as measured by the number of citations a paper received. However, the positive effect exerted by entrepreneurial activities on a scientist's performance only holds up to a certain threshold, above which the scientist's involvement in commercialising research results through patents has been proved to cause negative returns on scientific performance (Fabrizio & Di Minin, 2008; Gittelman & Kogut, 2003).

Notwithstanding the attention scholars have paid to disentangling the factors that affect academics' scientific productivity, few studies have investigated this issue by adopting a network perspective (except for Balconi et al., 2004). The importance of adopting this view is justified by the growing number of collaborations among academic scientists (e.g. Katz & Martin, 1997), which clearly shows how they are deeply embedded in networks of collaborative relationships where they exchange information, ideas, and resources (e.g.

Barabási, 2005; Granovetter, 1973; Moody, 2004). Networks, in fact, are critical sources for both knowledge exchange and recombination (e.g. McFadyen & Cannella, 2004; Tsai & Ghoshal, 1998). As suggested by Gulati (1995), "social networks are conduits of valuable information and have been observed in a variety of contexts, ranging from interpersonal ties [...] to interlocking directorates [...] The common theme throughout this body of research is that the social networks of ties in which actors are embedded shape the flow of information between them [...]" (p. 623-624).

The importance of networks for the knowledge-creation process has been intensely highlighted in the social capital theory, which proposes them as a valuable relational resource to conduct 'social affairs' (Nahapiet & Ghoshal, 1998). The core argument of this theory resides in 'goodwill' people involved in our personal relationships have towards us. This goodwill affects information exchange, social solidarity, and ability to influence and control others (Adler & Kwon, 2002; Sandefur & Laumann, 1998). According to this view, an individual's social capital can be conceived as residing in the network of ongoing exchange relationships with other people that he or she accumulates over time (Burt, 1992; Coleman, 1988; Pezzoni, Sterzi, & Lissoni, 2012; Rodan & Galunic, 2004). Nahapiet & Ghoshal's (1998) proposed a formal definition of social capital "as the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (p. 243).

Like other forms of capital, social capital is a source of potential value, which is a function of the network where an individual is embedded (Rodan & Galunic, 2004). Scholars found the value of social capital intrinsically related to the structure and nature of an individual's relationships (e.g. Burt, 1992; Coleman, 1990; Granovetter, 1985; Putnam, 1995). Those relationships are also source of shared representations, interpretations, and system of meaning among parties such as shared languages and codes and shared narratives (e.g. Cicourel, 1973; Nahapiet & Ghoshal, 1998). These basic concepts underlying the social capital theory were used to investigate a wide range of phenomena such as career success, product innovation, intellectual capital, inter-firm learning, and entrepreneurship (for a complete review, see Adler & Kwon, 2002).

Given the capability of the social capital theory in explaining micro-social dynamics, we adopt this theoretical lens to investigate the relationship between networks in academia and scientists' productivity. The aim of our study is then to develop a theoretical model that describes the influence social capital exerts on scientists' productivity. We refer to a scientist's social capital in terms of his or her structural position within the scientific community network. To this end, we use the concept of centrality (Bonacich, 1987; Freeman, 1979). In particular, centrality was found to be strongly associated with the status of the actor (Podolny, 1993), the power exerted by the actor (Brass, 1992; Brass & Burkhardt, 1993), the nature of the innovation process in which the individuals are involved (Ibarra, 1993), the variance in obtaining prestigious jobs (Hadani, Coombes, Das, & Jalajas, 2012), and the actor performance (e.g. Balkundi & Harrison, 2006; Cross & Cummings, 2004; Sparrowe, Liden, Wayne, & Kraimer, 2001). For instance, Brass and Burkhardt (1993) showed that an individual's network centrality is significantly related to others' perceptions of the individual's power. In addition, Ibarra (1993) demonstrated how central individuals are generally more involved in innovation activities inside organisations. Cross and Cummings (2004) found in knowledge-intensive networks a positive relationship between an individual's network centrality and their performance, since a central position allows the individual to obtain unique information and a diverse perspective to complete the tasks at work.

We believe an academic scientist's capability to create new relevant scientific knowledge positively related to the social capital he or she builds within academia by occupying central positions in the collaborative network. We propose three main logics that may lead this effect, as (i) knowledge recombination, (ii) access to knowledge and resources, and (iii) knowledge diffusion. Firstly, building social capital through centrality increases the number of relationships an academic has with other scientists within the network (Bonacich, 1987; Freeman, 1979). These relationships represent channels for the exchange of knowledge and resources (McFadyen & Cannella, 2004; Nahapiet & Ghoshal, 1998). Therefore, a central scientist is exposed to more knowledge-recombinant opportunities for the creation process compared to the more isolated colleagues, i.e. those having a lower level of social capital within the academic network. A central scientist is also more likely to be connected with other powerful actors in the network (Bonacich, 1987). This may enhance the likelihood of obtaining knowledge of higher quality as well as specific and exclusive resources needed for research such as instrumentations, labs, facilities, and databases. Secondly, social capital associated with highly central positions in network generates social solidarity, which can be conceived as the degree of mutual trust and commitment among individuals. Social solidarity reduces the need of formal control on relationships by increasing the closure of social networks and empowering the social norms and beliefs (Adler & Kwon, 2002). This favours knowledge exchange and allows a scientist gaining a superior and a more efficient access to knowledge and resources disseminated inside a network. Thirdly, incentives and norms in science lead academics to maximize the ratio of production and the diffusion of new scientific knowledge mainly by publishing in academic journals (Dasgupta & David, 1994; Merton, 1968). Relationships represent important channels through which a scientist may pursue this action (Reagans & McEvily, 2003). Social capital associated to highly central positions, therefore, provides a scientist with a better position to diffuse his or her knowledge within the scientific communities, hence increasing its impact.

However, as Coleman (1990) pointed out "a given form of social capital that is useful for facilitating certain actions may be useless or harmful for others" (p. 302). Adler & Kwon (2002) also observed that "investments in social capital, like investments in physical capital, are not costlessly reversible or convertible. Therefore, unbalanced investment or overinvestment in social capital can transform a potentially productive asset into a constraint and a liability" (p. 28). We believe the above discussed positive relationship applies only to a certain level of structural centrality beyond which social capital exerts negative returns in the knowledge-creation process. Three logics are proposed to substantiate these diminishing returns, as (i) limited attentional capability, (ii) time to maintain relationships, and (iii) hindrance behaviour. Firstly, building social capital by centrality requires considerable investment in establishing and maintaining relationships, and, as with any expensive investment, social capital investment may not be cost efficient. The limits of the use of social capital manifest in the form of humans' bounded capacity to be rational, i.e. limited attentional capability (e.g. Cyert & March, 1963; Hansen, 2002; Simon, 1947). According to this view, an excessive level of social capital may taper off a scientist ability to identify and process efficiently relevant knowledge flowing from his or her network peers (Borgatti, Mehra, Brass, & Labianca, 2009; O'Reilly, 1980). As centrality increases the attention a scientist can dedicate to each tie reduces (Mayhew & Levinger, 1976). This weakens the intensity of ties, hence undermining the exchange of tacit knowledge (Hansen, 1999; Simonin, 1999), which is a critical component for the knowledge-creation process. Secondly, time is another important constraint on the relationship between social capital and knowledge creation. Highly central positions require investments of time in maintaining and coordinating the set of relationships constituting an individual's social capital. This goes to the detriment of solo activities such as reading, writing, and running experiments, which constitute important elements for the creation of new knowledge (e.g. Latour & Woolgar, 1979;

McFadyen & Cannella, 2004). Finally, high levels of social capital expose a scientist to hindrance behaviour from other scientists in the same organization or community for resources allocation (Lechner, Frankenberger, & Floyd, 2010; Sparrowe et al., 2001). Thus, highly central scientists may face uncooperative behaviour, foot dragging, and even sabotage by other individuals or groups in the domain, which in turn may hinder central actors' knowledge-recombination process.

