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INGENIO [CSIC-UPV] Ciudad Politécnica de la Innovación | Edif 8E 4º | Camino de Vera s/n | 46022 Valencia
tel +34 963 877 048 | fax +34 963 877 991 | innco@ingenio.upv.es

Connections matter: the influence of network sparseness, network diversity and a tertius iungens orientation on innovation

Óscar Llopis [a], *Pablo D'Este* [b], *Adrian A. Díaz-Faes* [b]

[a] Rennes School of Business, France

[b] INGENIO (CSIC-UPV), Universitat Politècnica de València, Spain

Abstract: This study examines the relationship between personal network characteristics and innovation performance. Specifically, it investigates the effects of two properties of personal networks on actors' propensities to engage in innovation activities: network sparseness and network diversity. The study contributes also to decoupling social network structure and individual agency (i.e. tertius iungens orientation) as critical factors influencing engagement in innovation. The study highlights the importance of a particular strategic behavioral orientation of individuals to coordinate and mobilize network resources to foster the implementation of innovative ideas. Our findings show an inverted U-shaped relationship between network sparseness, network diversity and innovation, and a positive moderating role of a tertius iungens orientation on the curvilinear relationship between both network properties and innovation. Our hypotheses are tested on a large sample of Spanish biomedical scientists working in diverse institutional settings.

Keywords: network sparseness, network diversity, brokerage, tertius iungens, innovation.

1 Introduction

In this study we investigate the relationship between personal network configurations and innovation by unraveling the mechanisms that underlie one of the main tenets of social network research, that access to non-overlapping sources of information and knowledge through social networks is critical for individuals' creativity and innovativeness (Baer, 2010; Burt, 2004; Obstfeld, 2005; Tortoriello and Krackhardt, 2010; Wu, Chang, and Chen, 2008). A dominant perspective in network and innovation studies contends that personal networks that span holes in the social structure provide informational benefits and performance advantages to the focal individual (Burt, 2004). However, the specific social mechanisms through which non-overlapping sources of information and knowledge are accessed and mobilized to foster innovation are not fully understood (Obstfeld, 2005; Soda, Tortoriello, and Iorio, 2017).

We aim to contribute to this research stream by addressing two neglected issues. First, we investigate two different mechanisms through which individuals identify and access non-overlapping sources of information. This is in line with some recent contributions to the network literature that call for a conceptual and empirical distinction between network structure and network diversity (ter Wal et al., 2016). We separate the effect - theoretically and empirically - on individual innovativeness of two network properties: sparseness and diversity. Specifically, we contend that high degrees of sparseness and actor diversity can become alternative social mechanisms providing more opportunities for identification of and access to informational benefits. In the literature the relevance of these two mechanisms is mostly studied separately (e.g. Fleming, Mingo, and Chen, 2007; Rodan and Galunic, 2004); few attempts have been made to study them jointly as alternative sources of opportunities to exploit informational benefits.

However, disentangling the specific effect of each type of network configuration is important since they represent distinct mechanisms to tap into non-overlapping sources of information and knowledge.

Second, we examine the role of agency as a factor distinct from social network properties, in relation to the determinants of innovation performance. It is important to decouple personal network properties from the individual attributes of focal actors since not all personal network configurations are equally effective. Rather, actors embedded in similar or identical social network structures exhibit high levels of heterogeneity in their performance (Burt 1995; Soda, Tortoriello, and Iorio, 2017). Thus, the effect of agency could be a distinctive element that might explain the capacity for mobilizing social network resources to provide the conditions needed to implement new ideas and achieve successful innovation. To investigate this, we examine the influence of actors' strategic behavioral orientation toward connecting others - i.e. a tertius iungens orientation (Obstfeld, 2005; Quintane and Carnabuci, 2016). We argue that such a behavioral orientation is likely to have a strong impact on the individual capacity to enact coordination tasks in social networks. In this context, coordination increases the cohesion among weakly connected partners and facilitates knowledge exchange among partners with distinct perspectives or knowledge bases. By shedding light on whether this individual strategic orientation complements the generative knowledge attributes of sparse and diverse networks, we contribute to advance social network research from a contingency perspective (Anderson, 2008, Carnabuci and Diószegi, 2015) which considers network effects to be highly dependent on the focal actors' characteristics (Kilduff and Krackhardt, 2008). We extend this stream of work by showing that the strategic orientation of focal actors is important for connecting network structure, network diversity and innovation.

2 Theory and hypotheses

Networks and innovation: the distinct mechanics of network sparseness and network diversity

There is an abundant literature on how the social network configurations in which individuals are embedded influence individuals' creative outcomes. Research in management and innovation uses personal social network approaches to examine whether certain network configurations explain a range of individual-level outcomes such as job performance (Sparrowe et al., 2001), innovation (Obstfeld, 2005; Wu, Chang, and Chen, 2008) and creativity in organizations (Baer, 2010; Burt, 2004; Perry-Smith, 2006). This strand of work emphasizes the role of particular network configurations in facilitating knowledge creation (McFadyen and Cannella, 2004; McFadyen, Semadeni, and Cannella, 2009). Two particular rationales have been proposed to identify and evaluate the informational advantages of personal networks: the first refers to the network's structural properties, and the second refers to network composition properties (ter Wal et al., 2016). Both aspects account for differentiated social mechanisms for accessing non-overlapping sources of information and knowledge, and are described in detail below.

Sparse network structures

The rationale based on the structural properties of networks focuses on the overall degree of connectivity within an actor's network. Sparse personal networks are characterized by the existence of scarce connections among network members. This type of network structure allows the focal actors privileged access to information that is diverse by virtue of the missing connection between alters, and allows the inflow of fresh and different perspectives and ideas (Burt, 1995, 2004; Fleming, Mingo, and Chen, 2007). Weakly connected partners enable greater exposure to different approaches, outlooks and interests, and allow the focal actor to set goals and frame challenges from broader perspectives. Therefore,

sparse personal networks make additional cognitive material available to the focal actors, increasing the knowledge recombination possibilities and the subsequent generation of original ideas.

However, focal actors embedded in extremely sparse personal networks may find it difficult to obtain the potential informational benefits from disconnected alters. This is due mainly to the lack of mutual trust and fewer expectations about the credibility of partners, and the subsequent difficulty of coordinating highly diverse sources of information (Schilling and Phelps, 2007). Thus, extremely sparse network structures can lead to an 'action problem' (Obstfeld, 2005) because of their poor ability to articulate the coordination efforts required to implement new ideas. Some degree of network connectivity is required to facilitate the fast circulation of information and achieve reliable and trustful communication among actors (Coleman, 1988). In turn, this connectivity facilitates the exchange of sensitive information, contributes to addressing highly complex problem-solving processes and favors sustained collective efforts, all of which are necessary conditions for the implementation of new ideas and for successful innovation (Fleming, Mingo, and Chen, 2007; Powell, Koput, and Smith-Doerr, 1996; Reagans and McEvily, 2003; Uzzi, 1997).

Conceptual work that emphasizes the role of hybrid social structures in personal networks (Phelps, Heidl, and Wadhwa, 2012; Rogan and Mors, 2014) proposes a plausible way to reconcile these contrasting views. Hybrid social structures are characterized by the coexistence of sparse and dense network attributes within a particular personal network structure. The combination of sparseness and denseness allows exploitation of informational and knowledge advantages from the potential complementarities between these two network properties. While sparseness is needed to identify new ideas and opportunities, cohesion allows effective implementation of the identified alternatives by ensuring a context of mutual trust and collective sense of reciprocity (Kleinbaum and Tushman, 2007; Rogan and Mors, 2014; Zaheer

and Bell, 2005). To the extent that individuals manage to combine the attributes of sparseness and cohesiveness in their personal network structures, they are likely to be comparatively better equipped to engage in innovation activities.

Based on the above discussion, we hypothesize that:

Hypothesis 1: A greater degree of sparseness in a personal network structure is curvilinearly (inverted U-shape) related to an actor's level of participation in innovation activities.

Diverse network compositions

Social network research suggests an alternative mechanism through which actors can access dissimilar, non-overlapping sources of information and knowledge; that is, the range of actor diversity within a personal network. Actor diversity reflects the breadth of unique knowledge pools embodied in personal networks, and therefore, the variety of the knowledge sources available to a particular individual. This perspective argues that the value of social networks resides in the heterogeneity of the actors within the network, and suggests that it is the formation of ties to highly heterogeneous actors that offers the greatest access to informational advantages from the network (Tindall, Cormier, and Diani, 2012; Tortoriello, Reagans, and McEvily, 2012). In this view, cultivating heterogeneous networks is likely to favor the attainment of informational advantages for innovation since personal networks that tap into information from a range of highly diverse actors provide access to non-redundant information, thereby fostering the identification of new opportunities and generation of new ideas (Reagans and McEvily, 2003; Rogan and Mors, 2014). For instance, individuals embedded in personal networks that contain ties to actors who cross different professional boundaries will be better placed to participate in multiple innovation activities.

However, lack of shared cognitive frames and the risk of misunderstandings among network partners means that networks characterized by a high degree of actor diversity may not have the coherence required to interpret the information and make it valuable. The actor's capacity to process and benefit from the increased knowledge and resources available within the network is limited (Cyert and March, 1963; Ocasio, 1997; Simon, 1955). Too great a diversity of the information accessible from heterogeneous network partners can result in individuals experiencing information overload, which makes it difficult to integrate and assimilate the information and eventually could have a detrimental impact on innovation performance (Weick, Sutcliffe, and Obstfeld, 2005; Zhou et al., 2009). This is particularly likely in networks of actors from highly differentiated professional communities, who bring to the network contrasting perspectives about what constitutes legitimate performance and who often are driven by different norms and incentives (Ferlie et al., 2005). The distinct interests and priorities of diverse professional communities require investment of significant amounts of cognitive resources and attention from the focal actor in order to achieve the potential innovation performance benefits associated to diverse networks.

While a lack of common ground among network partners may limit the potential benefits to be derived from diverse networks, highly homogeneous networks can be also problematic. It has been argued that networks that are excessively homogeneous in terms of actor composition may preclude the assimilation of diverse information sources and risk entrapment in lock-in learning processes (ter Wal, et al., 2016).

For this reason, intermediate levels of actor diversity might provide the most effective composition in order to balance the informational costs and benefits associated to actor heterogeneity. Therefore, we expect that:

Hypothesis 2: A greater degree of diversity in the composition of personal networks is curvilinearly (inverted U-shape) related to an actor's level of participation in innovation activities.

