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Title

Scientists' Social Capital and Knowledge Creation: The Case Of Translational Research In Biomedicine

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Research Topic

The idea that scientific creativity is fostered when scientists work together and combine their knowledge stocks is well established in extant literature (He, Geng, & Campbell-Hunt, 2009; Rigby & Edler, 2005). The social capital perspective has provided valuable insights in exploring the effects of social interactions with others on the creation of knowledge. According to this view, scientists holding certain positions in the network are exposed to new ideas and methods, which provides a crucial information advantage over other actors (Burt, 1995, 2004). This advantage is seen as a critical factor in explaining differences between scientists knowledge creation performance, which is often referred as the network advantage (Nahapiet & Ghoshal, 1998). Evidence also reflects that the process of creating new knowledge has become highly collaborative across all scientific fields and in all levels of analysis – individual scientists, groups and regions - (Adams, Black, Clemmons, & Stephan, 2005; Consoli & Ramlogan, 2007; Wagner & Leydesdorff, 2005). Although the benefits of social capital for the production of knowledge seems to be well grounded, studies examining the interplay between social network characteristics and individual features of scientists are few in number.

To address this issue, our study adopts a contingent view to study the relationship between the scientists' social capital and its impact in knowledge creation. By conceiving the scientists' network structure as a potential opportunity from which actors may benefit to a greater or lesser extent (Adler & Kwon, 2002), we advocate that the value of ties with others for the production of knowledge depends on the particular ability of each scientist as well as on the nature of knowledge that each particular scientist aims to produce.

We use the biomedical research context to test these ideas. We believe that the biomedical field is an ideal framework to analyze the relation between knowledge networks and knowledge creation Biomedical scientists are expected to establish research networks not only to generate scientific breakthroughs, but also to contribute to the development of knowledge that results in effective clinical applications (Drolet & Lorenzi, 2011). Our study performs a longitudinal analysis of the knowledge networks and knowledge production of 381 biomedical scientists along a 13 years period. We examined how network patterns are related to the scientific and technological knowledge of each scientist, showing that the predictive power of the scientist's social network is stepped up when individual contingencies are considered.

Theory Background

Social network theorists study the consequences of network variables, such as the structural position in a network or the number of ties held by network actors (Brass, Galaskiewicz, Greve, & Tsai, 2004). Among the wide range of outcomes and behaviors that have been analyzed through a social network lens, new knowledge creation has received considerable attention in the literature (McFadyen & Cannella, 2004; McFadyen & Cannella, 2005; Perry-Smith, 2006). The distribution of knowledge production among scientists is highly skewed, with few scientists producing a substantially higher amount of knowledge than others (Rotolo & Messeni Petruzzelli, 2012). An argument commonly resorted to when explaining such differences is related to the "network advantage". The application of the social network mechanism traditionally adopts a structural perspective, meaning that a network-based variable is taken (e.g.: number of ties with others) to explain a certain proxy of the scientist'

knowledge creation (e.g.: number of papers published in a given period, number of patents).

However, the causal mechanism used to explain this link is usually assumed and rarely examined, and such a direct connection between structure and outcome does not take into account neither the scientists' attributes nor the attributes of the scientists' contacts in the network (Borgatti & Halgin, 2011). In other words, it is not simply a matter of the position of actors in a network, but also a question of the factors that shape the actors' capacity to exploit or enact these network positions and the nature of the knowledge flowing through the network ties. In this sense, social capital scholars have evidenced that similar structural patterns may lead to different outcomes when actors' attributes are considered (Fleming, Mingo, & Chen, 2007; Kilduff & Brass, 2010). Social cognition scholars also point to the idea that individuals are "cognitive misers" (Fiske & Taylor, 1991; Kilduff & Krackhardt, 2008), and hence not equally capable to assimilate and use all potential information coming from the social network. From a social network perspective, this idea implies that the greater the knowledge available in the scientists' network, the greater the cognitive ability required to process and benefit from that knowledge. In a similar vein, we aim to extend this idea to argue that the influence of each scientist' network position on their capability to create scientific and technological knowledge will be determined by the scientists' cognitive breath.

Social capital research also points to the idea that knowledge is heterogeneously distributed across the scientists' social ties. Network range refers to the diversity of contacts contained in a scientists' network (Reagans & McEvily, 2003; Wasserman & Faust, 1994). The more heterogeneous the range of contacts, the more diverse and richer the type of knowledge the scientist can draw on from his network. Compared with colleagues with a highly homogeneous network (e.g. connecting with actors in the same community), we expect that those with access to a more heterogeneous range of contacts will be able to obtain richer knowledge from the network, and hence, more likely to produce new scientific and technological knowledge. To put it differently, the social capital advantage is not simply a question of assessing the scientists' structural position and linking it to a given knowledge outcome. Rather, the nature and diversity of such linkages may provide useful insights about the predictive power of scientists' collaboration on knowledge creation.

Research setting, Data & Measures

Our research setting comprises the Spanish scientific biomedical field. The biomedical research is considered as an adequate setting for the study of knowledge creation among individual scientists (e.g.: He, Geng, & Campbell-Hunt, 2009; McFadyen, Semadeni, & Cannella, 2009) for a number of reasons. First, biomedical scientists are knowledge workers, and they are highly stimulated to constantly produce new knowledge. Second, biomedical scientists are currently facing a great challenge which has been captured by the label of translational research (Drolet & Lorenzi, 2011; Rubio et al., 2010). Empirical evidence reveals that less than 10% of the most promising biomedical discoveries reported any benefit to clinical practice two decades later (Contopoulos-Ioannidis, Ntzani, & J. P. A. Ioannidis, 2003; J. Ioannidis, 2004). Our sample consist of 382 leading biomedical scientists that are affiliated to an (at least) one Spanish research institution. Each scientist is the principal investigator of a biomedical research group sited in Spain. All research groups are connected through a collaborative research consortium funded by the Spanish government called CIBER (Centers of Biomedical

Research Networks), whose primary aim is the promotion of scientific collaboration among biomedical scientists.

Our dependent variable *knowledge created* is built over two main indicators. First, to capture scientific knowledge creation we assess the number of publications and the number of citations received per year of each scientist. Second, for each scientist's technological knowledge creation we draw on patent production downloaded from the PATSTAT database, considering all patents where at least one of the 381 scientists participated as an inventor. Following previous research on scientists' social networks (Abbasi, Chung, & Hossain, 2012; A. McFadyen & A. Cannella, 2004), our independent network-based variables were obtained through co-authorship analysis. The bibliometric data was downloaded from the ISI Web of Science for the period 1998–2010. After solving homonymy problems and cleaning the data we found 16,356 scientific publications (original articles and revisions) in which at least one of the 382 researchers participated as a co-author.

To mitigate endogeneity threads, we used 3-year moving windows between our regressors and our dependent variables. Each scientist *network centrality* (Freeman, 1978), is assessed by counting the number of different co-authors during the previous three years. To measure each scientists' *network range*, we classified each scientists' co-authors according to the nature of their affiliation institutions, distinguishing between hospitals, public research centers, university departments, public administration, international agencies and private firms. We also computed the country of affiliation of each scientist' contact in order to create a measure of network range based on country. We use the Herfindahl-Hirschman index (HHI) to capture the degree of diversity of each scientist's network.

Finally, our measure of the scientists' *cognitive breadth* is based on Shannon entropy index (Porter & Rafols, 2009), assigning a particular score to each scientist based on the number of subject categories and the degree of balance of the journal articles published by each scientist.

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