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Connecting who? Balancing benefits and costs of sparse knowledge networks through gatekeepers

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Abstract

Contrasting views exist on how patterns of social connections predict individual innovativeness. While structuralist approaches indicate that potential knowledge gains are maximized where individuals hold sparse network structures, critics highlight that it is the diversity of contacts what contributes to actors? capacity to innovate. This controversy may, however, be reconciled by including actors? structural position and contact diversity as joint predictors of innovativeness. Building on this, we take a personal network approach to go beyond a homogeneous conceptualization of brokerage by explicitly considering the attributes of actors forming triadic relationships as antecedents of individual innovativeness. Our findings based on a unique dataset of more than 1,000 biomedical scientists support the hypothesis that distinct brokerage roles have substantially different effects on innovation, suggesting that they offer divergent benefits and highlighting the key role of gatekeepers. Further, our analysis shows that the potential gains of social structures are contingent on the institutional settings where connections take place.

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Contrasting views exist on how patterns of social connections predict individual innovativeness. While structuralist approaches indicate that potential knowledge gains are maximized where individuals hold sparse network structures, critics highlight that it is the diversity of contacts what contributes to actors' capacity to innovate. This controversy may, however, be reconciled by including actors' structural position and contact diversity as joint predictors of innovativeness. Building on this, we take a personal network approach to go beyond a homogeneous conceptualization of brokerage by explicitly considering the attributes of actors forming triadic relationships as antecedents of individual innovativeness. Our findings based on a unique dataset of more than 1,000 biomedical scientists support the hypothesis that distinct brokerage roles have substantially different effects on innovation, suggesting that they offer divergent benefits and highlighting the key role of gatekeepers. Further, our analysis shows that the potential gains of social structures are contingent on the institutional settings where connections take place.

INTRODUCTION

Scholars dealing with the social structure of innovation have come to recognize that an actors' pattern of social relationships influences that actors' ability to innovate (Oh et al. 2004, Perry-Smith 2006, Sosa 2011). Social network theories have commonly resorted to the informational gains derived from certain positions in the network as the key ingredient to explain this potential advantage (Burt 1995, Reagans and McEvily 2003, Reagans and Zuckerman 2001). These theories vary, however, in how mechanisms underlying the informational advantages from social network structures are conceptualized. On the one hand, structuralist approaches typically emphasize the idea that potential informational gains are obtained by virtue of the missing connections between network members surrounding the focal actor (Burt 1995, 2004, Kleinbaum and Tushman 2007). Thus, structuralist dimensions often assumed that networks pays higher dividends in the form of information diversity when focal actors are surrounded by weakly connected contacts (Hansen et al. 2001). Along these lines, Wong and Boh (2014) recently argued that managers are better positioned to innovate when counting with a sparse network of contacts. In contrast, individualist approaches claim that individual actors cannot be treated as homogeneous and undifferentiated (Kilduff et al. 2006, Kilduff and Tsai 2003, Tortoriello et al. 2014), and that the information advantage of actors cannot be solely explained by social structures characterized by brokerage. Here, the primary focus is placed on the diversity of contacts surrounding a focal actor and not in the social linkages between them. For instance, evidence suggest that the network advantage of "innovation catalysts" in organizations is primarily driven by the diversity of their external contacts (Tortoriello et al. 2014).

Both approaches have generated a host of empirical findings with conflicting conclusions about the precise role of social structures on individual innovativeness, as the two underlying mechanisms are often confounded or insufficiently disentangled (Phelps et al. 2012, Tortoriello et al. 2014). While is it true that social network structures and contacts' diversity are correlated, they are not necessarily overlapped (Fleming et al. 2007). Thus, there may be a myriad of ways in which network structure and actors' diversity can be jointly configured to better understand actors' innovativeness. Bearing this in mind, this paper aims to reconcile both perspectives by offering a number of contributions. First, we draw upon the perspective of brokerage roles (Fernandez and Gould 1994, Gould and Fernandez 1989), to argue that the concept of brokerage represents a satisfactory compromise between the two approaches mentioned above, as brokerage

roles takes on board aspects associated to both network structure and network composition. Second, this paper disentangles the distinct impact of different brokerage roles on innovation. To do this, we discuss the particular balance of costs and benefits associated to each brokerage role, which in turn allows us to propose a number of hypotheses about the differentiated impact on innovation for the different brokerage role. These propositions aim to fill a gap in the current literature on social networks, which remains largely ambivalent about the pathways between the various types of brokerage roles and innovation (Kirkels and Duysters 2010, Lee 2010, Stovel and Shaw 2012). Our third contribution deals with the contingent perspective of social networks. Recent contributions have suggested that the specific context within which networks themselves exist deserves greater attention (Borgatti et al. 2014). That is, the direction and strength of the relationship between network structures and innovativeness depends on contextual and institutional contingencies, such as the extent to which the environment is cooperative or competitive (Kilduff and Brass 2010) or the national and organizational culture (Zhixing Xiao and Tsui 2007). In this paper, we discuss the role played by the institutional setting as a critical contingent factor to explain the realization of the informational gains derived from brokerage opportunities, providing systematic evidence on how different institutional environments condition the actual impact of brokerage on innovation. We tested the ideas outlined above in a sample of more than 1,000 biomedical scientists working under one of the most important publicly funded initiatives to support biomedical research in Spain: the Biomedical Research Networking Centres (i.e. CIBER). To date, most of the research on knowledge brokers in the biomedical context remains purely prescriptive, with few empirical studies on the direct effects of brokerage on medical innovation. The sector therefore is well suited for studying the impact of structural patterns on individual innovativeness.

SPARSE PERSONAL NETWORKS AND INNOVATION: THE PARADOX OF ACTOR DIVERSITY

Benefits of sparse personal networks

The social network literature related to knowledge creation, transfer and adoption has posited that the network advantage is echoed in a greater access to diverse pools of knowledge, which subsequently enhances individuals' capacity to develop novel knowledge recombinations (Rodan and Galunic 2004, Rost 2011, Sosa 2011, Zhou et al. 2009). This trend of incorporating sociological explanations to innovation has

given causal priority to brokerage and sparse personal networks as primary drivers of innovation (Burt 1995, Lee 2010, Perry-Smith 2006, Stovel and Shaw 2012). Formally, personal networks are social structures consisting of a focal actor (ego) and all alters to whom the focal actor is connected, as well as all the linkages among those alters (Everett and Borgatti 2005). Sparse networks are a particular type of personal network characterized by the absence or scarcity of linkages between the actors surrounding a focal individual. Two distinct features have been commonly associated to sparse networks: they provide greater opportunities to broker between disconnected social structures and they help mobilize knowledge and resources across the disconnected components of the network (Stovel and Shaw 2012). Preferential access to diverse knowledge and resources is the lifeblood accounting for the positive relationship between sparse personal networks and innovation. Within this perspective, the diversity of available knowledge from a person's social network should be higher depending on the extent to which the person's direct contacts do not known each other, since it is assumed that contacts belonging to different social circles provide non-overlapping knowledge and resources.