Individual strategic behavior toward connecting people: tertius iungens orientation

The above discussion highlighted the importance of social structures for allowing opportunities for the generation of new ideas through ties to network partners who are either weakly connected (sparse network structures) or display distinct attributes (diverse network compositions). However, research on social networks points to the contingent value of social capital (e.g.: Burt, 1995; Mehra, Kilduff, and Brass, 2001), suggesting that the social network structures in which actors are embedded are not the only determinant of individual behavior. This contingent perspective includes some qualifications related to the role of social networks as drivers of individual innovative behavior, and argues that the fundamental social mechanics of innovation behavior are poorly specified (Soda, Tortoriello, and Iorio, 2017). For instance, there is increasing evidence that people differ in their motivations and ability to capture and realize the potential benefits of social capital (e.g. Anderson, 2008; Carnabuci and Diószegi, 2015; Reinholt, Pedersen, and Foss, 2011).

A first aspect of this under-specification lies in the weak understanding of the connection between social network configurations and the capacity to jointly achieve idea generation and idea implementation (Baer, 2012; Perry-Smith and Mannucci, 2017). While sparse networks and diverse networks provide greater opportunities for idea generation, they also feature a critical action problem compared to denser

and more homogeneous networks: that is, a weaker capacity to implement new ideas. Networks that include individuals who are highly disconnected and/or have distinct knowledge backgrounds are more exposed to difficulties in achieving the coordination required for successful idea implementation. Therefore, social networks characterized predominantly by sparseness and diversity may facilitate just one of the mechanisms involved in innovation activity (i.e. knowledge generation) but are susceptible to aggravate the action problem associated with the implementation of new ideas (Burt, 2004; Obstfeld, 2005; Soda, Tortoriello, and Iorio, 2017).

The second reason for a lack of understanding of the social mechanics of innovation behavior is related to the need to decouple social structure and agency as distinct predictors of social action (Emirbayer and Mische, 1998; Mehra, Kilduff, and Brass, 2001). Since personal network configurations are not universally effective, agency may be critical for explaining the distinctive capacity to coordinate and mobilize the resources derived from a social network. In particular, and linked to the above discussion, explicit recognition of individual agency can be instrumental in overcoming the action problem associated to sparse and diverse networks. In other words, actors can play an active role in mobilizing the network's resources and facilitating the coordination required for effective implementation of novel ideas, despite of the particular (potentially unfavorable) attributes of the social network configurations in which actors are embedded.

Drawing on recent contributions to the network literature, we propose a particular individual characteristic likely to have a strong impact on the capacity to enact coordination tasks in social networks: a strategic orientation toward connecting people or a tertius iungens orientation. Tertius iungens refers to an individual behavioral orientation that leads to the creation and facilitation of ties among people in personal social networks. Following Obstfeld's (2005, p. 102) definition: "the tertius iungens orientation

is a strategic, behavioral orientation toward connecting people in one's social network by either introducing disconnected individuals or facilitating new coordination between connected individuals". This behavioral orientation is not determined by the individual's position in the network. Instead, this behavioral feature relates to an individual strategic orientation towards managing the information exchange processes among network partners, irrespective of the actor's network position. As pointed out by Quintane and Carnabuci (2016, p. 1) in the context of brokerage positions "it is difficult to understand how brokers broker by looking solely at actors' network-structural positions", since actors can purse different strategies with regard to the exchange of information among network partners. Some actors might be more oriented to facilitating knowledge flows and favor cooperation (i.e. a tertius iungens orientation), while others in similar network positions may be more oriented to act as intermediaries and adopt an arbitrage role in the exchange of information among network partners (i.e. a tertius gaudens orientation) (Quintane and Carnabuci, 2016; Soda, Tortoriello, and Iorio, 2017).

Actors with a tertius iungens orientation are likely to increase cohesion in sparse networks by enhancing connectivity among otherwise disconnected actors, and to favor cooperation in networks composed of diverse actors by identifying common ground and shared interests among network partners with contrasting perspectives or knowledge bases. This strategic orientation toward collaboration complements the generative knowledge attributes of sparse and diverse networks by favoring the development of social relationships among actors who are likely to face low levels of interpersonal trust and/or a lack of collective awareness of shared goals or common interests. We argue, in line with Obstfeld (2005), that this individual pro-cooperation orientation enhances cohesion in personal networks while also setting the ground for the creation of ties with new, unfamiliar partners.

Drawing on the preceding discussion, we argue that actors with a tertius iungens orientation should be able to mobilize their personal network resources to ensure greater engagement in innovation. Individuals with a stronger strategic orientation toward connecting people will be better positioned to take advantage of the greater sparseness and/or diversity in personal networks for innovation performance, compared to individuals with a weaker tertius iungens orientation. Thus:

Hypothesis 3a: Individual tertius iungens orientation moderates the relation between sparse personal networks and participation in innovation activities, such that the threshold level of sparseness at which diminishing returns set in will be higher for individuals with a stronger tertius iungens orientation.

Hypothesis 3b: Individual tertius iungens orientation moderates the relation between diverse personal networks and participation in innovation activities, such that the threshold level of diversity at which diminishing returns set in will be higher for individuals with a stronger tertius iungens orientation.

3 Methods

Research context and Data

Our analysis is based on the field of biomedical research in Spain. In recent years the Spanish Government has launched a number of public policy initiatives and programs aimed to promote translational and cooperative research across different biomedical fields. A milestone in this effort was the creation of the Spanish Biomedical Research Networking Centers (henceforth, CIBERs). In 2006, the Spanish Ministry of Health undertook an initiative to reorganize biomedical research in Spain to foster

excellence and to improve the quality, value and effectiveness of the healthcare services delivered to the general population. Participant groups were selected via different open calls, focusing on a specific range of pathologies or diseases of strategic interest in the Spanish National Health System. The selected range of pathologies led to the formation of nine biomedical research platforms: Bioengineering, Biomaterials and Nanomedicine (CIBER-BBN), Diabetes and Metabolic Associated Diseases (CIBER-DEM), Epidemiology and Public Health (CIBER-ESP), Hepatic and Digestive Diseases (CIBER-EHD), Obesity and Nutrition (CIBER-OBN), Mental Health (CIBER-SAM), Neurodegenerative Diseases (CIBER-NED), Rare Diseases (CIBER-ER) and Respiratory Diseases (CIBER-ES).

Our research population comprises all biomedical scientists and technicians affiliated to the research groups belonging to the nine CIBERs. We contacted CIBER Scientific Directors to obtain explicit support for our research, and collected e-mail addresses and complete names of the scientists and technicians in the CIBERs. To develop the survey questionnaire, between June 2012 and March 2013 we conducted a number of interviews with scientific directors, research group principal investigators and biomedical scientists. An extensive list of activities and outputs related to translational research was obtained from the biomedical literature and validated through fieldwork interviews. The questionnaire was organized in multiple sections, with a particular focus on the structure and content of the scientists' personal network. The questionnaire also collected information about scientists' involvement in a range of medical innovation activities, and included attitudinal and motivational questions plus a series of questions on respondents' socio-demographic aspects, such as age, gender and education level. In April 2013, the questionnaire was administered to 4,758 biomedical scientists and technicians in the nine CIBERs who were invited to participate in the study. We received 1,309 valid responses to the

questionnaire, an overall response rate of 27.5 percent, a rate similar to other surveys of academic scientists (Perkmann et al., 2013). Due to missing values in some of the observations, the number of usable responses was 1,261. The sample distribution was 31.9 percent affiliated to a university, 35.3 percent to a hospital, 28.9 percent to a public research institution and 4 percent affiliated to a private research body or other similar institution. Regarding research roles 10.7 percent of respondents are principal investigators of their CIBER research groups, 55.7 percent are post-doctoral scientists with different degrees of seniority, 18.8 percent are pre-doctoral scientists, 10.0 percent are in technician or similar positions and 4.8 percent reported occupying some other position.

We conducted several analyses to test for non-response bias. First, we compared response rates in terms of institutional affiliation, hierarchical position in the research group and the group size (according to archival analysis). Although we found significant differences for some aspects, the overall distribution of response rates was fairly homogeneous (see Appendix A1). We performed a wave analysis to check whether responses differed with regard to the date when the questionnaire was returned. This complements the archival analysis, since the response patterns of late respondents can be considered a proxy for the response patterns of non-respondents (Rogelberg and Stanton, 2007). We classified the sample into early respondents (45.8%) and late respondents (54.2%). We conducted an ANOVA-analysis of the differences in means for the two groups for a sample of survey variables (e.g. participation in medical innovation activities and ego-network size). The hypotheses of differences in means are all rejected, suggesting that our data do not suffer from non-response bias problems.

Variables

Dependent Variable: innovation breadth

To capture the scientists' degree of participation in various types of medical innovations, we conducted a review of the literature on translational research from the most representative biomedical journals. This allowed us to identify a set of breakthroughs representing a diversity of outputs and achievements through which biomedical knowledge moves backwards and forwards through different stages of the research pipeline. These breakthroughs include the discovery or invention stage, often associated with basic research on the root causes of diseases, and epitomized generally by the identification of a new molecular target for the discovery of a new drug or diagnostic device (product discovery). Another breakthrough in the research pipeline is the translation of basic findings and discoveries from the lab into specific human clinical research such as clinical trials and observational studies (product development). A critical challenge is the transit from new medical compounds or devices into clinical practice, for instance, through the development of evidence-based clinical guidelines that allow the incorporation of research discoveries into day-to-day clinical practice and delivery of healthcare (clinical guidelines). Biomedical scientists have proposed similar conceptualizations of the main achievements through the research pipeline (Dougherty and Conway, 2008; Khoury et al., 2007; Sung et al., 2003; Westfall, Mold, and Fagnan, 2007). While based predominantly on a linear from 'the bench to the bedside' approach, they provide a foundation to address the variety of indicators associated to medical innovation.

We obtained a list of 11 items reflecting this variety of medical innovations which was validated further by the biomedical scientists interviewed during the pilot survey phase. The full list is presented in Table 1, including a sample of academic references supporting the association between each category of items and medical innovations. We asked respondents to report whether they have been engaged in each

activity, and how often. Specifically, respondents were asked: *please indicate how frequently you obtained the following research results derived from your research activities during the year 2012*. For each item type selected, respondents were offered a drop-down menu where they could choose any number between 0 to 10 times, or more than 10 times. We conducted an Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA) for factor extraction which showed that our innovation-related outputs fell into four factors (see Appendix A2 for details). A Varimax orthogonal rotation was performed such that the number of items with high loadings in a particular factor was minimized making the factors more easily interpretable. Four factors were retained based on eigenvalues above 1. Factor 1 explained 22 percent of the total variance in the items, comprising outputs related to invention and commercialization (product generation: invention and commercialization). Factor 2 accounted for 16 percent of the variance in the items (drug development). Factor 3 explained 13 percent of the variance, with outcomes grouped according to the development of clinical practitioner and patient guidelines (clinical guidelines). Factor 4 accounted for 10 percent of the total variance in the items, and included all items related to the development of diagnostic devices and prevention-related activities (diagnostics and prevention).