Accordingly, we posit the following hypothesis:

Hypothesis 1. Social capital, in the form of structural centrality within the academic network, is expected to have a curvilinear effect (taking an inverted U-shape) on an academic scientist's productivity.

The Moderating Role of Research Specialization and Cross-community Ties

Hypothesis 1 addresses how academics' social capital, in the form of network centrality, curvilinearly affects scientific productivity. To our knowledge, the existing literature lacks a contingent view on this relationship. By considering the context of academia, we believe that this relationship may be further analysed taking into account a scientist's research activity and the nature of collaborative relationships. In particular, we focus on the moderating role played by research specialization and ties crossing the boundary of a scientist's academic community, as well as on how both can be leveraged to better exploit the advantages of building social capital by occupying central positions. Figure 1 describes the framework we develop.

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We believe that the degree of an academic scientist's research specialization, just as the different scientific fields in which he or she conducts research, may influence his or her ability to exploit the benefits high levels of social capital may provide. Specifically, while knowledge variety and complementarity increase recombination capability, by providing more opportunity to generate better ideas (Kanter, 1988) and better performance (Pelz, 1956), reduce unsuccessful research, and enhance successful outcomes (Coyle-Shapiro & Shore, 2007; Wong, 2008), the risk of knowledge myopia in the search process is more likely when a scientist's research is highly specialized. In fact, a specialized scientist tends to rely upon a limited variety of knowledge, whose potential as sources of novel solutions therefore diminishes over time (e.g. Fleming, 2007). In other words, specialization leads scientists to search locally, hence reducing the likelihood to generate breakthrough ideas (Levinthal & March, 1993; March, 1991). Local search therefore could lead a scientist to develop a narrow knowledge base, which in turn may weaken his or her ability to identify and process the diverse and novel knowledge-recombinant opportunities highly central positions provide. In addition, a scientist searching for knowledge locally may be less inclined to leverage the broader and more diverse knowledge to which he or she can have access by occupying highly central positions (e.g. Fleming, 2001). According to this view, a specialized scientist is less likely to derive the productivity benefits of high levels of social capital compared to his or her peers who are similarly positioned but are less specialized.

Furthermore, a scientist's research specialization may reinforce the negative returns high levels of social capital exert on the knowledge-creation process. As noted, a specialized scientist tends to search locally and develop a narrow knowledge base (e.g. Fleming, 2001, 2007). In addition, as a scientist's research specialization increases the difficulties in seeking out knowledge and resources that involve relationships with other scientists that operates in domains, which are distant from the one of his or her own specialization, also increase since the higher cognitive distance (Andrews & Delahaye, 2000). Therefore, a specialized scientist, compared to his or her less specialized peers occupying similar structural positions, has to invest more attention and time to identify, process, and access to the diverse and complementary knowledge and resources central positions may provide. Yet, as discussed, humans have a bounded rationality (e.g. Cyert & March, 1963) and therefore higher investments in attention may lead a specialized scientist to be less able to identify and process efficiently relevant knowledge flowing from his or her network peers as well as to maintain the intensity of ties. Similarly, the higher investments of time required to manage and maintain relationships, which represent potential sources of complementary and diverse knowledge, may further distract the specialized scientists from conducting solo activities critical for the knowledge creation as reading, writing, and running experiments (e.g. McFadyen & Cannella, 2004). In other words, the degree of research specialization may undermine a scientist's ability to exploit high levels of social capital for the knowledge-creation process.

According to this discussion, we posit that:

Hypothesis 2. The degree of an academic scientist's research specialization negatively moderates the curvilinear relationship between his or her social capital, in the form of structural centrality within the academic network, and scientific productivity. Specifically, at a given level of centrality as a scientist's research specialization increases his or her scientific productivity decreases.

A further factor we believe may influence an academic scientist's capability to benefit from building social capital by occupying central positions is represented by the establishment of collaborations across different communities. By doing so, a scientist tends to act as gatekeeper or broker of knowledge and resources to which he or she may gain an exclusive access (e.g. Burt, 1992; Cross & Cummings, 2004; Dahlander & Frederiksen, 2011; Tushman & Katz, 1980). This may increase the opportunities of knowledge recombination associated with high levels of social capital, thus enhancing the likelihood of high-impact scientific discoveries. Precisely, as a scientist maintains a certain level of social capital, by occupying central positions in the collaborative network, the variety and heterogeneity of knowledge and resources flowing from his or her network peers increase as he or she builds this position by establishing ties crossing multiple communities.

The variety and heterogeneity of knowledge and resources cross-community ties may provide, can also enhance the scientist's opportunities to recharge the freshness of his or her ideas and to explore new ones, hence limiting the threat of learning myopia (Levinthal & March, 1993). In fact, the scientist has potentially a direct access to people that possess different knowledge backgrounds, experience, and competences (Jeppesen & Lakhani, 2010). These individuals may provide feedbacks from multiple and non-redundant angles, hence helping the scientist to enlarge the scope of his or her scientific results (Gao & Guan, 2011; Hargadon & Sutton, 1997; Tushman & Katz, 1980). Therefore, while ties crossing different communities may avoid the risk of being trapped into a given community's conventions and norms (Perry-Smith & Shalley, 2003), they may support the scientist in exploiting the greater knowledge-recombinant opportunities high levels of social capital may provide.

Furthermore, cross-community ties may amplify the knowledge diffusion advantages highly central positions may offer (Reagans & McEvily, 2003). In fact, these connections may function as channels through which the scientist can more efficiently diffuse his or her knowledge across multiple communities, hence increasing its impact.

Finally, by being connected with different communities, the scientist can potentially draw resources from different parts. In fact, academics belonging to different realms are expected to follow distinct competitive paths (Lissoni, Mairesse, Montobbio, & Pezzoni, 2011). This may diminish the competitive pressure for resource allocation with other scientists and then, the likelihood of hindrance behaviour from colleagues.

Thereby, we expect that:

Hypothesis 3. The number of an academic scientist's cross-community ties positively moderates the curvilinear relationship between his or her social capital, in the form of structural centrality within the academic network, and scientific productivity. Specifically, at a given level of centrality as a scientist's number of cross-community increases his or her scientific productivity increases.

Methods

Research Context and Sample Data

Our research setting is based on the community of Italian tenured academic scientists listed in the disciplinary affiliation 'ING-IND/35 Ingegneria Economico-Gestionale' for the 2001-2008 period. The Italian Ministry of Education, University and Research (MIUR) provides the list of academics since the year 2000. However, while the population of academic scientists MIUR listed grows with an average of 10 new academics per year from 2001 to 2008, we observed a sudden increase of it with 84 new academics from 2000 to 2001; Therefore, we adopted a conservative approach by starting the data collection from 2001. The average annual population for 2001-2008 period was composed by 152 academics scientists, while 12.57 and 2.71 academics scientists on average annually entered and left the community, respectively. Considering these variations in the population's size (newcomers and dropouts), we observed 203 different academic scientists involved in the community across the observation period. The MIUR's database also provides academic scientists' universities and ranks. Specifically, three positions characterise the Italian academic system, as 'Ricercatore Universitario', 'Professore Associato', and 'Professore Ordinario'. These positions can be compared to the U.S. academic system as assistant professor, associate professor, and full professor positions, respectively. Unlike the U.S.

system, all positions are tenured and both teaching and research duties are expected for all of them (see also Lissoni et al., 2011).