Drawbacks of sparse personal networks

While the virtues of sparse personal networks have been well documented in a number of studies on social structure and innovation, a strong theme in recent research is that more access to heterogeneous knowledge sources does not invariably lead to higher innovation. This debate often revolves around a contingent perspective of networks (Kilduff and Brass 2010, Obstfeld 2005, Shipilov et al. 2014, Tortoriello and Krackhardt 2010). Indeed, Wong and Boh (2014) showed that the innovative potential of sparse networks among managers is higher when complemented with central positions within their own departments. Additionally, some studies have shown that the innovative potential of personal network configurations are not endlessly (Baer 2010, McFadyen and Cannella 2004, Zhou et al. 2009). That is, network sparseness pays off in the form of knowledge diversity only up to a threshold (Lechner et al. 2010). Beyond that point, costs associated to the formation of ties with unconnected others may overwhelm their potential information benefits. For example, Hansen et al. (2001) showed empirical evidence of decreasing returns between team network sparseness and team performance.

In essence, these insights implicitly suggest that coordinating and assimilating knowledge from distant, heterogeneous sources is complex, and its associated benefits may not be easy to realize (Hambrick

et al. 1996, Lovejoy and Sinha 2010, Smith and Hou 2014). In social interactions, focal actors incur in costs associated to the initiation and maintenance of network structures (Adler and Kwon 2002, Bala and Goyal 2000, Shipilov et al. 2014), and thus, information benefits of sparse networks must be balanced against its costs. From an individual perspective, cognitive efforts associated to sparse networks are salient. As disconnected contacts tend to be embedded in different social worlds (Coleman 1988), they are likely to respond to different (maybe competing) norms and interests (Obstfeld 2005). Those actors willing to hold an intermediary role between disconnected others may struggle to deal with, and understand the inherent and potential tensions between, the unconnected parties (Fleming and Waguespack 2007, Podolny and Baron 1997).

Besides the costs associated to the formation of ties, maintenance costs also operate behind personal network configurations. Keeping a balanced personal network connecting heterogeneous actors requires continuous investments of time, attention and additional resources. It is well recognized that, in dyadic relationships, individuals need to share a common knowledge ground in order to understand each other and successfully integrate others' perspectives in its own pool of knowledge and resources (Cohen and Levinthal 1990). Since brokers, by definition, are located between individuals who otherwise would be disconnected to each other, developing the necessary common base of knowledge across all network contacts demands significant efforts. Moreover, maintenance costs do not only arise from coordinating and acting upon heterogeneous sources. Even under situations in which all network contacts are homogeneous, maintenance costs still arise by virtue of the lack of direct linkages between contacts. Being surrounded by a set of unconnected actors involves higher exposure to opportunistic behavior, as compared to networks where actors are densely tied between each other, and individuals' deviant behaviors and actions are more rapidly sanctioned by network members (Coleman 1988, 1994).

Paradoxically, if on the one hand sparse networks provide the greatest access to diverse knowledge and resources, on the other hand they also involve the highest formation and maintenance costs for the focal actor to successfully transform potential recombination opportunities into higher innovativeness. In line with this, the extent to which sparse personal networks predicts focal individuals' innovativeness will ultimately depend on the intertwined combination of potential information benefits and its associated costs. To provide

insights on this tension, we examine how the balance between benefits and costs might depend on the particular features of sparse personal networks.

Balancing benefits and costs of sparse personal networks

As we noted before, most of the existing research on personal network sparseness and innovation has adopted a pure structuralist approach, where the information advantage of a sparse personal network is solely traced to network structure (Balkundi et al. 2007, Burt 1995, Burt et al. 2013). As stated by Kilduff and Brass (2010): "The characteristics of individual actors, to the extent that they are discussed at all, have tended to be treated as residues of social *structure"*. This can be a critical oversight, given that similar structural positions may bring disparate consequences when personal network structure and actors' characteristics are jointly considered (Boari and Riboldazzi 2014, Giuliani 2011, Rodan and Galunic 2004). To the extent that actors' differences are partly independent from network structure, there may be an optimal combination of personal network sparseness and actors' heterogeneity that leads to increased levels of innovation (Tortoriello et al. 2014). This contrast with the majority of research on network sparseness, where brokerage positions with different types of actors are often aggregated together, thus building an overall sparseness or brokerage indicator and obscuring potential differences based on actors' diversity.

Gould and Fernandez (1989) proposed that not all brokers are equivalent. According to their argument, brokerage roles are reconsidered as mediating positions between groups, emphasizing that the potential consequences of brokerage depend on different configurations of group membership among actors. Empirically, this suggest partitioning all actors composing a brokerage relation into non-overlapping categories, so that different roles can be distinguished depending on the groups of actors involved in the brokerage triad. First, actors are coordinators when they broker members from their own group. For instance, a clinical scientist may facilitate the flow of information between two disconnected clinical scientists. Second, actors behave as gatekeepers when they broker one member from their own group and one member from a different group. Gatekeepers connect actors from their own group with actors pertaining to different professional or social domains – who are disconnected to each other. Third, actors can be consultants when they connect two members from the same group but from a different group than the broker. For instance, a basic scientist may be located in an intermediate position between two firms'

representatives. Fourth, actors are liaisons when they mediate between members from different groups, who do neither belong to the group of the broker.

The innovation management literature has emphasized the importance of the gatekeeper role as a facilitator of innovation (Kleinbaum and Tushman 2007, Rothaermel and Hess 2007). Indeed, several contributions have suggested that actors combining internal and external knowledge sources are better suited to create and diffuse novel knowledge within their own domain (Allen 1977, Rogers 1983). However, our argument goes one step beyond these claims. We aim at providing a rationale to contrast and compare the benefits and costs associated to each type of brokerage role. Most precisely, we contend that each of the four brokerage roles - i.e. liaison, consultant, coordinator and gatekeeper - provides a distinct combination of associated benefits and costs. While actors in a network may fulfill several brokerage roles at the same time, the proposed rationale argues that the potential benefits and costs accrued from each role will differ.

Building on Gould and Fernandez (1989) and Fernandez and Gould (1994), we contend that gatekeeper positions provide the most conducive conditions for innovation and knowledge creation due to the favorable balance between the inherent benefits and costs associated to holding sparse personal networks. Even when in principle liaison and, to a lesser extent, consultant positions are characterized by offering the greatest access to heterogeneous knowledge, we argue that a number of reasons may tip the balance in favor of gatekeeper roles (as compared to liaisons and consultants). Firstly, the relationship between potential access to heterogeneous knowledge and innovativeness does not seem to be linear. Given that focal actors' attention towards new information is limited (Simon 1955), too much heterogeneous knowledge in the personal network may even be counterproductive due to an information overload (O'Reilly 1980, Paruchuri 2010, Zhou et al. 2009). Thus, holding broker positions maximizing actor heterogeneity does not necessarily guarantee that the focal actor will be able to act upon these brokerage opportunities. By the same token, liaison positions hold the greatest initiation and maintenance costs for the focal actors. Given that liaison positions occur when none of the three actors in a triad belong to the same group, individuals occupying many liaison positions face greater costs associated to maintain and coordinate their network contacts (Smith and Hou 2014). This line of reasoning also applies for personal networks characterized by a number of consultant positions, as none of the network members would belong to the same category of the focal actor. To put it differently, the increased complex information processing efforts

(Van Knippenberg et al. 2004) are directly associated to balancing too different perspectives and interests. And greater perspectives and interests are more likely to be found among sparse personal networks formed by many liaison and consultant positions.