Table 1. Grouping medical innovation items into categories: innovation breadth.

Medical Innovation Categories	Items	Key references
Product Generation (invention and commercialization)	Patent applications for new drugs Licenses granted from patents Participation in spin-offs	(Ding and Choi, 2011; Morgan et al., 2011)
New Drug Development	Clinical trials phase I, II or II for new drug development Clinical trials phase IV for new drug development Clinical trials phase IV for new diagnostic techniques*	(Duyk, 2003; Khoury et al., 2007; Westfall, Mold, and Fagnan, 2007)
Clinical Guidelines	Clinical guidelines for health practitioners Clinical guidelines for patients	(Cochrane et al., 2007; Dougherty and Conway, 2008)
Diagnostics and prevention	Patent application for new diagnostic mechanisms Clinical trials phase I, II or II for new diagnostic mechanisms Prevention guidelines for the general population	(Drolet and Lorenzi, 2011; Khoury et al, 2007)

* Note: We kept this item because factor analysis results indicated a high correlation between this item and the other two items included in the category "new drug development"

Table 2 shows the rate of scientists' participation at least once in a particular type of medical innovation category, according to their institutional affiliation. The results reported in Table 2 show that the most widespread medical innovation is development of clinical guidelines. About 23 percent of scientists had participated in the development of clinical guidelines during year 2012. Activities related to diagnostics and prevention were the least frequent form of medical innovation: only 10 percent of scientists had been involved in such activities. A deeper analysis of the results reveals significant differences in the level of involvement in medical innovation categories across respondent affiliations. Scientists affiliated to hospitals and clinics participate more frequently in all of the medical innovation categories except 'invention and commercialization'.

Table 2: Innovation breadth of scientists according to institutional affiliation*.

	Product Generation (Invention and commercialization)	**New drug development**	**Clinical guidelines**	**Diagnostics and prevention**	**Total cases**
University	19.2	7.5	11.7	8.8	386
Hospital	12.0	41.4	47.8	12.5	409
PRO	15.5	8.8	9.4	10.3	341
Others	15.2	8.8	12.0	7.2	125
Total	15.5	19.0	22.8	10.2	1,261

* Percent of scientists engaged at least once over the year 2012 in any of the items included in each of the four medical innovation categories.

We developed an indicator to assess the degree of participation in different forms of medical innovation (innovation breadth). We coded scientists 0 to 3. If they reported no participation in any of the four categories defined below, we coded them 0 (55.9% of our sample). If they had engaged at least once in one category, we coded them 1 (26.1%), if they had participated at least once in two of the defined

categories, we coded them 2 (13.7%), and if they had participated at least once in three or in all four categories, we coded them 3 (4.3%)**.**

Independent Variables

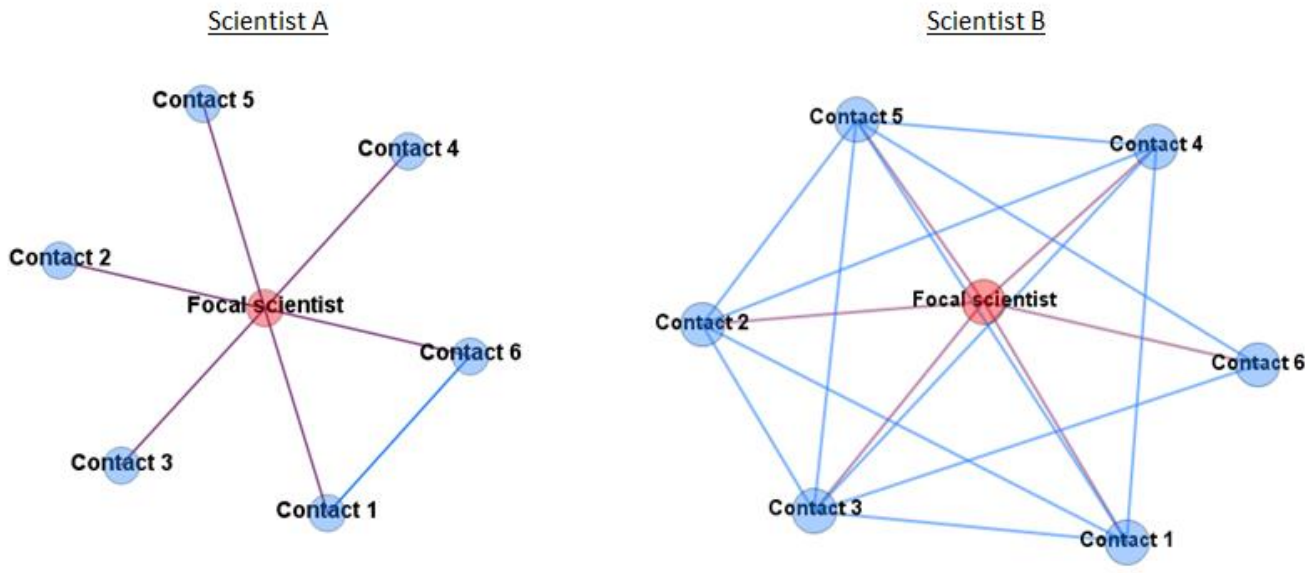
Network sparseness. We used an ego-centric network approach (e.g. Baer, 2010; Smith, Collins, and Clark, 2005; Wong and Boh, 2014) to capture each scientist's network of critical contacts. Our survey allowed each respondent (ego) to list the names of up to 10 contacts (alters) not in their research group whom they considered relevant informants for the advancement of their research activities. Specifically, we invited each scientist to *write down the names of those persons (up to ten) from outside your research group that are particularly important for the advancement of your research activities*. This question reflects our particular interest in capturing the network of contacts each scientist considered important for his/her research. This name-generator question produced an average number of 3.6 unique contacts outside the scientists' research groups. The survey also asked respondents for information on each alter-alter relationships (Burt, 1995; Podolny and Baron, 1997) (see Appendix A3 for more detail on the design of this questionnaire section).

Although ego-network approaches rely on individual perceptions, it has been shown that measures from ego-network data are highly correlated to measures collected from whole-network data (Everett and Borgatti, 2005) and to data collected from both members of a dyadic relationship (Battilana and Casciaro, 2013). Building on the previous literature, we computed personal network sparseness by counting the number of structural holes for each ego-network (Everett and Borgatti, 2005). That is, the absence of alter-alter ties between each ego-network contact. This number was divided by the total number of possible

alter-alter ties: [n (n – 1) / 2] (Wasserman and Faust, 1994). The maximum network sparseness score occurs when there are no connections between alters in the scientist's personal network (ego-network). Thus, for each individual, this ratio ranged from 0 to 1, with low values reflecting few structural holes and high values reflecting many structural holes, and therefore, a higher score for personal network sparseness. Since the ratio of structural holes is sensitive to ego-network size, in our regression model we controlled for the effect of size.

To clarify our measure of sparse networks, Figure 1 depicts the ego-networks of two of the scientists in our dataset to show how their personal network structures differ; we deliberately selected two cases of identical network size (i.e. number of network partners). Despite this, the two cases exhibit significant differences in their sparseness score. In the ego-network of Scientist A only two of the contacts (contacts 1 and 6) were connected to each other, (network sparseness score equals 0.933: one reported connection between alters from a total of 15 possible connections). This implies that, for the majority of alters, there is only an indirect path of connection through their mutual ties with the focal scientist. As outlined above, disconnected contacts are more likely to contribute different ideas and practices. It is this broader exposure to dissimilar sources of information that provides the focal individual with the opportunity to develop different ways of looking at medical problems, and access to a diverse range of resources and knowledge. Scientist B has a much more densely connected network (network sparseness score equals 0.267: 11 reported connections among alters out of 15 possible ones). The informational benefits of dense personal networks are related to more efficient coordination for resource mobilization since trust among network partners is more easily elicited in this type of network configurations. However, it is likely that much of the information and resources accessible through these contacts is redundant given that greater connectivity among network partners is associated to information flows that are more homogeneous and overlapping.

Figure 1: Graphical representation of sparse and dense networks.



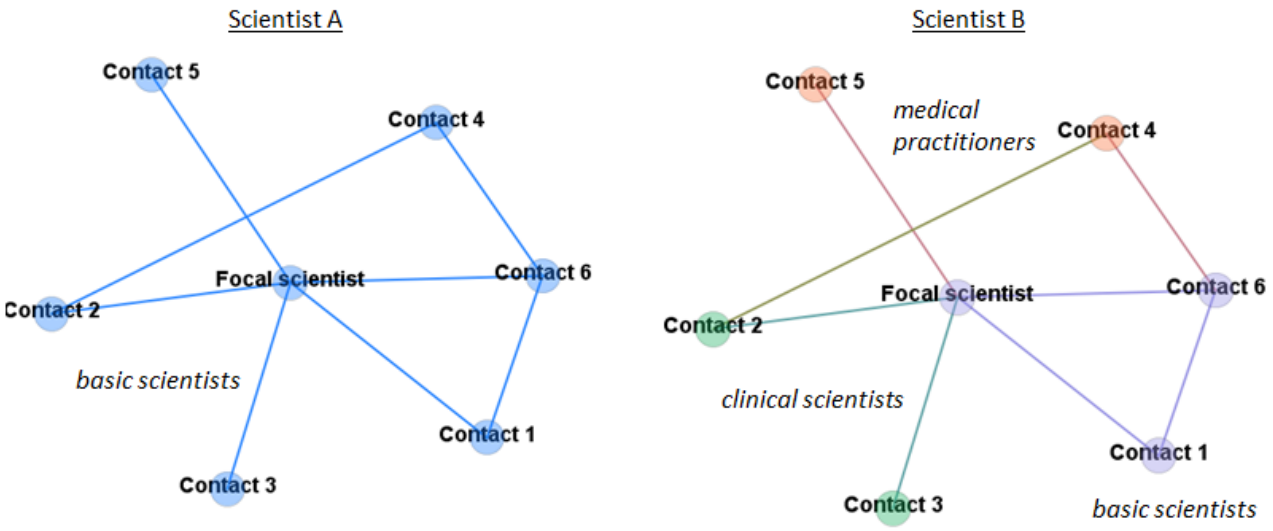
Network diversity. Respondents were asked specifically about each of the contacts listed as relevant informants, following standard ego-centric network survey techniques (Cross and Sproull, 2004). To obtain a measure of network diversity that captures the specific attributes of network partners associated to distinct knowledge and research perspectives, respondents were asked to classify each of their contacts into professional and social communities. The responses were grouped into four broad categories: 'basic scientists', 'clinical scientists', 'medical practitioners or patient representatives', and 'public administration, industry and other groups'. These categories were selected based on the theory and interviews with medical scientists[1]. The distribution of this variable shows that 38.2 percent reported ties with individuals from just one professional community, 33.9 percent reported ties with contacts from two

[1] The proportion of scientists with at least one critical contact from each category was: 73.2% had at least one contact classified as a basic scientist, 56.9% had at least one contact classified as a clinical scientist, 12.5 % indicated clinical practitioners or patient representatives, and 26.8% contacts in industry, public administration or other types of organization.

different communities, 9.5 percent reported three communities and 1.1 percent reported engagement with individuals from four different communities; 17.3 percent reported no external collaboration.