We selected this community because its research domain lies on the borderline of several disciplines such as management, operations research, industrial engineering, and economics. This makes collaboration a relevant means for scientists to acquire the different knowledge required to conduct research activity. In addition, the high level of interdisciplinarity of this community results in a significant variety of scientific specialization across academics, and it influences the nature of the collaborative ties they establish by opening networks to extra-community members.

Scientific articles can be adopted as a suitable proxy to evaluate scientific productivity and the impact of academic scientists' research. In fact, academia is characterised by a priority-based reward system where scientific knowledge is codified and diffused mainly by publications (Dasgupta & David, 1994; Merton, 1968). Thus, we gathered the published scientific articles for each academic scientist by querying the SCI-EXPANDED and the SSCI databases, which are produced by the Institute for Scientific Information (ISI). This process led to an initial sample of 564 articles published in international scientific journals. In this sample we had to manage the homonymy issue between the academic scientists' full names and the authors of the publications. Desktop research and bibliographic data (such as an author's affiliation) allowed us to exclude false matches and obtain a final sample of 484 articles. As depicted in Figure 2, our data confirm the presence of skewness in the distribution of scientific outputs across the community (Lotka, 1926). Table 1 shows the distribution of the sample of articles across the ISI subject categories in science and social science. The academic scientists conducted research in 46 different subject categories, confirming the interdisciplinary nature of this community. Specifically, 29 subject categories in science are covered and 'Operations Research & Management Science', 'Engineering, Industrial', and 'Engineering, Manufacturing' are the most frequent research areas with 172, 129, and 90 scientific articles, respectively. The academic scientists also published in 17 different subject categories in the social science area. In particular, the most frequent research areas are 'Management', 'Economics', and 'Business', with 198, 95, and 52 scientific articles, respectively.

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The Academic Network

Following previous studies in scientometrics, we explored bibliographic data in scientific articles to construct the academic community network. More precisely, we used co-authorship data since, as previous research has demonstrated, they meaningfully (though not perfectly) capture the knowledge exchange among authors (Melin & Persson, 1996; Newman, 2001a, 2001b). In addition, this form of collaboration is more tangible than other forms (for instance, sharing data, exchanging ideas, helping colleagues learn new techniques) since it captures two key elements, as working together for a common goal and sharing knowledge (Hara, Solomon, Kim, & Sonnenwald, 2003).

We adopted social network analysis to investigate the structural proprieties of these networks. Given the intensive interaction knowledge-creation process requires, network measures were evaluated considering a moving 3-year time window, thus assuming collaboration ties older than three years dissolved (e.g. Nerkar & Paruchuri, 2005; Paruchuri, 2010). To reduce simultaneity problems, we lagged the explained variable, other explanatory variables, and control variables by one year. Thus, if the dependent variable is evaluated at year *t*, the network measures were estimated from year *t-3* to year *t-1*. This produced a sample of 826 observations.

Variables

Explained Variable. An academic scientist's productivity was evaluated yearly by counting the number of scientific articles published weighted by the number of received citations (*Weighted Citation Index—WCI*) (e.g. Kelchtermans & Veugelers, 2010; McFadyen & Cannella, 2004). Accordingly, we evaluated academic scientist *i*'s scientific performance in the year *t* as:

$$WCI_{i,t} = \sum_{j} PubCit_{j,t}$$,

where $PubCit_{j,t}$ represents the number of citations article *j*, published in year *t*, received—the count of citations an article received stops on the date of data collection, i.e. the second week of February 2009. The sum across the scientist's published articles *j* in year *t* provides a measure of the yearly scientific productivity in terms of relevancy and impact of the scientific knowledge. For each scientific article, we excluded from the citation count those citations received by subsequent articles published by the same authors involved in the specific article (self-citations).

Explanatory Variable. We measured a scientist's social capital, in the form of structural centrality in the academic collaborative network, by using the Bonacich's (1987) power measure. As previously described, we used a 3-year moving time window evolving community network to assess a scientist's *Centrality*. The Bonacich's power measure takes into account the centrality of the other nodes to which the academic scientist is connected. Thus, a scientist is central to the extent that he or she co-publishes with other central scientists. Earlier research widely adopted this measure since, by considering the overall pattern of relationships, it captures a scientist's knowledge and resources access and gathering capability on global network scale (e.g. Nerkar & Paruchuri, 2005; Paruchuri, 2010; Sorenson & Stuart, 2001). Therefore, power measure provides a broader view on a scientist's network position compared to local measures such as degree centrality. We calculated the Bonacich's power measure of the *i-th* academic scientist according to the following formula:

$$c(\alpha,\beta)=\alpha\sum_{k=1}^{\infty}\beta^{k}R^{k+1}1_{i},$$

where $c(\alpha, \beta)$ is the vector of the centrality scores for each scientist, α is an arbitrary scaling factor, β is a weight, R is the matrix of relationships, and 1 denotes a vector column of ones. This measure evaluates the centrality of a node as the recursive sum of the power of its alters. The β parameter controls the nature of the recursion. More precisely, positive values of β imply that nodes become more powerful as their alters become more central and powerful (as occurs in cooperative relations). Conversely, negative values of β imply that nodes become more central and powerful only as their alters become weaker (as occurs in competitive or antagonistic relations). As is the norm in the social networks literature, we set β at ¾ of the reciprocal of the largest eigenvalue of the adjacency matrix (Bonacich, 1987; Podolny, 1993). UCINET VI was used to calculate the Bonacich's power measure of centrality (Borgatti, Everett, & Freeman, 2002).

Moderating Variables. Research specialization (*Specialization*) was evaluated on the set of articles a scientist published in the relative 3-year moving time window. In particular, the community published in 46 subject categories that represent a proxy for the scientific disciplines (Leydesdorff & Rafols, 2009; Porter & Rafols, 2009). We then constructed an array where each element was associated with the number of articles a given scientist published in each subject category. Subsequently, we measured the Herfindahl–Hirschman Index (HHI) on this array (for the general heuristic see Stirling, 2007). The resulting measure of an academic scientist *i*'s degree of specialization is defined by the following formula:

$$Specialization_i = \sum_{p=1}^{m} s_{ip}^2 ,$$

where s_{ip} is the share of scientist *i*'s published articles in subject category *p*. This score coefficient ranges from 0 to 1. As the degree of specialization approaches 0, a scientist conducts broader research.

We evaluated the number of cross-community ties (*Cross-community Ties)* by counting the direct ties an academic scientist established with other scientists outside the community (Cross & Cummings, 2004). Specifically, we considered a tie outside the community when it involved scientists not belonging to the disciplinary affiliation 'ING-IND/35 Ingegneria Economico-Gestionale', i.e. all those scientists belonging to others Italian disciplinary affiliations or not working in the Italian academic system.