In contrast, coordinators are characterized by connecting individuals from their own community, who would be otherwise disconnected. In line with our previous argument, the overall effect of coordinator positions can be theorized in terms of its potential benefits and costs for the focal actor. On the one hand, individuals acting as coordinators should have to invest less time and effort to develop a common knowledge background to successfully integrate their network contacts' knowledge. Given that both focal actors and partners belong to the same group or category, knowledge heuristics and contextual particularities will be more easily understood by all network members (Tortoriello and Krackhardt 2010), and coordination efforts will be lower. Arguably, lower diversity in the social network implies that joint goal alignment will be less demanding, as compared to individuals whose personal network is composed by linkages involving more diverse contacts (Currie and White 2012, Gulati and Singh 1998). Hence, even if two individuals are spanning the same number of structural holes, the inherent initiation and maintenance networking costs should be lower for focal individuals connecting others from the same group.

On the other hand, even coordinators hold a certain degree of networking costs, which is directly attributable to the network structure: i.e. the need to maintain connections between unconnected others. Most important for our argument, we claim that the overall impact of the personal knowledge network will be compromised in the case of coordinators, by virtue of their contacts' homogeneity. Coordinators will count with lower diversity of inputs from their connections, which will do less to bring out individual innovativeness. This implies that the benefits associated to knowledge diversity are expected to be the lowest compared to the other three types of broker roles. In sum, because of a greater balance between potential information benefits and inherent costs associated to network sparseness, we expect gatekeeper positions to be more effective in enhancing individuals' innovativeness, as compared to liaison, consultant and coordinator positions. Consequently, we predict that:

> Hypothesis 1. Occupying gatekeeper positions is more strongly associated to *individuals'* innovativeness, as compared to occupying liaison, coordinator or consultant positions.

Similarly, because of an inferior balance between potential information benefits and inherent costs associated to network sparseness, we expect coordinator positions to be less effective in enhancing individuals' innovativeness, as compared to liaison, consultant and gatekeeper positions. Thus, we hypothesize that:

Hypothesis 2. Occupying c*oordinator positions is less strongly associated to individuals'* innovativeness, as compared to occupying liaison, consultant or gatekeeper positions.

Influence of the context

This research also investigates the contingent effect of working in an institutional context, which may facilitate or obstruct participation in innovation activities. Conceptually, one limitation of most prior studies on personal network effects is that they have not explicitly considered contextual differences across individuals. Thus, an open question involves the institutional features that provide personal network configurations with the most favorable conditions to be enacted (Borgatti et al. 2014, Kilduff and Brass 2010). The ultimate value of a given personal network configuration will depend on the contextual particularities where potential network effects take place. For example, building a sparse and diverse network as a mean to get involved in innovation activities may be critical in certain contexts, whereas in another context might not be needed. As pointed out by Kilduff et al. (2006, p. 1042), *"*The meaning and relevance of network ties are likely to vary from one social context to another, even when the structural form is identical*."*

In our context of research - i.e. biomedicine - it has been proposed that the different institutional settings in which scientific activities are carried out display distinctive goals, norms, formal rules and available resources (Dasgupta and David 1994). This issue is particularly salient in the biomedical setting, where a myriad of well-defined epistemic and professional communities are involved at different stages of the medical innovation process (Bornstein and Licinio 2011). Nevertheless, there is a consensus that hospitals are particularly well positioned to support patient-centered research, as compared to university departments or biomedical research centers. Hospitals are the loci of clinical practice (Consoli and Mina 2009), and are critical to validate clinically relevant therapies. Such a context will make it more likely that scientists participate in medical innovation, even without being embedded in specific network structures, as compared to those scientists working in contexts situated further away from the locus of practice. Further, in

the same way that hospitals facilitate the required knowledge and resources to get involved in medical innovation, they also provide stronger social norms and expectations towards the engagement in medical innovation (Lowman et al. 2012). As such, we believe that hospitals favor individuals' engagement in medical innovativeness irrespective of individual differences regarding personal network structure and content. In contrast, for individuals working in more academic settings engaging in medical innovation may involve a significant challenge, since access to key expertise and resources is likely to be more constrained within the boundaries of the scientists' institutional environment. Moreover, social norms may not particularly favor the establishment of relationships outside the scientific domain, nor encourage direct involvement in specific applied outcomes from research. Hence, in such a context, the additional insights provided by external ties may be vital to spur individual innovativeness and, as a result, forming a diverse actor network may exert a distinct impact on individual behavior and set of expectations.

Following this line of reasoning, we anticipate that the association between individuals' brokerage positions and innovativeness will be more pronounced for individuals belonging to non-clinical institutional settings. More specifically, working in a hospital environment is likely to act as a substitute of occupying a particular type of brokerage position. Accordingly, we hypothesize:

> Hypothesis 3. Occupying brokerage positions will be more positively associated to the participation in medical innovation among scientists working at institutional settings distinct to hospitals, as compared to scientists working at hospital settings.

METHODS

Research context

The opportunity to establish the empirical value of our rationale is provided by primary data that we have collected from biomedical scientists. We conceive the biomedical context as particularly relevant to explore the role of personal network configurations because it is a setting formed by a range of epistemic and professional communities ruled by heterogeneous norms and practices (Currie and White 2012, Ferlie et al. 2005). The inherent complexity of achieving biomedical innovations requires insights and coordinated inputs from individuals located at different strands of the biomedical field. Studies have revealed examples of biomedical research discoveries that, for the most part, have not been successfully translated into specific

innovations and health benefits. The difficulties associated to knowledge translation are attributable to various factors, chief of which is the fact that the current configuration of biomedical science does not facilitate a fluent collaboration between diverse communities located in the field.

Research population and data collection

Our research population comprises all scientists and technicians affiliated to any of the Spanish Biomedical Research Networking Centers (henceforth, CIBERs). The intention of the CIBER platforms, launched in 2006 by the Spanish Ministry of Health, was to create decentralized structures to connect different research groups in Spain working around nine different medical pathologies of special interest for the Spanish National Health System. These pathologies include diabetes, obesity, hepatic and digestive diseases or neurologic diseases. The CIBER platforms have a number of features that make them attractive settings for exploring the current research questions. With respect to the scientists' engagement in medical innovation, CIBERs were born with an explicit objective to tailor the biomedical research agenda towards relevant public healthcare needs and to accelerate the translation of basic findings into health improvements. Thus, considerable investment at the institutional level has spurred CIBER scientists to intensify their efforts to get involved in research projects and activities with a clear clinical orientation, such as the design of clinical trials or the development of clinical guidelines. They also have additional research funds oriented to foster intra-institutional collaboration and develop research initiatives with clear clinical applicability. With respect to the contextual heterogeneity, scientists participating in the CIBER platforms can be located at universities, hospitals, public research institutions or private research bodies. It is this institutional heterogeneity between scientists' institutional affiliations what motivates us to analyze whether the effects of occupying brokerage roles are similar for all institutional contexts.

To test our hypotheses, we required data on scientists' engagement in medical innovation as well as the structure and content of their personal networks. The first step consisted on a number of semi-structured interviews with scientific directors, principal investigators and research scientists affiliated to CIBER platforms. The main objective at this stage was to ascertain whether our questions regarding the personal network where adequately capturing the desired information. We also obtained important feedback regarding the heterogeneity and outputs related to their participation in medical innovation, which where

refined and modified on the basis of their suggestions. The second step comprised the collection of survey data. Drawing into administrative data and public databases, we compiled all names, affiliations and e-mail addresses of all biomedical scientists and technicians belonging to all nine CIBER networks. That left us with a total population of 4,758 individuals. Using an on-line survey platform, in April 2013 we send a personalized invitation to each scientist, explaining our objectives and encouraging them to participate in the survey, which took about 30 minutes to complete. Overall, we obtained a response rate of 27, 5 %, which is in line with previous large-scale surveys to individual scientists (Perkmann et al. 2013).