Following prior work on personal network heterogeneity (Smith, Collins, and Clark, 2005; Wong and Boh, 2010), we measure diversity as the number of different categories in which respondents reported having at least one link. Consequently, our measure of diversity ranges between zero and 4, taking the value zero if respondents reported zero ties with relevant informants; 1 if respondents reported that all listed contacted belonged to the same professional community; and a maximum of 4 if the respondent reported that the reported contacts belonged to all of the professional categories described above. As mentioned above, having ties to heterogeneous actors provides access to non-overlapping sources of information and knowledge which may provide information advantages for innovation. Figure 2 depicts two identical personal networks in terms of actor ties but involving meaningful differences in actor degree of network diversity. All ties maintained by Scientist A are with similar others (network diversity score equals 1), whereas Scientist B is embedded in a highly heterogeneous network with ties to actors from different communities (network diversity score equals 3). This means that Scientist B, although facing greater coordination and integration problems, may benefit from a pool of more dissimilar knowledge.

Figure 2: Graphical representation of low and high diversity networks



Tertius iungens orientation. To measure the strategic orientation of researchers to connecting people, whether by bringing disconnected alters together or strengthening ties among those who already have ties to each other, we use the scale proposed by Obstfeld (2005). This involves a 7-point Likert scale and is computed as the average of the responses to the following 6 items: (1) *I introduce people to each other who might have a common strategic work interest;* (2) *I will try to describe an issue in a way that will appeal to a diverse set of interests;* (3) *I see opportunities for collaboration between people;* (4) *I point out the common ground shared by people who have different perspectives on an issue;* (5) *I introduce two people when I think they might benefit from becoming acquainted; and* (6) *I forge connections between different people dealing with a particular issue.* Overall, our data show that scientists report a relatively high strategic orientation towards facilitating knowledge flows and cooperation (i.e. mean score 5.1).

Control variables. We controlled for a range of factors in the statistical analysis which might influence the respondents' degree of participation in innovation activities. We accounted for control variables at the individual, research group and institutional level.

Individual-level controls. To control for the effect of accumulated learning and experience in the propensity to engage in innovation activities, we controlled for respondent's age and for holding a PhD degree (i.e. dummy taking the value of 1 if the respondent reported having a PhD degree, and zero otherwise). We controlled for scientist's gender (female) and academic rank whether respondents reported being principal investigators of CIBER research groups or research projects (i.e. principal investigator). A set of dummy variables was included to control for network size: netsize_small was coded 1 for respondents with small networks (0 to 1 contacts); netsize_med was coded 1 for respondents with intermediate personal networks (2 to 4 contacts); and netsize_large was coded 1 for respondents with large personal networks (5 to 10 contacts). These dummies allow us to control for two important aspects. First, since network sparseness and network diversity are likely to increase with network size, we wanted to ensure that our two indicators were capturing the structural properties of the network rather than just its size. Second, since calculation of network sparseness indicators requires that the focal actor has at least two alters, controlling specifically for those actors having less than two alters allows us to distinguish between zeros that are due to the absence of sufficient network contacts and those that are derived from the absence of structural holes.

We also controlled for breadth of cognitive skills by asking whether the respondent had pursued training in nine areas of biomedical research; and accounted of individual psychological traits using the accepted Big Five factors of personality scale developed by Goldberg (1999). Among, organizational and institutional-level controls, we account for the type of institutional affiliation (university, hospital/clinic, public research organization, other type of institution), research group size and nine dummy variables to control for respondents' scientific field (CIBER). Finally, we controlled for the research group leader's

previous academic and technological performance, since research group leaders can exert significant influence on the scientific and innovation orientation of the members of their group.

4 Results

Descriptive analyses and econometric results

Table 3 presents the descriptive statistics and correlations for the variables used in the model. The average scores for our independent variables are 0.47 (SD = 0.40) for network sparseness, 1.43 (SD = 0.90) for network diversity and 5.05 (SD = 1.22) for tertius iungens. Despite the large number of variables in the analysis, we found no evidence of multicollinearity or redundant information for our explanatory and control variables. The lowest tolerance values were for network diversity (0.35) and hospital setting (0.30).

Table 3: Descriptive Statistics and Correlations.

	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9
1	Innovation breadth	0.73	0.93	0.0	3.0	1.0000								
2	Sparseness	0.47	0.40	0.0	1.0	0,085*	1.000							
3	Diversity	1.43	0.90	0.0	4.0	0,190*	0.558*	1.000						
4	Tertius iungens	5.05	1.22	1.0	7.0	0,179*	0.181*	0.313*	1.000					
5	University	0.31	0.46	0.0	1.0	-0,159*	0.060	-0.010	-0.010	1.000				
6	Hospital	0.32	0.47	0.0	1.0	0,376*	0.000	0.104*	0.040	-0.454*	1.000			
7	PRO	0.27	0.45	0.0	1.0	-0,167*	-0.067*	-0.110*	-0.060	-0.412*	-0.423*	1.000		
8	Age	41.94	10.68	23.0	78.0	0,275*	0.151*	0.210*	0.148*	-0.040	0.204*	-0.119*	1.000	
9	PhD	0.66	0.47	0.0	1.0	0,104*	0.202*	0.208*	0.187*	0.077*	0.030	-0.081*	0.430*	1.000
10	Female	0.54	0.50	0.0	1.0	-0,213*	-0.040	-0.030	-0.086*	-0.010	-0.104*	0.151*	-0.269*	-0.113*
11	Netsize_med	0.43	0.50	0.0	1.0	-0,010	0.260*	0.098*	-0.040	0.050	-0.020	-0.040	0.020	0.083*
12	Netsize_large	0.31	0.46	0.0	1.0	0,126*	0.393*	0.531*	0.254*	0.000	0.050	-0.069*	0.137*	0.126*
13	Breadth of skills	2.83	1.83	0.0	9.0	0,204*	0.092*	0.174*	0.242*	-0.113*	0.185*	-0.050	0.112*	0.137*
14	Teaching time	10.06	14.29	0.0	90.0	0,089*	0.117*	0.098*	0.030	0.369*	-0.030	-0.268*	0.364*	0.266*
15	Contact w/patients	0.26	0.44	0.0	1.0	0,477*	-0.030	0.094*	0.074*	-0.263*	0.599*	-0.278*	0.258*	0.070*
16	Group size	18.43	10.84	2.0	79.0	-0,020	-0.069*	-0.096*	-0.088*	0.158*	-0.075*	-0.068*	-0.206*	-0.101*
17	PI	0.38	0.49	0.0	1.0	0,239*	0.224*	0.273*	0.218*	0.010	0.126*	-0.098*	0.563*	0.547*
18	PI publications	55.12	47.67	3.0	295.0	0,010	0.010	-0.040	0.020	-0.010	0.062*	-0.050	-0.020	0.079*
19	PI patents	1.03	2.32	0.0	21.0	-0,030	0.000	-0.020	-0.020	0.140*	-0.202*	0.089*	-0.087*	-0.004
20	Conscientiousness	5.62	1.01	1.3	7.0	-0,040	-0.089*	-0.061*	0.083*	-0.090*	0.040	0.040	-0.104*	-0.076*
21	Neuroticism	3.38	1.09	1.0	7.0	-0,010	-0.010	-0.03	-0.082*	0.061*	0.010	-0.030	-0.020	0.034
22	Openness	5.35	1.00	1.0	7.0	0,040	0.135*	0.132*	0.274*	0.000	-0.076*	0.020	-0.040	0.035
23	Extraversion	3.93	1.18	1.0	7.0	0,040	0.084*	0.105*	0.273*	0.000	-0.010	-0.020	-0.133*	-0.017
24	Agreeableness	5.69	0.92	2.0	7.0	0,030	0.060	0.087*	0.184*	-0.05	-0.020	0.063*	-0.077*	-0.035

	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
10	1.000														
11	-0.041	1.000													
12	-0.024	-0.576*	1.000												
13	-0.053	-0.027	0.144*	1.000											
14	-0.138*	0.107*	0.013	0.011	1.000										
15	-0.147*	0.037	-0.005	0.177*	0.105*	1.000									
16	-0.027	-0.032	-0.031	-0.158*	0.017	-0.031	1.000								
17	-0.240*	0.041	0.185*	0.149*	0.216*	0.176*	-0.112*	1.000							
18	-0.053	-0.003	-0.010	0.022	0.010	0.049	0.128*	0.034	1.000						
19	-0.035	-0.016	0.027	-0.093*	-0.059*	-0.152*	0.132*	-0.047	0.204*	1.000					
20	0.183*	-0.018	-0.061*	0.032	-0.088*	-0.016	-0.094*	-0.128*	0.019	0.004	1.000				
21	0.065*	0.003	-0.027	-0.027	0.020	-0.014	-0.011	-0.000	-0.034	0.026	-0.076*	1.000			
22	-0.091*	-0.027	0.129*	0.059	-0.010	-0.072*	-0.025	0.040	0.056	0.019	-0.003	-0.180*	1.000		
23	0.111*	0.012	0.093*	0.161*	-0.019	-0.004	-0.006	-0.042	0.031	-0.072*	-0.015	-0.094*	0.197*	1.000	
24	0.208*	0.015	0.071*	0.113*	-0.063*	-0.017	-0.050	-0.053	0.046	-0.043	0.182*	-0.063*	0.240*	0.245*	1.000