Control Variables. We included several additional control variables. First, we controlled for the number of direct ties a scientist has with other academic scientists in the community (*Community Ties*). Second, the degree of research specialization of a scientist's co-authors may influence his or her scientific productivity. We then identified all scientists' co-authors operating outside the community during the 2001-2007 period. Specifically, 199 different co-authors collaborate with the scientists in our sample and they published 378 scientific articles, which we retrieved from SCI-EXPANDED and SSCI databases. As previously, we used the HHI to evaluate co-authors' degree of research specialization. We then included a control variable (*Network Peers' Specialization*) defined as the coefficient of variation (standard deviation/mean) of the degree of research specialization of a scientist's co-authors. Third, we included a dummy variable (*Mobility*) taking value one if the scientist moves from a university to another, zero otherwise. Thereby, we take into account the effect that mobility may exert on an academic scientist's performance (Allison & Long, 1990). Fourth, a scientist's experience in publishing may be a relevant explanatory variable on the impact of scientific production (Fox, 1992). Thus, we included the number of years elapsed since the first scientific article (*Tenure*) a scientist successfully published, as well as the number of previous publications (*Previous Publications*) and books (*Books*). Fifth, we controlled for a scientist's *Gender* (code 0 = 'male' or code 1 = 'female') (Fox, 1999). Sixth, three dummy variables were defined to control for a scientist's position in the university. Specifically, as discussed, the categories are 'Ricercatore Universitario' (*Researcher*), 'Professore Associato' (*Associate Professor*), and 'Professore Ordinario' (*Full Professor*). The last is omitted in the econometric analysis. Seventh, given the scientists in our sample conducting research both in science and social science, we controlled for the different research processes that may characterize these domains. Precisely, we controlled for a scientist's research orientation (*Scientific Orientation*) by the ratio of his or her number of publications in science to his or her total number of publications in both science and social science. This measure ranges between 0 and 1 and it was evaluated according to a 3-year time window preceding the observation year of the explained variable. Eighth, we also controlled for those scientists involved in more than one university in a given time window by including a dummy variable named *Multiple Affiliations*. We retrieved this information from the bibliographical data reported on academics' publications. Ninth, being involved in academic journals' editorial boards may exert an important effect on scientist's productivity since these boards may represent important sources for new collaborations. Therefore, we included a dummy variable (*Editorial Position*) taking value one if a given scientist was found involved in an academic journal's editorial board, zero otherwise. Tenth, all scientists in our sample are formally involved in the Italian Association of Business Engineering, namely 'Associazione Italiana Ingegneria Gestionale (AiIG)'. This no-profit association was founded in 1989 and is engaged in various scientific activities, such as the organization of conferences, meetings, and workshops. AiIG has a formal president elected every two years. We controlled for those scientists in our sample that were elected president of this association by including a dummy variable (*Community's President*) (code 0 = 'elected' or code 1 = 'not elected'). Finally, we included regional-dummy and year-dummy variables to control for unobserved heterogeneity. Specifically, we included three regional-dummy variables, as *South*, *Centre*, and *North*, to take into account of scientists' university location in Italy.

Estimation Model

The dependent variable—*Weighted Citation Index*—is a count variable, taking only integer and positive values. Thus, the use of linear regression modelling is inadequate since the distribution of residuals will be heteroskedastic non-normal. In this case, the use of a Poisson regression approach can be suitable. However, this method makes the strong assumption that mean and variance are equal while, citation data often present over-dispersion because variance exceeds the mean (Hausman, Hall, & Griliches, 1984). The over-dispersion is also confirmed by the coefficient of variation, which is 3.697. Thus, we deemed the negative binomial estimation more suitable to our data as it allows for the variance to differ from the mean, and thus can handle over-dispersion (Hausman et al., 1984). Specifically, this estimation considers a variable y_i following a Poisson regression model with parameter λ_i and omitted variable u_i such that $exp(u_i)$ follows a gamma distribution with mean 1 and variance α:

$$y_i \sim \text{Poisson}(\mu_i^*),\quad \mu_i^* = \exp(x_i\varphi_i + u_i),\quad \exp(u_i) \sim \text{Gamma}(1/\alpha, 1/\alpha).$$

The φ_i is the vector of the parameter associated with the vector of explanatory variables x_i and α is the over-dispersion parameter. Accordingly, we report the model specification in the following:

$$\hat{\lambda}_i = \exp\left(\sum_m \beta_m ExpVar_i + \sum_k \delta_k ContrVar_i + \varepsilon_i\right),$$

where λ_i ($i = 1, \ldots, 826$) is the estimator of the Poisson parameter explaining the dependent variable. The error term is indicated with ε_i. The vector of the parameter to estimate is [$\beta_1, \ldots, \beta_m, \delta_1, \ldots, \delta_k$] where the β_m parameter refers to explanatory variables (*ExpVar*) and control variables (*ContrVar*). We estimated the models by using the 'nbreg' routine included in the STATA 10.0 software package. We reported significance levels based on Huber-White robust standard errors to control for any residual heteroskedasticity.

Results

Table 2 and Table 3 report the variables' descriptive statistics in terms of means, standard deviations, minimum, maximum, and correlations. The examination of the pairwise correlations shows that the correlations are low (results did not change when we separately regressed variables associated with the highest correlations). Furthermore, we standardised the variables used for the squared and the interaction terms before entering them into regression analysis in order to minimise potential multicollinearity problems (Aiken & West, 1991).

Table 4 presents the results from the regressions predicting academic scientists' productivity. Model 1 reports the baseline estimation including only the control variables. Model 2 includes the linear and the squared terms of centrality measure. Model 3 provides the test for the moderation effect of an academic scientist's degree of research specialization. Finally, Model 4 tests the moderation effect of the cross-community ties. Indeed, we separately test Hypotheses 2 and Hypothesis 3 in order to avoid multicollinearity issues caused by the interaction and squared terms. We used the log-likelihood χ^2 ratio post-estimation test to analyse model improvement, and significant improvement was always observed ($p < 0.001$). In addition, the estimation of the over-dispersion parameter alpha (α) for each estimated model confirmed negative binomial estimation more suitable than Poisson.

In fact, the estimated over-dispersion parameter alpha (α) is significantly different from zero in each model ($p < 0.001$).

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Insert Table 2, Table 3, and Table 4 about here.
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We hypothesised an inverted U-shaped relationship between the academic scientist's centrality in the community and scientific productivity. As indicated in Model 2, our analysis supports this effect since both the linear and squared terms are highly significant and in the expected direction ($\beta = 0.953$, $p < 0.001$; $\beta = -0.587$, $p < 0.001$, respectively). In addition, we found evidence of this effect in Model 3 and Model 4.

In Model 3, results confirm the moderation effect of an academic scientist's degree of research specialization on the relationship occurring between structural centrality and scientific productivity. Specifically, this moderation effect is negative, thus supporting Hypothesis 2. Moreover, Figure 3 provides a clearer interpretation of this moderation effect. In particular, we evaluated the relationship at mean value of research specialization, as well as one standard deviation below and above the mean (Aiken & West, 1991; Hoetker, 2007). Figure 3 shows that, at a given level of centrality, as an academic scientist's degree of research specialization increases his or her scientist's productivity decreases. In addition, the threshold value of structural centrality beyond which structural centrality exerts negative returns on a scientist's productivity also decreases as research specialization increases. Specifically, the threshold value of standardised power centrality that maximises the scientific performance is equal to 0.410 at the mean value of the degree of research specialization. Conversely, at one standard deviation below and above the mean of the degree of research specialization, this threshold is 0.686 and 0.395, respectively.

Model 4 confirms Hypothesis 3, by revealing the positive moderation effect of cross-community ties on the relationship between structural centrality and scientific performance. We represented this moderation in Figure 4, by evaluating the cross community ties at mean value, and one standard deviation below and above the mean. Figure 4 shows that, at a given level of centrality, as an academic scientist establishes more ties crossing the boundary of the community he or she better benefits from structural centrality to create new scientific knowledge. Moreover, the threshold value of structural centrality beyond which social capital exerts negative returns on a scientist's productivity also increases with the number of cross-community ties. In particular, the threshold value of standardised power centrality that maximises the scientific performance is equal to 0.685 at the mean value of cross-community ties variable. Conversely, at one standard deviation below and above the mean of cross-community ties, this threshold is 0.675 and 0.702, respectively.