We checked for possible non-response bias by using two tests. First, we compared late and early respondents along key study variables (Rogelberg and Stanton 2007). The assumption behind this test is that these individuals that provided late responses would have fallen in the "non-respondents" category if a survey reminder would not have been sent. Thus, no differences between both groups indicate a lower risk of non-response bias. We performed an ANOVA analysis comparing scores of both groups for a number of key variables (participation in medical innovation categories, ego-network size), and we found no significant differences between both groups. Second, we performed an archival analysis to compare respondents to non-respondents on a number of dimensions available for both groups (Armstrong and Overton 1977). After data collection, we partitioned all our research population into respondents and non-respondents. We compared both groups in terms of institutional affiliation, CIBER platform, research group size and hierarchical position in the group. Although we found slight differences in terms of CIBER platform and institutional affiliation, response rates are quite homogeneously distributed, thus ensuring that our results are not primarily driven by non-response bias.

The first part of the survey comprised the collection of network data at the individual level by using a standard procedure for egocentric network surveys (Burt 2004, Levin and Cross 2004, Perry-Smith 2006, Podolny and Baron 1997). The survey began by asking individuals to respond to a name generator question to recall their critical personal contacts located outside their own research group. Thus, they were presented ten blank spaces and invited 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". Next, respondents were presented a set of name interpreter questions about each contact, where they had to classify each mentioned contact in a professional field. Specifically, a drop-down menu was presented for

each contact, and respondents had to classify them into one of these four categories: "basic scientist", "clinical scientist", "healthcare professional" or "public/private organization representative". These four groups were defined on the basis of the previous interviews with biomedical scientists, which ensured us that most of their personal contacts outside their own research group fell into one of these categories. Finally, respondents were asked to fill in a matrix showing all potential connections between each pair of contacts that they previously named. That allowed us to calculate the number of times that each respondent acted as a bridge between two unconnected contacts.

Measures

Dependent variables: medical innovation

A key element in this analysis is the degree of biomedical scientists' innovativeness. Literature has often captured medical innovation by recurring to indicators such as the participation in patenting or licensing activities. However, the generic appellation of medical innovation is extremely diverse in terms of the activities and outputs involved (Mogoutov et al. 2008), and patenting may be only capturing a narrow, commercial-related aspect of a much complex process. For instance, a common procedure to improve existing medical practices is though the development and adoption of clinical guidelines (Berwick 2003). Additionally, the analysis of the scientists' participation in the design or conduction of clinical trials at different stages is informative on how close to clinical application is a given intervention (Friedman et al. 2010). Bearing this in mind, we conjecture that medical innovation has multiple facets and intermediate steps, and these are reflected in a myriad of activities and outputs that can be carried out by biomedical scientists and are not necessarily explained by the same set of factors. Our purpose in this study was to develop an array of different activities and outputs that can be carried out by biomedical scientists reflecting an explicit effort and interest to move fundamental knowledge into more tangible healthcare improvements.

The insights that we obtained from interviews with biomedical scientists as well as a literature review in medical journals allowed us to develop an extensive list of candidate activities and outputs located at different stages of the medical innovation process. Our survey asked respondents to report the extent to which they had been involved in an extensive list of activities and outputs. A drop-down menu allowed them to indicate their frequency of participation in each activity, ranging from 0 (never) to more than 10 times.

We conducted a principal components factor analysis with varimax rotation to explore whether the proposed items are actually reflective of different dimensions related to medical innovation. The obtained results yielded four dimensions (as shown in Table 1), illustrating that medical innovations activities are quite heterogeneous. The first factor explained 22% of the total variance of the items. We labeled the respective dimensions based on the nature of activities and outputs captured by each group. Factor 1 (Product generation: invention and commercialization) is the first group of medical innovation activities, capturing aspects related to the commercial disclosure of knowledge. Factor 2 (Drug development) is the second group of activities and relates to the participation in the design of clinical trials. The group Clinical guidelines correspond to the Factor 3 and captures activities and outputs related to the development of clinical guidelines. Factor 4 (Diagnostics and prevention) grouped activities related to diagnostics and prevention. The former results suggest a division of medical innovation between four categories. Thus, we treated them separately in our regression models.

Independent variables

To calculate the different brokerage roles, we linked the Gould & Fernandez (1989) brokerage typology to the biomedical context. As previously outlined, all our respondents and their direct contacts were classified in any of these four non-overlapping groups:: i) basic scientists, ii) clinical scientists, iii) healthcare practitioners / patient representatives and iv) professionals from public or private institutions. Information on the category of our respondents as well as on their direct contacts allow us to count the number of times each respondent is playing each brokerage role, as in previous studies (Lissoni 2010, Shi et al. 2009). For instance, basic scientists would find themselves in liaison positions when connecting a patient representative with an industry professional. This procedure allow us to assign a score on each brokerage roles for each respondent.

Control variables

Previous research indicates that individual factors such as the career status and previous research experience influences their degree of participation in different activities related to knowledge transfer (Carayol 2007, Stephan et al. 2007). In our context, one may expect that, as researchers gain experience and move up to higher academic positions, they may be in a better position to invest a larger portion of their time

and resources in participating in different medical innovation activities, as compared to younger scientists that may lack the experience or resources to participate in such activities. Accordingly, we control for the scientists' age and academic position. Potential gender biases were controlled by adding respondents' gender. The size of respondents' personal network was included to rule out the possibility that network size rather than brokerage roles were responsible for differences in medical innovation participation (net_size). As some of the respondents reported having less than two external contacts, they cannot play any brokerage role by definition. Thus, we included a dummy (net_less_two) to differentiate between scientists that do not play any brokerage role because they have less than two contacts and scientists that reported zero brokerage roles even with counting with more than two external contacts.

Individuals' tendency to engage in creative and innovative behaviors is also partly dependent on their personality characteristics and traits (Shalley et al. 2009, Somech and Drach-Zahavy 2013), as well on their different degrees of motivation (De Stobbeleir et al. 2011, Zhang and Bartol 2010). Accordingly, we accounted for personality differences by controlling for the Big Five personality traits of all respondents (Extraversion, Agreeableness, Conscientiousness, Neuroticism, Intellect/Imagination) (Brent et al. 2006). Furthermore, we controlled for the scientists' intrinsic motivation and extrinsic motivation to perform research activities. The Self-Regulation Questionnaire (Ryan and Connell 1989) was adapted to the current context to identify reasons for engaging in research activities. More specifically, respondents were asked "Why do engage in research activities?", and presented a set of diverse motives such as "because I enjoy it" (intrinsic), "because it make me feel good" (intrinsic), "because it allows me to get the professional recognition from my peers" (extrinsic), or "because it helps me to get promoted" (extrinsic). A seven–point Likert scale ranging from 1 (lowest) to 7 (highest) was presented for each indicated motive. Alpha coefficients for the intrinsic motivation and extrinsic motivation constructs were .84 and .80, providing strong evidence for the reliability of both constructs.