* $p < 0.05$. Note: N=1088

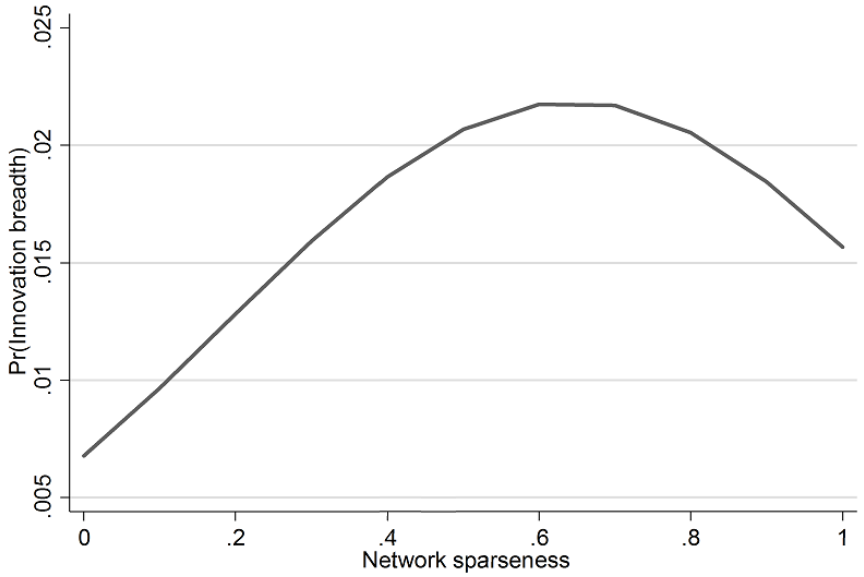
Given that our dependent variable takes non-negative integer values (between 0 and 3), standard regression techniques such as OLS are not appropriate. To accommodate the bounded and ordered nature of our dependent variable, we conducted an ordered Probit model, clustering standard errors by institution type (Table 4). Model 1 includes all the control variables. Model 2 tests the validity of Hypothesis 1 of a curvilinear (inverted U-shaped) relationship between network sparseness and innovation breadth. We find that the linear term for network sparseness is positive and statistically significant ($\beta = 0.243$, $p < 0.05$), and the quadratic term for network sparseness is negative and significant ($\beta = -1.018$, $p < 0.05$), providing support for Hypothesis 1 and showing that the greatest innovation breadth is achieved for intermediate levels of network sparseness. Figure 3 depicts this relationship. Model 3 shows that network diversity displays an inverted U-shaped relationship with innovation breadth. Specifically, the linear term of network diversity is positive and statistically significant ($\beta = 0.180$, $p < 0.01$), while the quadratic term is negative and significant ($\beta = -0.058$, $p < 0.01$), providing support for our Hypothesis 2. We plot this relationship in Figure 4. The curvilinear effects of both sparseness and diversity persist in the fully saturated model (Model 4) where the linear and squared terms of sparseness and diversity are introduced jointly (network sparseness linear term: $\beta = 0.201$, $p < 0.05$, quadratic term: $\beta = -0.930$, $p < 0.05$; network sparseness linear term: $\beta = 0.162$, $p < 0.01$, quadratic term: $\beta = -0.056$, $p < 0.10$).

Table 4. Results for Ordered Probit: effects of sparseness and diversity on innovation breadth.

	M1 Baseline		M2 Sparseness		M3 Diversity		M4 Sparseness & Diversity	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Sparseness			0.243**	(0.08)			0.201**	(0.07)
Sparseness_sqr			-1.018**	(0.32)			-0.930**	(0.32)
Diversity					0.180***	(0.04)	0.162***	(0.05)
Diversity_sqr					-0.058*	(0.02)	-0.056*	(0.02)
Tertius iungens	0.095*	(0.04)	0.089*	(0.04)	0.084*	(0.04)	0.080*	(0.04)
Age	0.012	(0.01)	0.012	(0.01)	0.012	(0.01)	0.012	(0.01)
PhD	-0.105	(0.14)	-0.100	(0.13)	-0.106	(0.14)	-0.101	(0.13)
Female	-0.269***	(0.08)	-0.278***	(0.08)	-0.283***	(0.07)	-0.288***	(0.07)
Net_size_small	-0.055	(0.05)	0.141	(0.08)	0.179**	(0.06)	0.325***	(0.09)
Net_size_large	0.211**	(0.08)	0.121	(0.06)	0.160	(0.09)	0.089	(0.08)
Breadth of skills	0.065**	(0.02)	0.066**	(0.02)	0.065**	(0.03)	0.066**	(0.02)
Teaching time	0.000	(0.01)	0.000	(0.01)	0.000	(0.01)	0.000	(0.01)
Contact w/patients	0.935***	(0.17)	0.942***	(0.18)	0.941***	(0.16)	0.946***	(0.17)
University	0.022	(0.06)	0.016	(0.06)	0.032	(0.06)	0.026	(0.06)
Hospital	0.399***	(0.06)	0.388***	(0.06)	0.393***	(0.06)	0.384***	(0.06)
PRO	0.080*	(0.04)	0.073	(0.04)	0.095**	(0.03)	0.089**	(0.03)
Group size	0.006	(0.00)	0.006	(0.00)	0.006	(0.00)	0.007	(0.00)
PI	0.207***	(0.05)	0.201***	(0.05)	0.190***	(0.05)	0.187***	(0.05)
PI publications	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)
PI patents	0.043	(0.03)	0.043	(0.03)	0.044	(0.03)	0.043	(0.03)
Conscientiousness	-0.003	(0.03)	0.000	(0.03)	-0.002	(0.03)	0.000	(0.03)
Neuroticism	0.021	(0.04)	0.018	(0.03)	0.021	(0.03)	0.019	(0.03)
Openness	0.039	(0.02)	0.036	(0.02)	0.037*	(0.02)	0.036	(0.02)
Extraversion	0.022	(0.02)	0.021	(0.02)	0.025	(0.02)	0.024	(0.02)
Agreeableness	0.047	(0.04)	0.048	(0.05)	0.046	(0.04)	0.047	(0.05)
cut1								
Constant	0.317**	(0.12)	0.167	(0.16)	0.161	(0.16)	0.175	(0.17)
cut2								
Constant	1.228***	(0.15)	1.082***	(0.19)	1.077***	(0.19)	1.093***	(0.19)
cut3								
Constant	2.181***	(0.17)	2.040***	(0.21)	2.035***	(0.21)	2.051***	(0.21)
CIBER dummies	Yes		Yes		Yes		Yes	
N	1088		1088		1088		1088	
McKelvey & Zavoina's R^2	0.356		0.361		0.361		0.366	

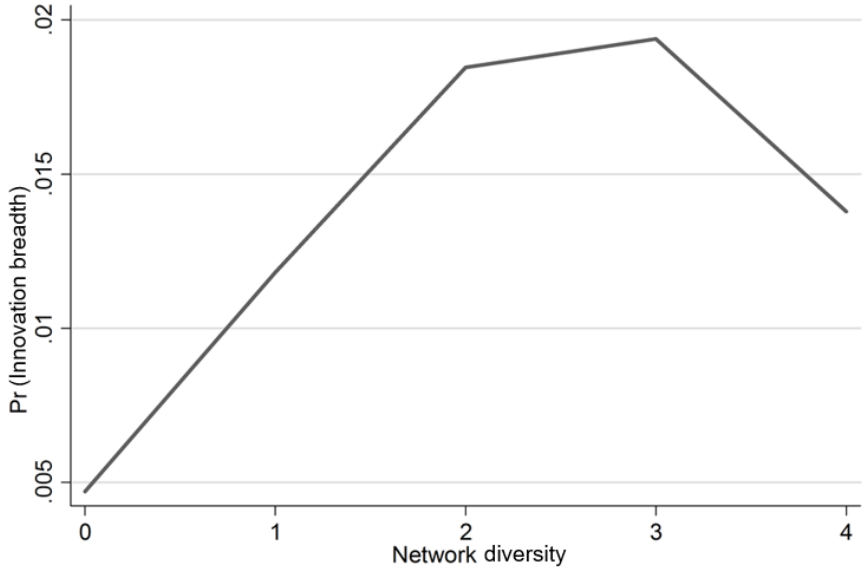
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by institution type.

Figure 3: Curvilinear effect of network sparseness on innovation breadth.



Note: The figure shows marginal effects when dependent variable scores 3. X-axis reports non-centered values to facilitate interpretation.

Figure 4: Curvilinear effect of network diversity on innovation breadth.



Note: The figure shows marginal effects when dependent variable scores 3. X-axis reports non-centered values to facilitate interpretation.

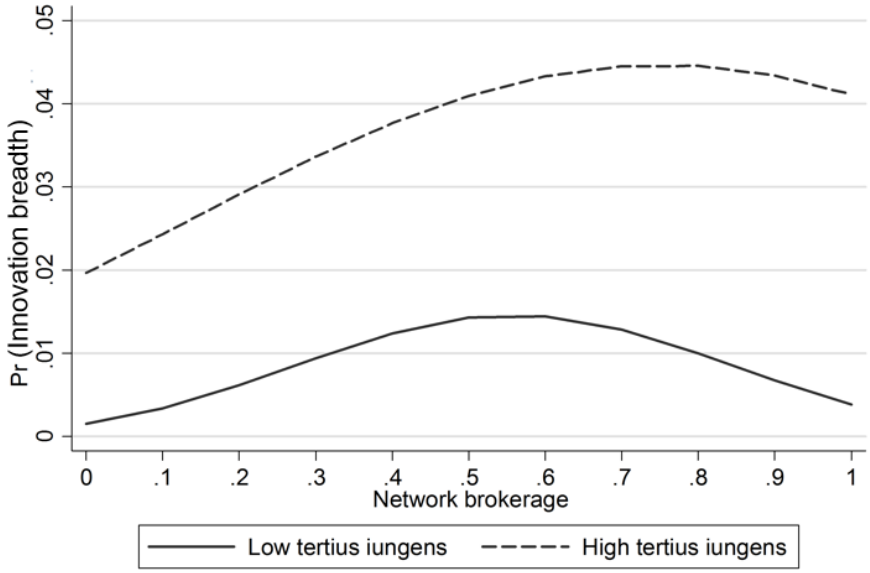
Since network configurations are unlikely to be universally effective, Hypothesis 3a and Hypothesis 3b explore whether a tertius iungens orientation moderates the relationship between network sparseness and network diversity on innovation breadth. In particular, we propose that high levels of behavioral orientation towards connecting others and facilitating knowledge flows will increase the level when diminishing returns set in. The support for our first two hypotheses suggests that the information benefits of personal network sparseness and diversity on participation in medical innovation do not occur in a linear manner. Accordingly, we examined the interaction between tertius iungens and the two aspects of personal network configurations (i.e. sparseness and diversity, including both linear and quadratic terms). The results are reported in Table 5 which shows (see Model 5) that the interplay between tertius iungens and the quadratic term of network sparseness is positive and statistically significant ($\beta = 0.205$, $p < 0.01$). These results provide support for hypotheses H3a and H3b. Figure 5 depicts the moderating effect of tertius iungens by showing how low and high values of tertius iungens influence the relationship between network sparseness and innovation breadth, i.e. a strong individual *tertius iungens* orientation counters the decreasing returns from increasing levels of sparseness, contributing to facilitating participation in innovation activities among actors embedded in highly sparse networks.

Table 5. Results for Ordered Probit: moderation effect of tertius iugens.