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Insert Figure 3 and Figure 4 about here.
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Robustness Checks

We conducted several additional analyses to probe the validity of our findings. First, since articles achieved earlier in time naturally tend to have higher citation counts and citation patterns reflect the nature of the scientific field, we also tested an alternative measure of scientific productivity, i.e. the count of scientific articles weighted by the yearly journal impact factor available in the Journal Citation Reports of the ISI (McFadyen & Cannella, 2004; Stephan & Levin, 1991). Results were not significantly different from those of the first analysis. Second, degree centrality may represent an alternative measure to capture the knowledge exchange. It is worth noting that degree measure, by simply counting the number of links incident upon a node, provides a local view (ego-network) of a scientist's network position (Freeman, 1979). We tested the effect of degree centrality and we found similar results. Yet, the model including the Bonacich's measure still provided more significant estimates and it was a better improvement over its baseline model. Third, co-authors' degree of research specialization may play an important effect on the relationship between a scientist's centrality and scientific productivity. We tested a degree measure of centrality where each tie was weighted with the degree of research specialization of a scientist's co-authors. Also in this case, we found an inverted U-shaped relationship. Third, given the skewness of the *Specialization* variable, we also addressed the effect outliers may exert on our results. In particular, we regressed the models by excluding the scientists-year observations relative to 1%, 2%, or 5% of the most diversified scientists in our sample. The number of observations reduced to 822, 810, and 807, respectively. Results on the variables of main theoretical interest did not significantly change. Fourth, we adopt 1-year lag between the dependent and independent variables. However, results did not significantly change also considering a 2-year time. Fifth, as noted, older publications have been exposed for a longer period to be cited by future scientific articles. While year-dummy variables allow controlling for the 'age effect' as well as for unobserved heterogeneity from one year to another, we also regressed models including a variable that counts the number of years elapsed from a publication's year to 2009, i.e. the year in which we collected the data. In this case, we excluded year-dummy variables that otherwise would create multicollinearity issues. Results on the variables of main theoretical interest did not change. Finally, city-level dummy variables may provide a more fine-grained control for the geography effect compared to those defined at regional level. We then substituted the *Regional-dummy* variables with dummy variables taking into account for the city in which a given university is located. While results did not significantly change, the regression models including *Regional-dummy* variable reported a better fitting.

Discussion

The purpose of our study was to disentangle the variance of academic scientists' outcomes by adopting a network perspective. To this end, we drew from the social capital theory, which provides important insights on the micro-social dynamics in networks. We proposed a theoretical model according to which scientists that build social capital by occupying central positions outperform their more isolated colleagues. We argued that the benefits of social capital hold up to a certain level of centrality above which negative returns appear. We also characterised this relationship by offering a contingent perspective based on a scientist's degree of research specialization and number of cross-community ties. Analysing a novel longitudinal dataset of 203 academic scientists involved in the Italian academic community listed in the disciplinary affiliation 'ING-IND/35 Ingegneria Economico-Gestionale', our study provided evidence that building social capital through central positions within the scientific community matters for productivity. More precisely, we found centrality to be curvilinearly related to scientific performance, assuming the shape of an inverted 'U'. This pattern of results implies that social capital associated to centrality includes an opportunity cost. In particular, while increasing social capital offers several benefits—greater knowledge-recombinant opportunities, a superior access to knowledge and resources, and a better position to diffuse scientific knowledge—excessive social capital produces important negative returns on knowledge-creation process. Specifically, given an individual's cognitive and time limits, a scientist is able to manage a limited amount of knowledge and resources associated with high levels of social capital. Therefore, he or she is increasingly overwhelmed as his or her centrality augments. In addition, high levels of social capital may hamper knowledge-creation process by exposing a scientist to uncooperative behaviour, foot dragging, and even sabotage by other individuals or groups in the same organization or community.

We found also that the extent to which an academic scientist diversifies or specializes his or her research activity and establishes social ties that cross the boundary of the scientific community moderates the abovementioned relationship. In particular, the degree of research specialization exerts a negative moderation effect by hindering a scientist's ability to identify diverse and complementary knowledge high levels of social capital may provide access to. In addition, a specialized scientist needs to invest more attention and time to benefit of the diverse knowledge-recombinant opportunities highly central position may offer, compared to his or her less specialized peers. Therefore, as the degree of research specialization increases also the negative effects of high levels of social capital on knowledge-creation process reinforce. Conversely, we found a positive moderation in the number of cross-community ties. In particular, the results provided evidence that collaborations crossing the scientific community enhance the opportunity to successfully exploit social capital deriving from central positions. In fact, cross-community ties enrich the variety of knowledge and resources, reduce resource competition and obstructive behaviours, and favour the impact of a scientist's knowledge across multiple domains.

Implications for Theory

Our study contributes to previous research in several ways. First, we contributed to the debate on skewness characterising scientific outcomes distribution (Lotka, 1926). In fact, this has constantly been a relevant concern for scholars and policy makers because scientific research outcomes are fundamental inputs for industrial R&D, technological and economic progress, and social welfare (e.g. Dasgupta & David, 1994; Henderson et al., 1998; Mansfield, 1995; Narin et al., 1997). Individual demographics, laboratory composition, the 'Matthew effect', and university-industry relationships were found to affect scientists' research outcomes. We demonstrated that a scientist's action in building social capital, in the form of central structural positions within an academic community network, significantly affects scientific productivity, and that this effect depends on the degree of research specialization and number of cross-community ties. Second, we provided further evidence of the relationship between social capital and knowledge creation. We demonstrated that social capital, in terms of the structural configuration of the relationships established by an individual, provides both opportunities and costs for the creation of new knowledge. Specifically, we showed that relationships are an expression of how social capital provides access to knowledge and resources and can be used to channel and diffuse the information within a community. Nevertheless, there are limits to the capability to fully exploit the advantages of social capital. In addition, we showed the importance to disentangle the relationship between social capital and knowledge creation by introducing contingent drivers that may reshape this relationship. Third, we empirically investigated this issue in an Italian academic community, thus contributing to unravelling the distribution of scientific research outcomes in a context where few scholars have dedicated attention. In fact, little is known of the determinants of academic scientists' productivity in European countries because most of the available studies are based upon U.S. data (Lissoni et al., 2011). Fourth, our research speaks to organisational scholars studying communities by providing additional evidence of the importance of spanning boundaries to nourish performance. Finally, our study is one of few works (Balconi et al., 2004) that investigated the performance implications of individuals' network relationships in academia, whereas previous research mainly focused on individuals' networks within and among firms' networks (e.g. Cross & Cummings, 2004; Nerkar & Paruchuri, 2005).

Practical Implications

Our study offers interesting practical implications for scientists, research managers, as well as policy makers. Specifically, results reveal that building social capital by occupying a central position within the academic collaborative networks is beneficial to scientific productivity up to a certain level, beyond which negative returns appear. Hence, scientists should be aware of this double-edged sword effect, by investing time and resources to establish and maintain more promising and potentially valuable relationships. However, we encourage scientists to diversify their research activities and collaborate with individuals belonging to different academic communities, thus being able to reduce some of the costs associated with the excessive level of social capital, while enhancing its benefits. Furthermore, findings provide useful guidance for policy makers and academic managers in designing incentive schemes and research patterns for enhancing scientific productivity. In particular, these should be devoted to promote cooperation among scientists, especially belonging to distinct communities, as well as to incentivise academics to enlarge their research interests, in order to increase their capability to benefit from research collaborations.