We also controlled for various aspects associated to the research group where each scientist was affiliated. We resorted to administrative data to obtain information about the research group size (group_size), measured as the number of scientists belonging to the same research group. Survey data allowed us to build a measure of internal network density of each scientist (int_net_density), assessed as the proportion of existing alter-alter ties out of all potential alter-alter ties between members of the same

research group as the focal respondent (Rodan 2010, Wasserman and Faust 1994). The result is an index that ranges from 0 to 1, with high scores representing greater density. We also controlled for potential geographical agglomeration effects by adding a dummy variable that takes the value of 1 when the respondents' research group is located in Madrid or Barcelona, the two largest cities in Spain and the areas where most of the research groups are concentrated (region_dummy). To control for the type of affiliation between the respondent and the research group, we added a categorical variable controlling whether the respondent is employed by the CIBER, ascribed to the group or has any other type of linkage with the research group (CIBER_link). Institutional heterogeneity was captured by assigning the value of 1 if research groups belong to university, two if belong to a hospital, three if belong to a public research center and four if belong to a private research center or any other institution type (institution_dummy). Finally, we included 9 dummies to account for the CIBER platform where each research group belongs to. (CIBER_dummy).

Academics have recently pointed that Principal Investigators (PI) have a great responsibility and influence in determining the nature and objectives of the research activities carried out by the whole research group (Boehm and Hogan 2014, O'Kane et al. 2014). Therefore, we incorporated bibliometric and patent data from ISI Web of Science and PATSTAT to control for the previous scientific and technological performance of the PI. We searched for the number of patent applications hold by each PI (PI_patents), as well as the number of top cited papers hold by each PI (PI_top papers). The propensity of PI's to get involved in networking activities was captured by adding three variables computed for all the PIs: the logarithm of the number of different co-authors (PI_coauthors), the rate of co-authors that are affiliated to companies (PI_pp_companies) and the rate of co-authors that belong to hospitals (PI_pp_hospitals).

Statistical method

Our four dependent variables (commercialization, drug development, clinical guidelines and diagnostics and prevention) takes on only whole number values. Given that count models are better suited to provide more accurate estimations (Cameron and Trivedi 2001), we performed four negative binomial regressions, one for each medical innovation category identified in the previous section. The negative binomial regression was chosen over the Poisson regression to accommodate the skewed nature of our

dependent variables[1]. In a Poisson model, variance is assumed to be identical to the mean. Our dependent variables include a larger number of zeros than predicted in a Poisson distribution. Negative binomial models are a generalization of Poisson models that account for overdispersion in the data by relaxing this assumption (Hausman et al. 1984).

RESULTS

Table 1 displays means, standard deviations and correlations for the variables. The examination of the results show that the average frequency of participation in any of the four medical innovation categories is quite low. The scientists were well distributed across the nine CIBER and represented a broad range of ages (23 to 78 years).

{Insert Table 1 Here}

An important insight from this study is that results confirm that occupying any type of brokerage role is a rather exceptional issue. The main statistics on the distribution of roles among our sample of scientists can be viewed in Figure 1. Data shows that most of the biomedical scientists do not play any brokerage role at all, meaning that they do not occupying mediating positions between other biomedical actors. It is also important to note that being a liaison or a consultant is quite exceptional: 1,139 and 1,101 scientists, respectively, have never played such roles. These results are consistent with the idea that brokerage roles are fundamentally different between them, thus requiring substantially different efforts and providing diverse benefits for the focal actor, and are in line with previous results showing the exceptional nature of liaison positions (Lissoni, 2010).

{Insert Figure 1 Here}

Table 2 presents the results of the negative binomial regression analysis on the four types of medical innovation. For each type, we began by estimating a baseline model where we only included the control variables. The subsequent models added the four brokerage roles to explore whether they influence the scientists' participation in each of the four categories. Thus, Model I, Model III, Model V and Model VII presents the effects of control variables on each form of medical innovation. Regarding the individual

[1] We used the function "nbvargr" in Stata 12 to compare dispersion to evaluate which model better suited the skewed distribution of our dependent variables.

factors, results indicate that age and gender have a significant influence on the scientists' participation in any of the four categories, pointing to the importance of controlling for individual-level differences. Motivation and personality traits also exert influence in certain forms of medical innovation. Results also expose that the participation in medical innovation activities is highly dependent on the institutional context where scientists perform their research activities. Scientists working in hospital settings are more likely to engage in activities related to drug development, (such as the participation in clinical trials design) and activities related to the elaboration of clinical guidelines. Results also indicate that the control variables associated to the PI of each group exert significant influence on the scientists' innovativeness. We found that scientists belonging to research groups where the PI counts with a larger patenting experience are more likely to engage in commercialization and drug development activities. Similarly, a greater proportion of co-authors affiliated to hospitals and firms exerts a positive influence over the scientists' participation in medical innovation activities. This is consistent with our expectations, since principal investigators with higher experience in collaborating with industry and medical institutions may have deployed the external connections and needed skills to develop medical innovations, and to translate these insights to their members in the research group.

Models II, IV, VI and VII shows the effects of each brokerage role on the propensity to engage in commercialization, drug development, clinical guidelines and diagnostics and prevention activities. Overall, results confirms that holding gatekeeper positions exert a positive influence on the scientists' participation in medical innovation, as proposed in Hypothesis 1. It is particularly noteworthy that this relationship remains statistically significant ($p < .05$) and consistent for all four forms of medical innovation, thus indicating a robust connection. Specifically, to the extent that a scientist occupies a large number of gatekeeper positions, he or she will be more likely to participate in a range of different activities related to medical innovation. Regarding the relationship between coordinator positions and medical innovation (Hypothesis 2), we predicted a negative relationship between holding coordinator positions and participating in different forms of medical innovation. As shown in the table, this hypothesis is partly confirmed. The coefficients for drug development and diagnostics and prevention are negative and highly significant ($p < .001$), thus indicating that costs associated to coordinator positions overwhelms it potential benefits for these two innovation types. For commercialization and clinical guidelines, results indicate no significant relationship.

{Insert Table 2 Here}

To test whether the influence of holding gatekeeper positions remains homogeneous between scientists working in hospital and non-hospital settings (Hypothesis 3), we used a split sample procedure (e.g.: (Laursen and Salter 2014). We predicted that gatekeeper positions would be particularly critical for scientists working at institutional contexts different from hospitals. Results are presented in Table 3. Models consistently show that gatekeeper positions are significantly associated to all four types of medical innovation categories when scientists are located at institutions different from hospitals. However, for scientists working at hospitals, the influence of gatekeeper does not appear to be decisive in their participation in medical innovation. Specifically, for this group we find that gatekeeper positions are significantly associated to the participation in drug development and diagnostics and prevention, while it is not determinant for commercialization and clinical guidelines. We perform two Wald tests that take account of the covariance in the parameters across the two models, which ensures that the tests for the equality of the coefficients are correct. We find that the gatekeeper coefficient for the participation in clinical guidelines is significantly higher for scientists not working at hospitals, as compared to those working at other type of institutions ($p = 0.0356$). That lends partial support to Hypothesis 3.

{Insert Table 3 Here}

DISCUSSION AND CONCLUSIONS

Innovation processes are collective and social in nature. Based on this premise, the use of social network lenses to predict individual innovativeness has become increasingly popular among organizational and innovation management scholars. The insights generated by previous studies have shown that sparse networks provide greater opportunities for innovation. From a policy perspective, these arguments have been reflected in policies aiming to promote cooperative linkages between distant and unconnected actors as a way to enhance the generation of innovations. In this paper we contribute to social network and innovation research by advancing on the relationship between innovation performance and actor heterogeneity within personal sparse networks. Although the informational benefits of building bridges among disconnected actors (i.e. brokerage roles) are well anchored in the literature, in this paper we have tried to evidence that not all brokerage positions are equally conducive to innovation. Specifically, our findings reveal that the

individual's ability to generate innovations will depend on the specific type of brokerage role carried out, and that the impact of these bridging roles should be analyzed in conjunction with the institutional setting in which individuals conduct their professional activities.