	M5 Sparseness*Tertius		M6 Diversity*Tertius		M7 Full	
	Coef.	SE	Coef.	SE	Coef.	SE
Sparseness	0.246**	(0.08)			0.228**	(0.07)
Sparseness_sqr	-1.055***	(0.31)			-1.077***	(0.30)
Sparseness*Tertius	-0.007	(0.02)			-0.109*	(0.05)
Sparseness_sqr*Tertius	0.205***	(0.05)			0.473***	(0.09)
Diversity			0.153***	(0.04)	0.127*	(0.05)
Diversity_sqr			-0.098**	(0.03)	-0.105**	(0.03)
Diversity*Tertius			0.051**	(0.02)	0.101**	(0.04)
Diversity_sqr*Tertius			0.043***	(0.01)	0.040**	(0.01)
Tertius iungens	0.054	(0.04)	0.056	(0.04)	-0.023	(0.03)
Age	0.012	(0.01)	0.012	(0.01)	0.012	(0.01)
PhD	-0.099	(0.13)	-0.114	(0.14)	-0.110	(0.13)
Female	-0.277***	(0.08)	-0.280***	(0.08)	-0.287***	(0.07)
Net_size_small	0.147	(0.08)	0.177**	(0.06)	0.352***	(0.10)
Net_size_large	0.122	(0.06)	0.172	(0.09)	0.100	(0.08)
Breadth of skills	0.066**	(0.02)	0.061*	(0.02)	0.061**	(0.02)
Teaching time	0.000	(0.01)	-0.000	(0.01)	-0.000	(0.01)
Contact w/patients	0.944***	(0.18)	0.939***	(0.16)	0.946***	(0.17)
University	0.017	(0.07)	0.038	(0.06)	0.045	(0.05)
Hospital	0.387***	(0.06)	0.405***	(0.06)	0.407***	(0.07)
PRO	0.071	(0.04)	0.099***	(0.03)	0.097***	(0.03)
Group size	0.006	(0.00)	0.006	(0.00)	0.007	(0.00)
PI	0.204***	(0.04)	0.195***	(0.05)	0.197***	(0.05)
PI publications	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)
PI patents	0.043	(0.03)	0.045	(0.03)	0.045	(0.03)
Conscientiousness	0.001	(0.03)	-0.000	(0.03)	0.005	(0.03)
Neuroticism	0.018	(0.03)	0.023	(0.04)	0.021	(0.03)
Openness	0.037	(0.02)	0.035	(0.02)	0.035	(0.02)
Extraversion	0.022	(0.02)	0.023	(0.02)	0.024	(0.02)
Agreeableness	0.048	(0.05)	0.044	(0.04)	0.043	(0.04)
cut1						
Constant	0.314*	(0.12)	0.304*	(0.12)	0.152	(0.15)
cut2						
Constant	1.230***	(0.15)	1.222***	(0.15)	1.075***	(0.18)
cut3						
Constant	2.184***	(0.17)	2.179***	(0.17)	2.038***	(0.19)
CIBER dummies	Yes		Yes		Yes	
N	1088		1088		1088	
McKelvey & Zavoina's R^2	0.362		0.364		0.370	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are clustered by institution type.

Figure 5: Network sparseness and innovation breadth: moderation effects.

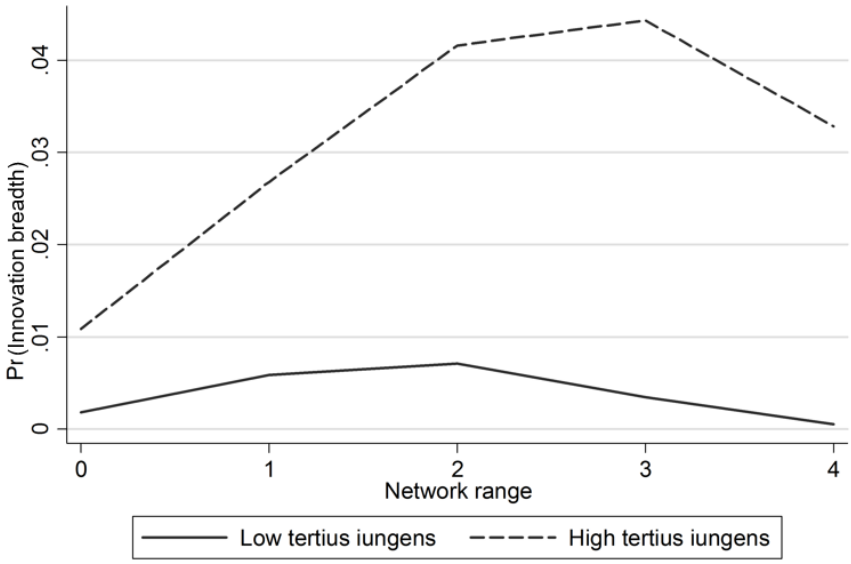


Note: The figure shows marginal effects when dependent variable scores 3. X-axis reports non-centered values to facilitate interpretation.

We followed a similar procedure to test the moderating effect of a tertius iungens orientation on network diversity. The estimates in Model 6 indicate that the interaction between tertius iungens and network diversity is positive and significant for both the linear ($\beta = 0.051$, $p < 0.05$) and quadratic ($\beta = 0.043$, $p < 0.01$) terms, indicating that scientists who facilitate an effective flow of knowledge between distinct social and professional communities exhibit higher levels of participation in innovation activities. Figure 6 depicts this moderating effect; it shows how the relationship between network diversity and innovation breadth differs for low and high values of tertius iungens. A high tertius iungens orientation enhances innovation breadth among actors embedded in networks that include a wider diversity of communities of practice: the point at which decreasing returns from network diversity set in shifts to the right. Finally, the full (saturated) model (Model 7) is consistent with our findings of a significant

moderating effect of tertius iungens on the inverted U-shaped relationships between sparse and diverse network configurations and innovation breadth.

Figure 6: Network diversity and innovation breadth: moderation effects.



Note: The figure shows marginal effects when dependent variable scores 3. X-axis reports non-centered values to facilitate interpretation.

5 Conclusions and implications

This research contributes to our understanding of the social mechanisms underlying access to dissimilar sources of knowledge associated to innovation activities. Although access to external sources of information and knowledge has for long been considered beneficial for idea generation (Salter et al., 2015; Hargadon and Sutton, 1997), few studies have explored the distinct mechanisms related to accessing dissimilar sources of knowledge which lead to innovation, or examined the individual-level factors that moderate these mechanisms. The present study focused on two specific properties of personal network configurations (i.e. network sparseness and network diversity) as potential conduits allowing access to

diverse knowledge sources. We examined whether these network properties are associated systematically to individual participation in innovation activities. We also investigated the moderating effects of individual-level strategic orientations toward connecting others (i.e. tertius iungens orientation). The study was based on the biomedical context where collaborative research networks and innovation are high on the agendas of both public health and healthcare management organizations.

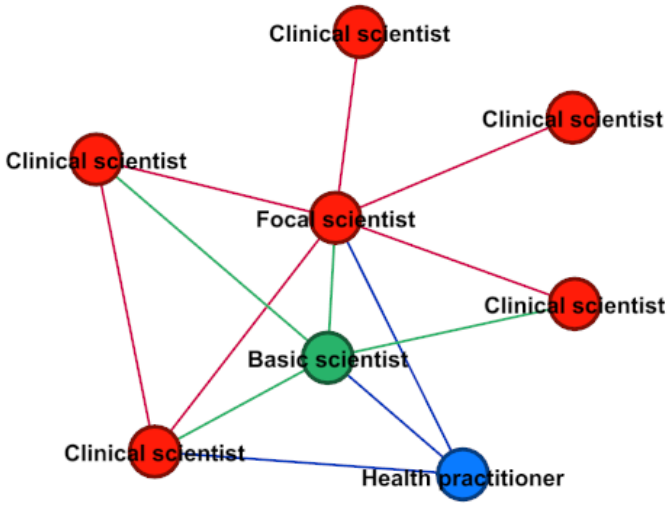
Contributions to theory

This study makes three contributions to the literature on social network research and innovation management. First, building on previous research in social networks, we suggest that personal network configurations characterized by high levels of sparseness and/or high levels of actor diversity are particularly conducive to individual engagement in innovation activities. This argument is based mainly on the rationale that access to diverse information and knowledge from social structures is critical for individual innovativeness (Baer, 2010; Burt, 2004; Obstfeld, 2005; Tortoriello and Krackhardt, 2010). Our study contributes to this stream of research by highlighting two types of non-linearities in the relationships between the structure and composition of personal networks on the one hand, and innovation on the other. First, our findings indicate that sparseness and actor diversity in personal network configurations do not show a monotonic relationship with individual participation in innovation activities. Rather they display an inverted U-shaped relationship both between level of sparseness in personal networks and individual participation in innovation, and between degree of actor diversity in personal networks and participation in innovation.

Our finding about sparseness we interpret as reflecting the theorized trade-off between sparse and dense personal networks, which suggests that while actors forming and maintaining sparse networks of contacts are expected to be in an advantageous position in relation to participating in innovation activities,

these informational benefits come at a cost. Beyond a certain level of sparseness, sustaining a sparse network is likely to compromise informational advantages due to the increased efforts required to coordinate network partners with a low degree of mutual connectivity. Our results show that the most effective personal network structure lies at an intermediate level between a very dense network (high levels of connectivity among network partners) and very sparse network (low level of connectivity among network partners). This finding implies that the highest informational advantages derive from a hybrid network structure which combines some of the attributes of dense and sparse networks. This is in line with the claims in Rogan and Mors (2014); they argue that hybrid network structures foster actor ambidexterity. In other words, a hybrid network enhances actors' capacities to identify new opportunities based on the attributes of the sparse component of the hybrid structure, and also, based on the cooperative norms engendered by the dense component of the hybrid structure, it enhances actors' capacities to mobilize the resources required to act on those opportunities. Figure 7 depicts a hybrid network structure based on our research sample, corresponding to a scientist who exhibits above average performance in participation in innovation activities.

Figure 7: Illustration of a personal hybrid network.



Our results provide evidence also of a similar non-linear, inverted U-shaped relationship for network diversity. Our findings show that access to a pool of diverse bodies of knowledge afforded by the heterogeneous attributes of network members, enhances actors' participation in innovation activities up to an optimal level. The evidence from our analysis indicates that a personal network with an increasing level of actor heterogeneity is positively associated to the focal actor's propensity to engage in innovation. However, in line with personal network sparseness, the informational benefits derived from an increasingly diverse range of actors in a personal network not only display decreasing returns but confirm the existence of an inverted U-shaped relationship. This finding supports our theoretical expectations; we expected that personal networks characterized by focal actors connecting dissimilar others would be subject to potentially conflicting sets of role expectations and cognitive challenges that eventually would undermine the informational gains derived from actor heterogeneity (Soda and Zaheer, 2012).