Limitations and Future Research

Our study has some limitations that may represent avenues for future research. First, we examined only the effect of the structural dimension of a scientist's relationships constituting his or her social capital. While other measures of the network structural properties—such as brokerage positions (e.g. Ahuja, 2000; Burt, 1992) and core-periphery structures (e.g. Cattani & Ferriani, 2008)—may reveal other facets of knowledge-creation process, future research should extend this investigation by encompassing the relational and cognitive dimensions of social capital. Second, to further advance our understanding of the relationship that occurs between networks and scientific outcomes, we need more studies that investigate the casual mechanisms that lead a scientist to occupy certain structural positions within a collaborative network. Why are certain scientists more able to build their network positions within the academia? Which psychological and demographic factors may stimulate or hinder a scientist's action to build a network position, which may provide benefits for knowledge creation? Third, we introduce research specialization and cross-community ties as contingent effects on the relationship between social capital, in the form of centrality, and scientific productivity. However, other moderating effects may exist. For instance, we found that the variance in the degree of research specialization of a scientist's network peers significantly predicts his or her productivity. Future studies may further explore this effect by investigating the extent to which the 'cognitive' composition of a scientist's network may reshape the relationship between structural position and knowledge creation. Fourth, we used co-authorship in publications to track the networks of academic scientists as adopted in a growing body of published works (e.g. Melin & Persson, 1996; Newman, 2001a, 2001b). Nevertheless, other possible types of more informal ties among academics may be established. In fact, scientists may mentor one another, taking collaborative actions that do not result in published scientific articles. Thus, co-authorship captures only those relationships that successfully led to published articles. Accordingly, future research should focus on the identification of alternative approaches for capturing collaborative dynamics among individuals. Finally, while our sample composed by scientists operating on the borderline of different disciplines represents a very interesting setting to investigate the effect of social capital on scientific knowledge creation, it may not be representative of other areas in science and social science. Future research may assess the generalizability of the findings by extending our inquiry to other academic communities, since the relationship between network position and scientific productivity, as well as the effect of the moderators we investigated, may depend on specific research regimes characterising a given field.

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Figure 1. Proposed theoretical model.

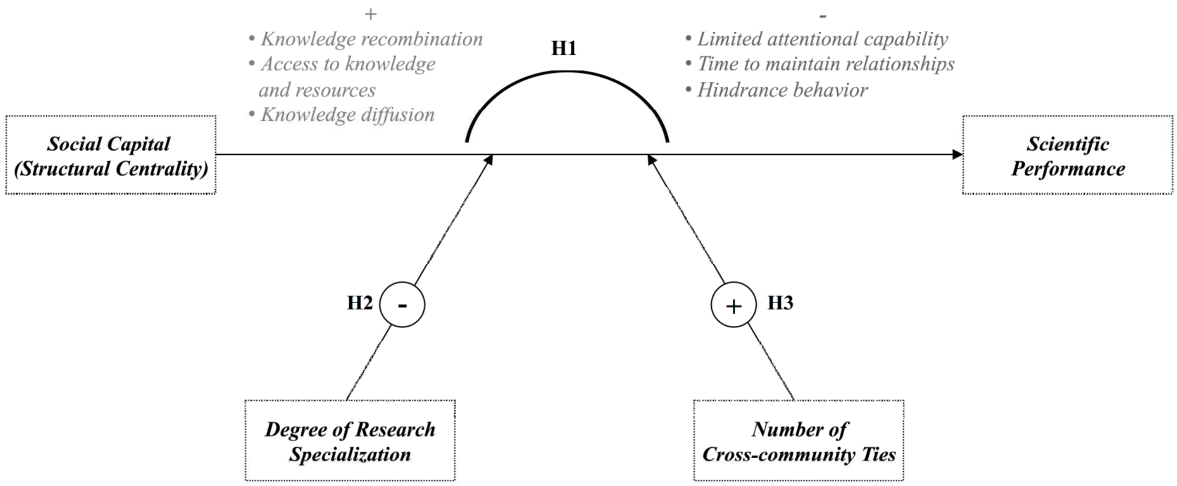

Figure 2. Lorenz Curve of the academics' publications.

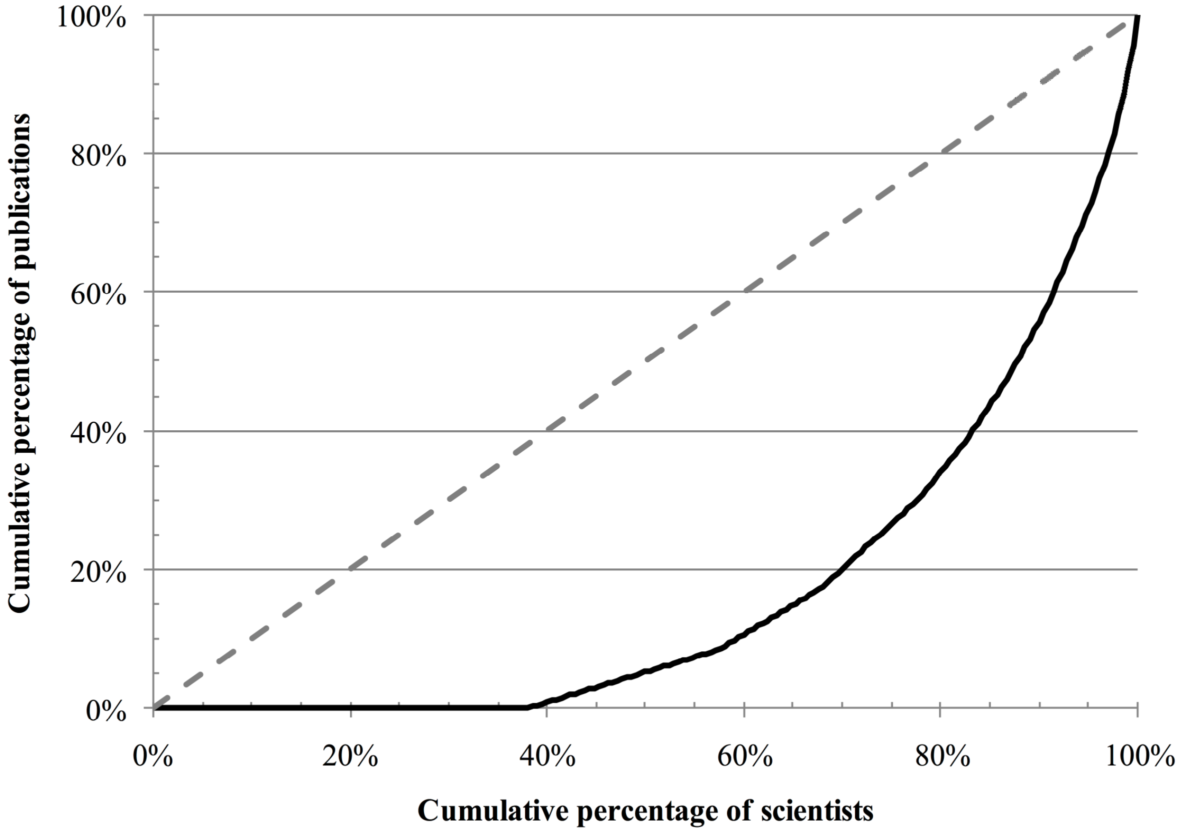

Figure 3. The moderating role of the degree of research specialization.