Drawing from Gould and Fernandez (1989) approach, we explore the frequency of different brokerage roles that biomedical scientists play when tapping into external actors. To do so, we have drawn upon the classification of direct contacts between basic scientists, clinical scientists, medical practitioners or patient representatives, and public organizations and firms' employees. We have used a personal network perspective to construct each scientist direct network based on responses from a large-scale survey. By adopting this approach, we are able to identify the specific number of times each scientist plays any of the four defined brokerage roles: liaison, gatekeeper, coordinator and consultant. We find that gatekeepers are in a better position to participate in medical innovation, as compared to scientists holding alternative brokerage roles. Additionally, our results show that coordinators are particularly disadvantaged to participate in medical innovation.

Consistent with previous contributions on the contingent role of social networks (Kilduff and Brass 2010, Zhixing Xiao and Tsui 2007), we find that institutional settings matter with regards to the actual impact of brokerage roles on individual innovativeness. Researchers located at universities and public (or private) research organizations are much more sensitive to the knowledge gains generated from brokerage roles in order to engage in innovation activities, as compared to researchers located at hospitals and clinical environments.

Managerial implications

Demands from policymakers in the biomedical field seem to espouse brokerage and network sparseness among biomedical actors as the elixir for eliciting a quicker and better translation of biomedical findings into specific health benefits (e.g. Lomas, 2007). Up to a point, our empirical results corroborate these statements. However, our analysis also proves that this relationship is more complex than initially observed, and offers some cautionary remarks. First, although nurturing sparse networks may enhance scientists' propensity to participate in different forms of medical innovation, our research indicates that we should specifically consider the nature of the contacts to which the focal scientist is connected to. It is sparse

networks formed by gatekeeper positions that offer the greatest balance between the potential benefits and costs of brokerage and thus, the ones that elicit a higher propensity to enhance individual innovativeness. Thus, sparse network structures that involve a balance between ties to actors who share attributes with the focal actor, and ties to actors who are dissimilar to the focal actor, are particularly conducive to innovation performance. Therefore, holding sparse networks per se does not provide a necessary pathway to or a favorable condition for innovation, unless informational gains form actor diversity more than compensate for the costs of formation and maintenance of high heterogeneous social structures.

Our contention that holding brokerage positions per se may not necessarily be advantageous is further evidenced by the case of coordinators. While coordinator roles are by far the most frequent brokerage roles in our sample of scientists, it is not the coordinator role that provides the key to innovation performance; on the contrary, actors who overplay this type of brokerage role are less likely to engage in innovation activities. By contrast, it is important to highlight that, according to our findings, gatekeeper roles, which are not particularly frequent in our sample, are particularly conducive to innovation, irrespective of the type of innovation we examine.

Finally, it is also important to note that gatekeeper roles are found to be significantly associated to innovation in both university and hospital institutional settings. However, there is partial evidence suggesting that the effects of gatekeepers on innovation are particularly sensitive in the case of universities and public/private research organizations. These findings suggest that favoring actor heterogeneity in academic settings may particularly benefit the potential for innovation performance among scientists working at universities and public or private research organizations. We contend that this is likely to be a result of the specific norms and incentive structures at universities, which often lead to the establishment of networks formed of homogeneous sets of actors and where actors have little incentives to engage in innovation-related activities (as compared to hospital and clinical environments).

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FIGURE 1: DISTRIBUTION OF BROKERAGE ROLES