Our second contribution lies in showing that the informational benefits derived from network sparseness and network diversity constitute distinct social mechanisms to accessing non-overlapping information and knowledge. Social network research suggests that these network configurations represent different mechanisms for tapping into dissimilar pools of knowledge. Sparse network configurations are conducive to informational benefits that derive from structures rich in structural holes, while the informational benefits elicited from network diversity draw on the heterogeneity of the attributes embodied in network partners. Our findings extend this discussion by showing that both network configurations represent valuable alternative mechanisms which provide informational gains for innovation activities. In other words, actors might rely on the lack of connectivity among network partners in order to access dissimilar knowledge to contribute to idea generation; alternatively, they might rely on partners with distinctive attributes (e.g. belonging to different professional communities). On the one

hand, we observe that our measures of network sparseness and network diversity are positively but only partially statistically correlated, suggesting that actors embedded in very sparse networks are not necessarily involved in highly diverse networks, and vice versa. On the other hand, we find that both types of network configurations are similarly conducive to engagement in innovation activities. These results suggest that these two types of network properties constitute alternative and non-overlapping social mechanisms to tap into dissimilar sources of knowledge conducive to innovation activities.

Finally, we show that the effects of personal network structures are not universally effective but are instead contingent on the particular individual-level attributes of the focal actors. Our results provide strong support for a contingent approach to analysis of the impact on innovation of personal network configurations. An important contribution of the current study is how individual agency is dealt with. We propose a tertius iungens orientation in our conceptual discussion and empirical model as a contingency that shapes the influence of social networks on innovation. Also, by differentiating between network sparseness and network diversity, we show that the contingencies from tertius iungens appear to influence both network characteristics.

Contributions to practice

Our findings are relevant to the specific context of collaborative research and innovation in biomedicine. Policy initiatives to foster translational research and innovation in healthcare frequently emphasize the importance of promoting collaborative links between biomedical scientists belonging to different communities of practice. However, the literature on biomedical translational research is largely prescriptive, and provides little empirical evidence which suggests the need for a deeper analysis of the consequences of personal network configurations on innovation in the biomedical context.

Our research offers a number of insights relevant to the specific context of biomedical research. Our analysis provides substantive evidence that the formation of research networks that include highly heterogeneous partners is likely a necessary condition for successful translational research but is not sufficient to ensure innovation performance. The informational and knowledge benefits derived from connections among actors with different notions about what constitutes legitimate research goals may be offset by the conflict raised by the contrasting institutional logics in such networks. For instance, the care logic that is instilled in clinical scientists may cause significant coordination problems when combined with the science logic characteristic of university-based biomedical scientists. Their joint participation in a research network could lead to conflicting perspectives on research priorities, absence of shared norms and lack of a common language required to facilitate flows of information among network partners (Dunn and Jones, 2010). The actor diversity mix in the formation of biomedical research networks needs to be carefully considered to balance homogeneity and heterogeneity attributes among network partners.

However, finding the appropriate balance among actor heterogeneity within research networks makes the role of agency particularly important. The presence of actors (in our case, biomedical scientists) able to identify some common ground, align conflicting interests and build trust among network partners who respond to distinct institutional logics, is particularly important to enact and shape the innovation value of network diversity. Our results show that agency characterized by an individual tertius iungens orientation is fundamental for the formation of hybrid networks conducive to innovation performance. A tertius iungens orientation facilitates knowledge flows and promotes the establishment of a cohesive environment in the context of highly heterogeneous partners; thus, it contributes to better innovation performance in settings characterized by either lack of connectivity or excess heterogeneity among network partners.

To sum up, our discussion of personal network configurations distinguishing between dense and sparse structures, and consideration of different degrees of actor variety are valuable in the context of increased interest within the medical community in the role of knowledge brokers as actors capable of facilitating knowledge flows among network partners. Our paper proposes a personal network approach to examine the mechanisms through which different network structures and compositions lead to different levels of medical innovation among scientists. It also proposes a theoretical framework enabling a contingent approach that takes account of the importance of an underlying individual-level strategic orientation towards connecting others in the relationship between personal network configurations and participation in innovation activities.

Limitations

Our study has some limitations which suggest directions for future research. Similar to most studies based on survey and cross-sectional research, it is difficult to establish a directional causal structure between the independent and dependent variables. Therefore, we have taken care to avoid causal inferences, and confine the analysis to provide systematic and robust statistical association between the key variables used in our study. In our research design, we tried to mitigate endogeneity and reverse causality concerns through the application of three types of precautionary measures. First, our analysis includes a range of individual-level covariates to control for important differences in individuals' experience, abilities, knowledge and personality traits. Second, we used secondary sources to derive variables to control for previous involvement in specific types of innovation (i.e. patenting) during the 10 years prior to the study; this captures individual heterogeneity in the disposition to engage in innovation-related activities. Moreover, by relying on multiple data sources, our research design reduces concern over common method bias. Third, we conducted several robustness checks which show that our findings are robust to alternative measures and regression analyses.

References

Adler, P. S., and S. W. Kwon (2002). "Social capital: Prospects for a new concept." Academy of Management Review, 27: 17–40. Academy of Management.

Anderson, M. H. (2008). "Social networks and the cognitive motivation to realize network opportunities: A study of managers' information gathering behaviors." Journal of Organizational Behavior, 29: 51–78. Wiley Online Library.

Baer, M. (2010). "The strength-of-weak-ties perspective on creativity: a comprehensive examination and extension." Journal of Applied Psychology, 95: 592. American Psychological Association.

Baer, M. (2012). "Putting creativity to work: The implementation of creative ideas in organizations." Academy of Management Journal, 55: 1102–1119. Academy of Management.

Battilana, J., and T. Casciaro (2013). "Overcoming resistance to organizational change: Strong ties and affective cooptation." Management Science, 59: 819–836.

Burt, R. S. (1995). "Structural Holes: The Social Structure of Competition". Harvard university press.

Burt, R. S. (2004). "Structural holes and good ideas." American Journal of Sociology, 110: 349–399. The University of Chicago Press.

Cannella, A. A., and M. A. McFadyen (2016). "Changing the exchange: The dynamics of knowledge worker ego networks." Journal of Management, 42: 1005–1029. SAGE Publications Sage CA: Los Angeles, CA.

Carnabuci, G., and B. Diószegi (2015). "Social networks, cognitive style, and innovative performance: A contingency perspective." Academy of Management Journal, 58: 881–905. Academy of Management.

Cochrane, L. J., C. A. Olson, S. Murray, M. Dupuis, T. Tooman, and S. Hayes. (2007). "Gaps between knowing and doing: understanding and assessing the barriers to optimal health care." Journal of Continuing Education in the Health Professions, 27: 94–102. Wiley Online Library.

Coleman, J. S. (1988). "Social capital in the creation of human capital." American Journal of Sociology, 94: S95–S120. University of Chicago Press.

Cross, R., and L. Sproull (2004). "More than an answer: Information relationships for actionable knowledge." Organization Science, 15: 446–462.

Currie, G., and L. White (2012). "Inter-professional barriers and knowledge brokering in an organizational context: the case of healthcare." Organization Studies, 33: 1333–1361. SAGE Publications Sage UK: London, England.

Cyert, R. M., and J. G. March (1963). "A behavioral theory of the firm." Englewood Cliffs, NJ, 2.

Ding, W., and E. Choi (2011). "Divergent paths to commercial science: A comparison of scientists' founding and advising activities." Research Policy, 40: 69–80. Elsevier.

Donnellan, M. B., F. L. Oswald, B. M. Baird, and R. E. Lucas (2006). "The mini-IPIP scales: tiny-yet-effective measures of the Big Five factors of personality." Psychological Assessment, 18: 192. American Psychological Association.

Dougherty, D., and P. H. Conway (2008). "The '3T's' road map to transform US health care: the 'how' of high-quality care." Jama, 299: 2319–2321. American Medical Association.

Drolet, B. C., and N. M. Lorenzi (2011). "Translational research: understanding the continuum from bench to bedside." Translational Research, 157: 1–5. Elsevier.

Dunn, M. B., and C. Jones (2010). "Institutional logics and institutional pluralism: The contestation of care and science logics in medical education, 1967–2005." Administrative Science Quarterly, 55: 114–149. SAGE Publications.

Duyk, G. (2003). "Attrition and translation." Science, 302: 603–605. American Association for the Advancement of Science.

Emirbayer, M., and A. Mische (1998). "What is agency?" American Journal of Sociology, 103: 962–1023. The University of Chicago Press.

Everett, M., and S. P. Borgatti (2005). "Ego network betweenness." Social Networks, 27: 31–38. Elsevier.

Ferlie, E., L. Fitzgerald, M. Wood, and C. Hawkins (2005). "The nonspread of innovations: the mediating role of professionals." Academy of Management Journal, 48: 117–134. Academy of Management.

Fleming, L., S. Mingo, and D. Chen (2007). "Collaborative brokerage, generative creativity, and creative success." Administrative Science Quarterly, 52: 443–475. SAGE Publications.

Gittelman, M. (2016). "The revolution re-visited: Clinical and genetics research paradigms and the productivity paradox in drug discovery." Research Policy, 45: 1570–1585. Elsevier.

Goldberg, L. R. (1999). "A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models." Personality Psychology in Europe, 7: 7–28. The Netherlands.

Hargadon, A., and R. I. Sutton (1997). "Technology brokering and innovation in a product development firm." Administrative Science Quarterly, 716–749.

Khoury, M. J., M. Gwinn, P. W. Yoon, N. Dowling, C. A. Moore, and L. Bradley (2007). "The continuum of translation research in genomic medicine: how can we accelerate the appropriate integration of human genome discoveries into health care and disease prevention?" Genetics in Medicine, 9: 665–674. Nature Publishing Group.

Kilduff, M., and D. Krackhardt (2008). Interpersonal Networks in Organizations: Cognition, Personality, Dynamics, and Culture Vol. 30. Cambridge University Press.

Kleinbaum, A. M., and M. L. Tushman (2007). "Building bridges: The social structure of interdependent innovation." Strategic Entrepreneurship Journal, 1: 103–122. Wiley Online Library.

Lomas, J. (2007). "The in-between world of knowledge brokering." BMJ, 334: 129–132. British Medical Journal Publishing Group.

McFadyen, M. A., and A. A. Cannella. (2004). "Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships." Academy of Management Journal, 47: 735–746. Academy of Management.

McFadyen, M. A., M. Semadeni and A. A. Cannella (2009). "Value of strong ties to disconnected others: Examining knowledge creation in biomedicine." Organization Science, 20: 552–564.

Mehra, A., M. Kilduff, and D. J. Brass (2001). "The social networks of high and low self-monitors: Implications for workplace performance." Administrative Science Quarterly, 46: 121–146. SAGE Publications.