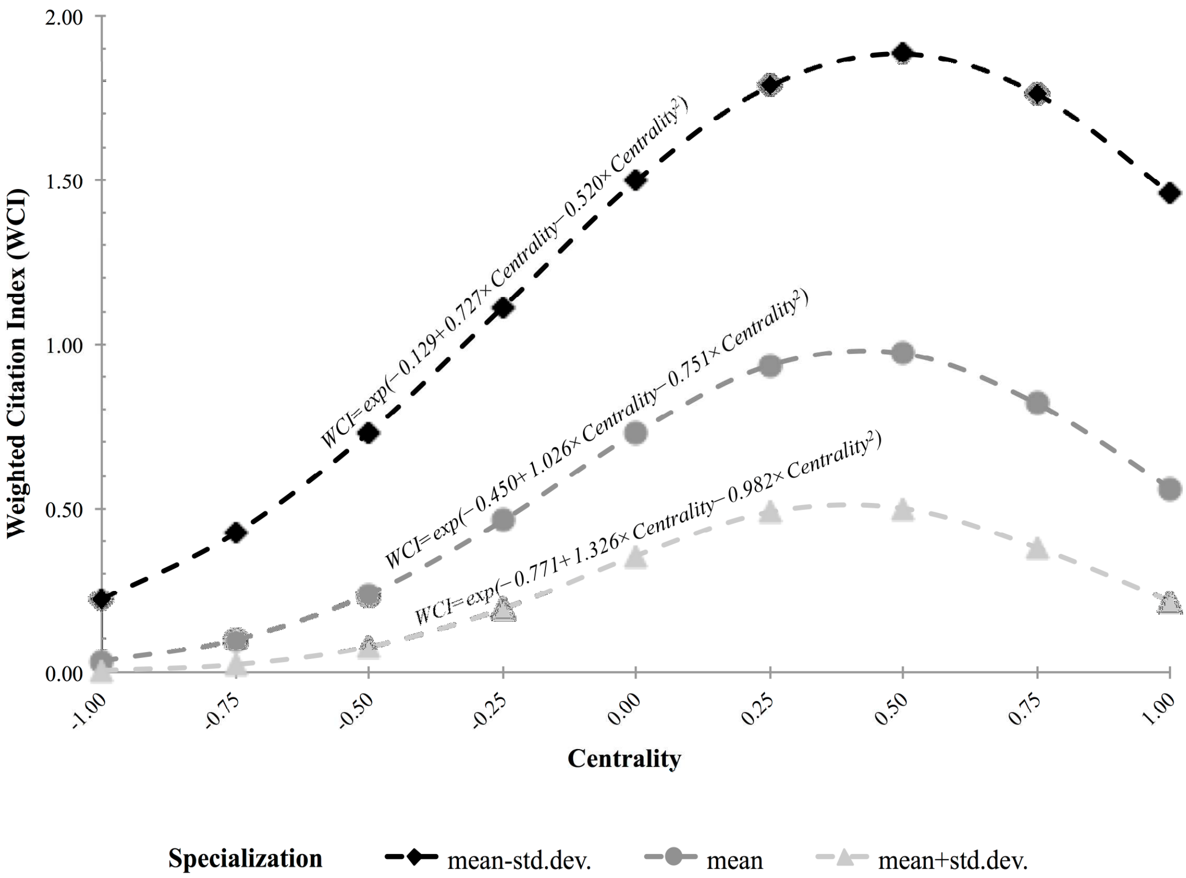

Figure 4. The moderating role of cross-community ties.

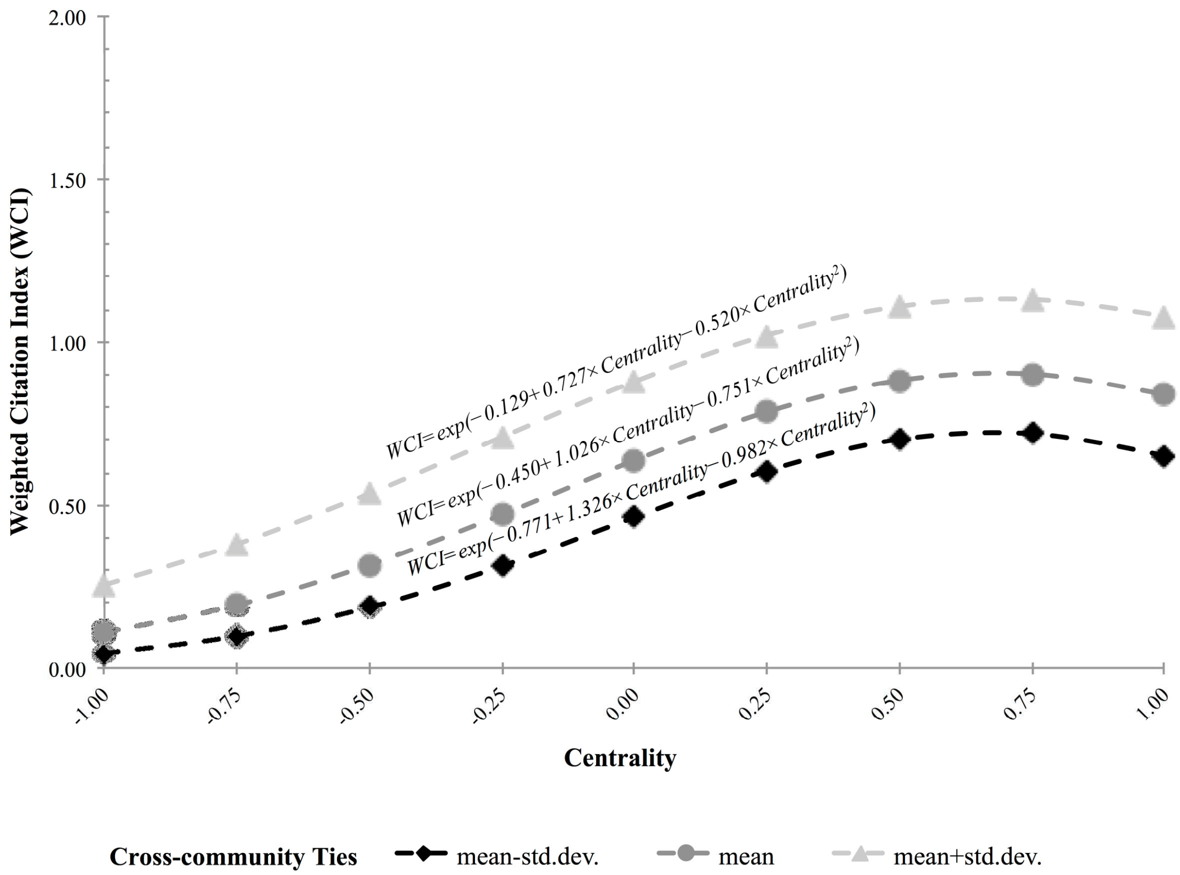

Table 1. Publications by ISI subject categories.

Area	ISI Subject Category	Publications
Science	Operations Research & Management Science	172
	Engineering, Industrial	129
	Engineering, Manufacturing	90
	Engineering, Multidisciplinary	58
	Computer Science, Artificial Intelligence	25
	Computer Science, Interdisciplinary Applications	18
	Computer Science, Theory & Methods	7
	Computer Science, Software Engineering	5
	Environmental Sciences	5
	Computer Science, Information Systems	4
	Mathematics, Applied	4
	Multidisciplinary Sciences	4
	Transportation	4
	Engineering, Environmental	3
	Transportation Science & Technology	3
	Energy & Fuels	2
	Engineering, Civil	2
	Engineering, Electrical & Electronic	2
	HealthCare Sciences & Services	2
	Mathematics	2
	Mechanics	2
	Medical Informatics	2
	Public, Environmental & Occupational Health	2
	Robotics	2
	Cardiac & Cardiovascular Systems	1
	Computer Science, Hardware & Architecture	1
	Engineering, Biomedical	1
	Engineering, Mechanical	1
	Water Resources	1
Social Science	Management	198
	Economics	95
	Business	52
	Planning & Development	28
	Information Science & Library Science	21
	Business, Finance	8
	Social Sciences, Interdisciplinary	6
	Communication	4
	Environmental Studies	4
	Psychology, Applied	3
	Ergonomics	3
	Education & Educational Research	2
	Social Sciences, Mathematical Methods	2
	Telecommunications	2
	Geography	1
	Sociology	1
	Urban Studies	1

Note. A journal can be assigned to more than one ISI subject category.

Table 2. Descriptive statistics (N = 826).