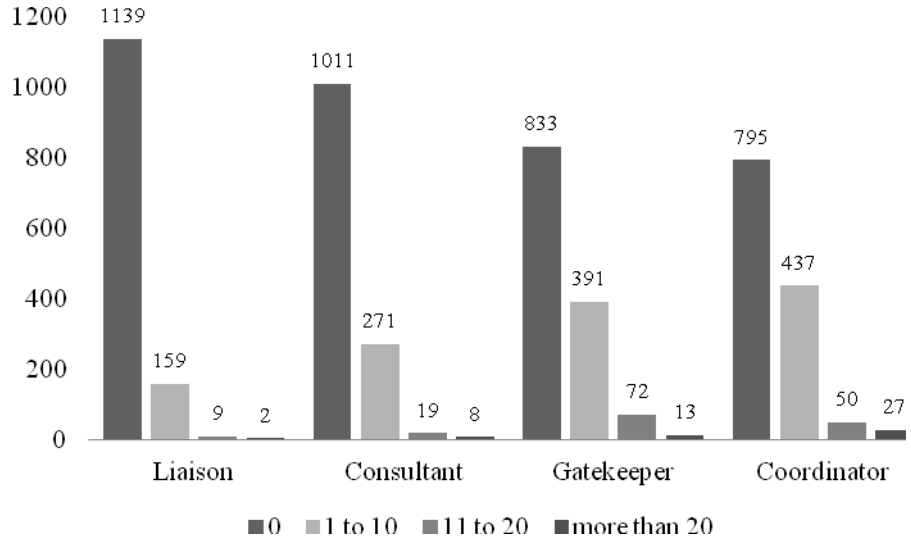

TABLE 1: SUMMARY STATISTICS AND CORRELATION MATRIX

		mean	sd	min	max	1	2	3	4	5	6	7	8	9	10	11	12
1	Gatekeeper	2.220	4.393	0.000	24.000	1.000											
2	Liaison	0.529	1.979	0.000	27.000	0.207*	1.000										
3	Consultant	0.970	3.103	0.000	32.000	0.282*	0.382*	1.000									
4	Coordinator	2.163	4.852	0.000	45.000	0.400*	-0.043	-0.072*	1.000								
5	Age	37.109	10.820	17.000	65.000	0.148*	0.072*	0.066*	0.074*	1.000							
6	Intrinsic motivation	6.175	0.800	1.000	7.000	0.057	0.008	0.032	0.048	-0.049	1.000						
7	Extrinsic motivation	3.713	1.175	1.000	7.000	-0.009	-0.030	-0.007	-0.035	0.107*	0.248*	1.000					
8	group_size	18.776	10.824	4.000	79.000	-0.081*	-0.001	0.015	-0.058	-0.177*	-0.102*	-0.026	1.000				
9	net_size	0.308	0.462	0.000	1.000	0.616*	0.335*	0.393*	0.478*	0.122*	0.078*	-0.012	-0.035	1.000			
10	int_net_density	0.709	0.265	0.000	1.000	-0.078*	-0.032	-0.031	-0.030	-0.063*	0.059	0.005	-0.206*	-0.066*	1.000		
11	Political skills	5.569	0.772	2.667	7.000	0.095*	0.064*	0.071*	0.047	-0.029	0.253*	0.064*	-0.103*	0.119*	0.089*	1.000	
12	region_dummy	0.628	0.483	0.000	1.000	0.027	0.020	0.039	0.053	0.007	0.003	-0.035	0.043	0.047	-0.001	0.042	1.000
13	CIBER_link (3)	1.844	0.514	1.000	3.000	0.030	-0.055	-0.057	0.050	0.323*	-0.006	0.114*	0.034	0.002	-0.100*	-0.055	-0.013
14	conscientiousness	5.631	1.002	1.250	7.000	-0.056	-0.050	-0.035	-0.076*	-0.098*	0.130*	0.083*	-0.098*	-0.069*	0.097*	0.219*	-0.003
15	neuroticism	3.376	1.094	1.000	7.000	-0.044	-0.004	-0.064*	-0.015	-0.009	-0.103*	0.006	-0.006	-0.041	0.008	-0.289*	-0.071*
16	openness to experience	5.354	1.000	1.000	7.000	0.118*	0.043	0.065*	0.078*	-0.032	0.264*	-0.037	-0.032	0.125*	0.001	0.284*	-0.013
17	extraversion	3.962	1.179	1.000	7.000	0.088*	0.045	0.021	0.066*	-0.124*	0.105*	0.112*	-0.008	0.088*	-0.035	0.323*	0.011
18	agreeableness	5.715	0.911	2.000	7.000	0.052	-0.006	0.028	0.018	-0.056	0.158*	-0.021	-0.057	0.076*	0.012	0.509*	0.059
19	academic position (6)	3.054	1.272	1.000	6.000	-0.171*	-0.051	-0.025	-0.174*	-0.493*	-0.080*	-0.097*	0.120*	-0.195*	0.084*	-0.034	-0.003
20	institution_dummy (4)	2.007	0.863	1.000	4.000	0.019	0.001	0.006	0.074*	0.039	-0.012	-0.054	-0.158*	0.024	0.058	0.020	0.327*
21	CIBER_dummy (9)	4.521	2.549	1.000	9.000	-0.002	-0.022	-0.038	-0.016	-0.005	-0.022	-0.005	-0.143*	-0.025	0.040	0.073*	-0.006
22	net_less_two (<2 contacts)	0.252	0.434	0.000	1.000	-0.293*	-0.155*	-0.181*	-0.259*	-0.162*	-0.034	0.017	0.068*	-0.387*	0.007	-0.142*	-0.017
23	Gender (Female)	1.555	0.497	1.000	2.000	-0.001	-0.002	0.020	-0.037	-0.254*	0.056	-0.103*	-0.047	-0.029	0.124*	0.170*	0.071*
24	PI_top papers	7.303	7.258	0.000	56.000	-0.012	0.020	0.027	0.013	0.016	-0.013	-0.014	0.035	0.002	-0.033	-0.018	-0.134*
25	PI_patents	1.055	2.377	0.000	21.000	-0.009	0.023	0.017	0.017	-0.081*	0.033	0.017	0.135*	0.013	-0.030	-0.043	-0.025
26	PI_coauthors	5.389	0.771	2.398	7.268	0.036	0.062*	0.127*	0.017	-0.101*	0.038	0.104*	0.012	0.031	-0.053	0.010	0.023
27	PI_pp_companies	0.055	0.069	0.000	0.400	-0.002	0.067*	0.129*	-0.002	-0.075*	-0.027	0.034	0.001	0.012	0.017	-0.041	-0.010
28	PI_pp_hospitals	0.508	0.330	0.000	1.000	-0.041	-0.000	-0.122*	0.092*	-0.032	0.008	0.143*	-0.008	0.064*	-0.053	-0.070*	0.036

TABLE 1: SUMMARY STATISTICS AND CORRELATION MATRIX (Cont.)

		13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
13	CIBER_link (3)	1.000															
14	conscientiousness	-0.099*	1.000														
15	neuroticism	0.002	-0.068*	1.000													
16	openness to experience	-0.030	-0.001	-0.173*	1.000												
17	extraversion	-0.026	-0.034	-0.087*	0.194*	1.000											
18	agreeableness	-0.060	0.162*	-0.038	0.247*	0.226*	1.000										
19	academic position (6)	-0.291*	0.127*	-0.009	-0.057	-0.002	0.037	1.000									
20	institution_dummy (4)	-0.051	-0.007	-0.035	-0.022	0.018	0.038	0.039	1.000								
21	CIBER_dummy (9)	0.008	0.003	-0.053	0.024	0.091*	0.118*	0.042	0.065*	1.000							
22	net_less_two (<2 contacts)	-0.055	0.090*	0.025	-0.093*	-0.110*	-0.086*	0.245*	0.043	0.025	1.000						
23	Gender (Female)	-0.213*	0.178*	0.073*	-0.093*	0.111*	0.208*	0.204*	0.079*	0.027	0.074*	1.000					
24	PI_top papers	0.051	-0.008	0.020	-0.015	-0.010	-0.036	-0.044	-0.104*	-0.143*	-0.044	-0.055	1.000				
25	PI_patents	-0.058	0.005	0.029	0.011	-0.073*	-0.041	0.006	-0.111*	-0.278*	-0.002	-0.036	-0.051	1.000			
26	PI_coauthors	0.044	-0.080*	-0.028	0.156*	0.034	-0.071*	0.052	0.019	1.000	0.034	-0.071*	0.052	0.019	1.000		
27	PI_pp_companies	-0.056	0.002	0.045	-0.001	0.006	0.029	-0.070*	0.005	0.052	0.006	0.029	-0.070*	0.005	0.052	1.000	
28	PI_pp_hospitals	-0.001	0.025	0.254*	0.229*	-0.032	0.008	0.035	-0.365*	0.083*	-0.032	0.008	0.035	-0.365*	0.083*	0.082*	1.000