Morgan, M., C. A. Barry, J. L. Donovan, J. Sandall, C. D. A. Wolfe, and A. Boaz (2011). "Implementing 'translational'biomedical research: convergence and divergence among clinical and basic scientists." Social Science & Medicine, 73: 945–952. Elsevier.

Obstfeld, D. (2005). "Social networks, the tertius iungens orientation, and involvement in innovation." Administrative Science Quarterly, 50: 100–130. SAGE Publications.

Ocasio, W. (1997). "Towards an attention-based view of the firm." Strategic Management Journal, 187–206.

Perkmann, M., V. Tartari, M. McKelvey, E. Autio, A. Broström, P. D'Este, R. Fini, et al. (2013). "Academic engagement and commercialisation: A review of the literature on university–industry relations." Research Policy, 42: 423–442. Elsevier.

Perry-Smith, J. E. (2006). "Social yet creative: The role of social relationships in facilitating individual creativity." Academy of Management Journal, 49: 85–101. Academy of Management.

Perry-Smith, J. E., and P. V. Mannucci (2017). "From creativity to innovation: The social network drivers of the four phases of the idea journey." Academy of Management Review, 42: 53–79. Academy of Management.

Phelps, C., R. Heidl, and A. Wadhwa (2012). "Knowledge, networks, and knowledge networks: A review and research agenda." Journal of Management, 38: 1115–1166. SAGE Publications Sage CA: Los Angeles, CA.

Podolny, J. M., and J. N. Baron (1997). "Resources and relationships: Social networks and mobility in the workplace." American Sociological Review, 673–693.

Porter, A., and I. Rafols (2009). "Is science becoming more interdisciplinary? Measuring and mapping six research fields over time." Scientometrics, 81: 719–745. Springer.

Powell, W. W., K. W. Koput, and L. Smith-Doerr (1996). "Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology." Administrative Science Quarterly, 116–145. SAGE Publications.

Quintane, E., and G. Carnabuci (2016). "How Do Brokers Broker? Tertius Gaudens, Tertius Iungens, and the Temporality of Structural Holes." Organization Science, 27: 1343–1360.

Reagans, R., and B. McEvily (2003). "Network structure and knowledge transfer: The effects of cohesion and range." Administrative Science Quarterly, 48: 240–267. SAGE Publications.

Reinholt, M. I. A., T. Pedersen, and N. J. Foss (2011). "Why a central network position isn't enough: The role of motivation and ability for knowledge sharing in employee networks." Academy of Management Journal, 54: 1277–1297. Academy of Management.

Rodan, S., and C. Galunic (2004). "More than network structure: How knowledge heterogeneity influences managerial performance and innovativeness." Strategic Management Journal, 25: 541–562. Wiley Online Library.

Rogan, M., and M. L. Mors (2014). "A network perspective on individual-level ambidexterity in organizations." Organization Science, 25: 1860–1877.

Rogelberg, S. G., and J. M. Stanton (2007). "Introduction: Understanding and dealing with organizational survey nonresponse." Sage Publications Sage CA: Los Angeles, CA.

Salter, A., A. ter Wal, P. Criscuolo, and O. Alexy (2015). "Open for ideation: individual-level openness and idea generation in R&D." Journal of Product Innovation Manangement, 32: 488-504. Wiley Online Library.

Schilling, M. A., and C. C. Phelps (2007). "Interfirm collaboration networks: The impact of large-scale network structure on firm innovation." Management Science, 53: 1113–1126.

Simon, H. A. (1955). "A behavioral model of rational choice." The Quarterly Journal of Economics, 69: 99–118. MIT Press.

Smith, K. G., C. J. Collins, and K. D. Clark (2005). "Existing knowledge, knowledge creation capability, and the rate of new product introduction in high-technology firms." Academy of Management Journal, 48: 346–357. Academy of Management.

Soda, G., and A. Zaheer (2012). "A network perspective on organizational architecture: performance effects of the interplay of formal and informal organization." Strategic Management Journal, 33: 751–771. Wiley Online Library.

Soda, G., M. Tortoriello, and A. Iorio (2017). "Harvesting value from brokerage: individual strategic orientation, structural holes, and performance." Academy of Management Journal, amj-2016. Academy of Management, published ahead of print June 29, 2017, doi:10.5465/amj.2016.0123

Sparrowe, R. T., R. C. Liden, S. J. Wayne, and M. L. Kraimer (2001). "Social networks and the performance of individuals and groups." Academy of Management Journal, 44: 316–325. Academy of Management.

Sung, N. S., W. F. Crowley Jr, M. Genel, P. Salber, L. Sandy, L. M. Sherwood, S. B. Johnson, et al. (2003). "Central challenges facing the national clinical research enterprise." JAMA, 289: 1278–1287. American Medical Association.

Ter Wal, A., O. Alexy, J. Block, and P. Sandner (2016). "The best of both worlds: The benefits of specialized-brokered and diverse-closed syndication networks for new venture success." Administrative Science Quarterly, 61: 393–432. SAGE Publications.

Tindall, D. B., J. Cormier, and M. Diani (2012). "Network social capital as an outcome of social movement mobilization: Using the position generator as an indicator of social network diversity." Social Networks, 34: 387–395. Elsevier.

Tortoriello, M., and D. Krackhardt (2010). "Activating cross-boundary knowledge: The role of Simmelian ties in the generation of innovations." Academy of Management Journal, 53: 167–181. Academy of Management.

Tortoriello, M., R. Reagans, and B. McEvily (2012). "Bridging the knowledge gap: The influence of strong ties, network cohesion, and network range on the transfer of knowledge between organizational units." Organization Science, 23: 1024–1039.

Uzzi, B. (1997). "Social structure and competition in interfirm networks: The paradox of embeddedness." Administrative Science Quarterly, 35–67. SAGE Publications.

Wasserman, S., and K. Faust (1994). Social Network Analysis: Methods and Applications Vol. 8. Cambridge university press.

Weick, K. E., K. M. Sutcliffe, and D. Obstfeld (2005). "Organizing and the process of sensemaking." Organization Science, 16: 409–421. Informs.

Westfall, J. M., J. Mold, and L. Fagnan (2007). "Practice-based research—'Blue Highways' on the NIH roadmap." JAMA, 297: 403–406. American Medical Association.

Wong, S. S., and W. F. Boh (2010). "Leveraging the ties of others to build a reputation for trustworthiness among peers." Academy of Management Journal, 53: 129–148. Academy of Management.

Wong, S. S., and W. F. Boh (2014). "The contingent effects of social network sparseness and centrality on managerial innovativeness." Journal of Management Studies, 51: 1180–1203. Wiley Online Library.

Wu, W., M. Chang, and C. Chen (2008). "Promoting innovation through the accumulation of intellectual capital, social capital, and entrepreneurial orientation." R&d Management, 38: 265–277. Wiley Online Library.

Yegros-Yegros, A., I. Rafols, and P. D'Este (2015). "Does Interdisciplinary Research Lead to Higher Citation Impact? The Different Effect of Proximal and Distal Interdisciplinarity." Plos One, 10: e0135095.

Zaheer, A., and G. G. Bell (2005). "Benefiting from network position: firm capabilities, structural holes, and performance." Strategic Management Journal, 26: 809–825. Wiley Online Library.

Zhou, J., S. J. Shin, D. J. Brass, J. Choi, and Z.-X. Zhang (2009). "Social networks, personal values, and creativity: evidence for curvilinear and interaction effects." Journal of Applied Psychology, 94: 1544. American Psychological Association.

Appendix. A1. Response rate by CIBER

	Population surveyed	Nº of completed returned questionnaires	Response rate (%)
CIBER – BBN	872	238	27.3
CIBER – DEM	331	96	29.0
CIBER – EHD	459	154	33.6*
CIBER – ER	517	177	34.2*
CIBER – ES	439	159	36.2*
CIBER – ESP	610	107	17.5*
CIBER – NED	750	186	24.8
CIBER – OBN	303	71	23.4
CIBER – SAM	477	121	25.4
Total	4758	1309	27.5

Note: *indicates significant statistical difference in response rates ($p < 0.05$). Statistical significance was calculated by comparing the relative frequency with which the surveyed scientists are classified into the categories of non-respondents and respondents (using a Chi-square test).

Appendix. A2. EFA of medical innovation outputs. PCA used as extraction method (Varimax rotation).

Appendix. A2. EFA of medical innovation outputs. PCA used as extraction method (Varimax rotation).

	Product generation	Drug development	Clinical guidelines	Diagnostics/ prevention
Patent applications for new drugs of therapeutic substances	**0,763**	0,055	-0,035	0,059
Licenses granted from patents	**0,729**	0,090	0,003	-0,053
Participation in spin-off companies	**0,733**	-0,001	-0,012	0,088
Clinical trials phases I, II, III, new drugs or therapeutic substances	0,188	**0,620**	0,363	-0,079
Clinical trials phase IV, new drugs or therapeutic substances	0,155	**0,818**	0,204	-0,046
Clinical trials phase IV, new diagnostic techniques	-0,120	**0,730**	-0,222	0,219
Development of guidelines for healthcare professionals	-0,048	0,204	**0,772**	0,237
Development of guidelines for patients	-0,025	0,018	**0,811**	0,067
Patent applications for new diagnostic techniques	0,216	-0,051	0,128	**0,764**
Clinical trials phases I, II, III, new diagnostic techniques	-0,062	0,276	-0,026	**0,693**
Development of guidelines for the general population	-0,041	-0,166	0,395	**0,632**

Appendix. A3. Egocentric network survey

Please write down the name of those persons (up to 10) from outside your own research group and who had been a critical source of information or advice for your research activities during the year 2012. You can include not only scientific contacts, but also from other professional or institutional fields (patient associations, firms, etc.). In the following section you will be asked to provide detailed information about the professional field of each of the mentioned contacts. Further, please indicate the each contact' category.

Contact name	Category
1.	
2.	
3.	
4.	
5.	
6.	
7.	
8.	
9.	
10.	

Categories: Basic scientist, clinical scientist, health practitioner, patients' representative, private sector, public administration, other fields.

The following matrix shows all the potential linkages between all contacts you mentioned above. Please indicate whether, according to your perception, each pair of contacts frequently exchange information or work-related advice between them.

Contact 1	1									
Contact 2	☐	2								
Contact 3	☐	☐	3							
Contact 4	☐	☐	☐	4						
Contact 5	☐	☐	☐	☐	5					
Contact 6	☐	☐	☐	☐	☐	6				
Contact 7	☐	☐	☐	☐	☐	☐	7			
Contact 8	☐	☐	☐	☐	☐	☐	☐	8		
Contact 9	☐	☐	☐	☐	☐	☐	☐	☐	9	
Contact 10	☐	☐	☐	☐	☐	☐	☐	☐	☐	10