Variable	**Mean**	**Std.Dev.**	**Min.**	**Max.**
Weighted Citation Index	1.418	5.242	0.000	73.00
Centrality	9.490	17.77	0.000	143.0
Specialization	0.966	0.021	0.880	0.980
Cross-community Ties	0.857	1.740	0.000	16.00
Community Ties	0.785	1.249	0.000	7.000
Network Peers' Specialization	0.175	0.404	0.000	1.879
Mobility	0.008	0.092	0.000	1.000
Tenure	8.788	8.466	0.000	41.00
Previous Publications	0.322	0.693	0.000	5.000
Books	0.685	0.956	0.000	5.000
Gender	0.791	0.407	0.000	1.000
Full Professor	0.345	0.476	0.000	1.000
Associate Professor	0.323	0.468	0.000	1.000
Researcher	0.332	0.471	0.000	1.000
Scientific Orientation	0.201	0.331	0.000	1.000
Multiple Affiliation	0.019	0.138	0.000	1.000
Editorial Position	0.218	0.413	0.000	1.000
Community's President	0.006	0.078	0.000	1.000
Regional-dummy (3)	-	-	South	North
Year-dummy (5)	-	-	2004	2008

Table 3. Correlation matrix (N = 826).

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1.Weighted Citation Index	1.000								
2.Centrality	0.196 ***	1.000							
3.Specialization	-0.235 ***	-0.341 ***	1.000						
4.Cross-community Ties	0.142 ***	0.441 ***	-0.454 ***	1.000					
5.Community Ties	0.169 ***	0.512 ***	-0.556 ***	0.185 ***	1.000				
6.Network Peers' Specialization	0.085 *	0.166 ***	-0.108 **	0.271 ***	0.063 †	1.000			
7.Mobility	0.164 ***	0.025	-0.065 †	0.030	0.016	0.054	1.000		
8.Tenure	-0.007	0.023	-0.031	0.011	0.037	-0.028	-0.032	1.000	
9.Previous Publications	0.127 ***	0.505 ***	-0.422 ***	0.416 ***	0.362 ***	0.158 ***	0.091 **	-0.004	1.000
10.Books	0.007	0.050	-0.127 ***	0.061 †	-0.006	0.022	0.058 †	0.249 ***	0.080 *
11.Gender	-0.076 *	-0.125 ***	0.130 ***	-0.027	-0.201 ***	0.036	0.015	0.156 ***	-0.053
12.Full Professor	0.023	-0.031	-0.021	0.001	-0.003	-0.009	-0.012	0.494 ***	-0.018
13.Associate Professor	0.012	0.045	-0.054	0.036	0.018	0.083 *	0.077 *	-0.015	0.026
14.Researcher	-0.035	-0.013	0.074 *	-0.037	-0.014	-0.074 *	-0.065 †	-0.484 ***	-0.008
15.Scientific Orientation	0.099 **	0.407 ***	-0.537 ***	0.459 ***	0.350 ***	0.258 ***	-0.009	-0.014	0.274 ***
16.Multiple Affiliation	0.088 †	0.046	-0.164 ***	0.143 ***	0.024	0.025	0.179 ***	0.067 †	0.150 ***
17.Editorial Position	0.114 **	0.160 ***	-0.187 ***	0.170 ***	0.117 ***	0.117 ***	0.015	0.220 ***	0.140 ***
18.Community's President	0.012	0.020	-0.056	0.006	0.076 *	0.001	-0.007	0.061 †	0.054

Variable	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
10.Books	1.000								
11.Gender	0.104 *	1.000							
12.Full Professor	0.252 ***	0.236 ***	1.000						
13.Associate Professor	0.016	0.006	-0.502 ***	1.000					
14.Researcher	-0.271 ***	-0.244 ***	-0.511 ***	-0.487 ***	1.000				
15.Scientific Orientation	-0.014	-0.047	-0.073 *	0.028	0.045	1.000			
16.Multiple Affiliation	0.111 **	0.072 *	0.064 †	0.034	-0.099 **	0.043	1.000		
17.Editorial Position	0.272 ***	0.128 ***	0.277 ***	-0.039	-0.241 ***	0.069 *	0.117 ***	1.000	
18.Community's President	0.124 ***	0.040	0.107 *	-0.054	-0.055	0.047	0.215 ***	0.148 ***	1.000

Note. † 10% ($p < 0.10$); * 5% ($p < 0.05$); ** 1% ($p < 0.01$); *** 0.1% ($p < 0.001$).

Table 4. Negative binomial regression models (N = 826).

Explained variable: Weighted Citation Index		**Model 1**			**Model 2**			**Model 3**			**Model 4**		
Explanatory variables													
Centrality	*(H1)*				0.953	(0.252)	***	1.406	(0.449)	***	1.026	(0.316)	***
Centrality^2	*(H1)*				-0.587	(0.165)	***	-1.671	(0.519)	***	-0.751	(0.215)	***
Specialization								-0.718	(0.148)	***			
Centrality × Specialization	*(H2)*							0.457	(0.219)	**			
Centrality^2 × Specialization	*(H2)*							-0.695	(0.245)	***			
Cross Community Ties											0.321	(0.214)	†
Centrality × Cross-community Ties	*(H3)*										-0.300	(0.177)	*
Centrality^2 × Cross-community Ties	*(H3)*										0.231	(0.128)	*
Control variables													
Community Ties		0.347	(0.085)	***	0.155	(0.099)		0.040	(0.099)		0.171	(0.112)	
Network Peers' Specialization		1.301	(0.259)	***	1.343	(0.261)	***	1.448	(0.264)	***	1.353	(0.265)	***
Mobility		0.965	(0.759)		1.138	(0.856)		0.486	(0.600)		1.268	(0.807)	
Tenure		-0.028	(0.020)		-0.028	(0.020)		-0.030	(0.021)		-0.030	(0.021)	
Previous Publications		0.309	(0.139)	**	0.061	(0.151)		-0.161	(0.135)		0.015	(0.149)	
Books		0.167	(0.150)		0.113	(0.145)		0.030	(0.132)		0.081	(0.137)	
Gender		-1.157	(0.258)	***	-1.184	(0.257)	***	-1.187	(0.265)	***	-1.179	(0.261)	***
Associate Professor		-0.396	(0.317)		-0.359	(0.311)		-0.358	(0.314)		-0.348	(0.310)	
Researcher		-0.444	(0.419)		-0.368	(0.402)		-0.516	(0.406)		-0.361	(0.406)	
Scientific Orientation		0.536	(0.343)		0.072	(0.335)		-0.622	(0.351)	*	-0.156	(0.363)	
Multiple Affiliation		1.296	(0.595)	**	1.212	(0.600)		0.518	(0.460)		0.895	(0.625)	
Editorial Position		0.419	(0.259)	†	0.324	(0.257)		0.159	(0.249)		0.291	(0.252)	
Community's President		0.284	(0.898)		1.057	(0.974)		0.879	(0.914)		1.234	(0.969)	
Regional-dummy (3)			Included			Included			Included			Included	
Year-dummy (5)			Included			Included			Included			Included	
Intercept		1.016	(0.543)	***	1.072	(0.545)	***	1.319	(0.576)	***	1.231	(0.559)	***
Alpha (dispersion)		8.014	(0.865)	***	7.721	(0.836)	***	7.079	(0.788)	***	7.621	(0.830)	***
df						21			24			24	
Log-likelihood χ^2 *ratio test*			-823.39			-819.48			-810.28			-818.10	
(over baseline model)			-			7.82	***		26.20	***		10.58	***

Notes. † 10% (*p < 0.10*); * 5% (*p < 0.05*); ** 1% (*p < 0.01*); *** 0.1% (*p < 0.001*);
The table gives parameter estimates;
The standard error is reported in parentheses.