* $p<0.05$

TABLE 2: NEGATIVE BINOMIAL REGRESSION MODELS

	Commercialization		Drug development		Clinical guidelines		Diagnostics & prevention	
Main variables	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Liaison		0.040 (0.03)		-0.055 (0.04)		0.014 (0.03)		0.056** (0.03)
Gatekeeper		0.045** (0.02)		0.046** (0.02)		0.048** (0.02)		0.061*** (0.02)
Consultant		0.007 (0.02)		0.029 (0.04)		-0.025 (0.02)		-0.022 (0.02)
Coordinator		-0.024 (0.02)		-0.073*** (0.02)		-0.024 (0.02)		-0.057*** (0.02)
Age	0.007 (0.01)	0.005 (0.01)	0.030*** (0.01)	0.025*** (0.01)	0.020*** (0.01)	0.018** (0.01)	0.030*** (0.01)	0.027*** (0.01)
Intrinsic motivation	0.341*** (0.12)	0.329*** (0.12)	-0.015 (0.11)	-0.038 (0.11)	-0.331*** (0.10)	-0.308*** (0.10)	0.006 (0.11)	0.009 (0.11)
Extrinsic motivation	-0.035 (0.06)	-0.030 (0.06)	0.208*** (0.07)	0.201*** (0.07)	0.120* (0.07)	0.124* (0.07)	0.071 (0.08)	0.081 (0.07)
group_size	0.007 (0.01)	0.006 (0.01)	0.017* (0.01)	0.014 (0.01)	0.016* (0.01)	0.018** (0.01)	0.019** (0.01)	0.019** (0.01)
net_size	0.428** (0.18)	0.169 (0.26)	-0.009 (0.19)	-0.008 (0.27)	-0.021 (0.17)	-0.144 (0.24)	0.297* (0.18)	0.092 (0.23)
int_net_density	-0.010 (0.33)	0.050 (0.33)	0.108 (0.30)	0.117 (0.31)	0.518** (0.26)	0.535** (0.26)	-0.192 (0.29)	-0.157 (0.29)
Political skills	0.158 (0.15)	0.137 (0.15)	-0.188 (0.16)	-0.188 (0.16)	0.185 (0.12)	0.205* (0.12)	0.150 (0.14)	0.140 (0.14)
region_dummy	-0.163 (0.20)	-0.091 (0.19)	0.002 (0.20)	0.002 (0.20)	-0.027 (0.16)	-0.039 (0.16)	0.041 (0.16)	0.026 (0.16)
CIBER_link (3)	Included	Included	Included	Included	Included	Included	Included	Included
conscientiousness	-0.074 (0.08)	-0.067 (0.08)	0.113 (0.09)	0.104 (0.09)	0.089 (0.08)	0.088 (0.08)	-0.015 (0.08)	-0.022 (0.08)
neuroticism	-0.058 (0.08)	-0.063 (0.08)	-0.085 (0.08)	-0.099 (0.08)	0.060 (0.08)	0.060 (0.08)	0.190** (0.08)	0.189** (0.08)
openness to experience	-0.078 (0.09)	-0.077 (0.09)	0.051 (0.09)	0.051 (0.09)	0.145* (0.08)	0.130* (0.08)	0.226** (0.09)	0.199** (0.09)
extraversion	0.041 (0.09)	0.028 (0.09)	0.121 (0.08)	0.128* (0.08)	0.207*** (0.07)	0.206*** (0.07)	-0.058 (0.08)	-0.082 (0.07)
agreeableness	0.065 (0.11)	0.076 (0.10)	0.242** (0.12)	0.244** (0.12)	-0.070 (0.10)	-0.102 (0.10)	0.208* (0.11)	0.210* (0.11)
academic position (6)	Included	Included	Included	Included	Included	Included	Included	Included
institution_dummy (4)	Included	Included	Included	Included	Included	Included	Included	Included
CIBER_dummy (9)	Included	Included	Included	Included	Included	Included	Included	Included
net_less_two (<2 contacts)	-0.035 (0.25)	-0.022 (0.25)	0.051 (0.23)	0.035 (0.23)	0.184 (0.21)	0.194 (0.21)	-0.014 (0.24)	-0.038 (0.24)
Gender (Female)	-0.714*** (0.17)	-0.759*** (0.17)	-0.375** (0.19)	-0.421** (0.19)	-0.130 (0.17)	-0.149 (0.17)	-0.414** (0.18)	-0.448** (0.18)
PI_top papers	0.001 (0.01)	0.002 (0.01)	-0.016 (0.01)	-0.016 (0.01)	0.012 (0.01)	0.012 (0.01)	-0.008 (0.01)	-0.009 (0.01)
PI_patents	0.166*** (0.04)	0.160*** (0.04)	0.092** (0.04)	0.089*** (0.03)	0.031 (0.04)	0.023 (0.04)	-0.010 (0.04)	-0.015 (0.04)
PI_coauthors	-0.118 (0.12)	-0.118 (0.12)	0.103 (0.12)	0.140 (0.12)	-0.040 (0.11)	-0.045 (0.11)	-0.173 (0.12)	-0.155 (0.12)
PI_pp_companies	-0.140 (1.26)	0.058 (1.26)	5.118*** (1.44)	5.131*** (1.42)	-1.371 (1.26)	-1.535 (1.25)	-0.150 (1.30)	0.248 (1.33)
PI_pp_hospitals	-0.625* (0.35)	-0.676* (0.35)	1.041*** (0.39)	1.069*** (0.39)	1.909*** (0.35)	1.889*** (0.36)	0.252 (0.35)	0.174 (0.36)
Constant	-3.006** (1.41)	-2.854** (1.42)	-7.052*** (1.51)	-6.806*** (1.47)	-5.327*** (1.28)	-5.331*** (1.29)	-5.482*** (1.33)	-5.213*** (1.33)
Observations	1009	1009	1010	1010	1010	1010	1010	1010
Pseudo-R^2	0.196	0.204	0.217	0.226	0.214	0.221	0.102	0.115

Note: * p < 0.1; ** p < 0.05; *** p < 0.01

TABLE 3: NEGATIVE BINOMIAL REGRESSION MODELS. SPLIT SAMPLE BETWEEN HOSPITAL VS. NON-HOSPITAL SCIENTISTS

	Hospitals				Non-hospitals			
	Commercialization	Drug development	Clinical Guidelines	Diagnostics and prevention	Commercialization	Drug development	Clinical Guidelines	Diagnostics and prevention
Liaison	0.044 (0.03)	-0.077 (0.07)	0.008 (0.04)	0.077* (0.04)	0.004 (0.07)	-0.062 (0.07)	0.068 (0.07)	0.054 (0.05)
Gatekeeper	-0.004 (0.04)	0.071** (0.03)	0.009 (0.03)	0.091** (0.04)	0.057** (0.02)	0.073** (0.04)	0.094*** (0.03)	0.058** (0.03)
Consultant	0.031 (0.04)	-0.070* (0.04)	-0.007 (0.04)	0.030 (0.05)	0.016 (0.03)	0.078** (0.04)	-0.054 (0.04)	-0.067** (0.03)
Coordinator	-0.016 (0.05)	-0.024 (0.03)	0.005 (0.02)	-0.068 (0.04)	-0.021 (0.02)	-0.128*** (0.05)	-0.036 (0.03)	-0.046** (0.02)
Age	-0.008 (0.01)	0.007 (0.01)	0.012 (0.01)	-0.011 (0.02)	0.003 (0.01)	0.034** (0.02)	0.031*** (0.01)	0.046*** (0.01)
Intrinsic motivation	0.633** (0.26)	-0.061 (0.13)	-0.138 (0.10)	0.398** (0.19)	0.221* (0.13)	-0.288 (0.21)	-0.369** (0.15)	-0.157 (0.14)
Extrinsic motivation	-0.011 (0.11)	0.199** (0.09)	0.049 (0.08)	0.023 (0.12)	-0.087 (0.08)	0.104 (0.10)	0.241** (0.11)	0.155 (0.10)
group_size	0.051** (0.02)	-0.016 (0.02)	-0.034** (0.02)	-0.013 (0.02)	0.004 (0.01)	0.024* (0.01)	0.034*** (0.01)	0.023** (0.01)
net_size	0.218 (0.56)	-0.451 (0.35)	-0.045 (0.32)	-0.213 (0.37)	0.156 (0.30)	0.401 (0.39)	-0.305 (0.36)	0.232 (0.30)
int_net_density	0.527 (0.59)	0.126 (0.38)	0.443 (0.30)	-0.104 (0.46)	-0.322 (0.38)	0.284 (0.55)	0.674 (0.42)	-0.606 (0.39)
Political skills	0.164 (0.25)	0.066 (0.18)	0.283** (0.14)	0.264 (0.18)	0.109 (0.18)	-0.141 (0.28)	0.242 (0.20)	0.149 (0.18)
region_dummy	0.014 (0.32)	0.009 (0.25)	0.290 (0.20)	-0.134 (0.26)	-0.324 (0.24)	-0.615* (0.34)	-0.587** (0.29)	-0.307 (0.22)
CIBER_link (3)	Included	Included	Included	Included	Included	Included	Included	Included
conscientiousness	-0.289* (0.16)	-0.149 (0.11)	0.054 (0.10)	0.048 (0.13)	0.031 (0.10)	0.371** (0.16)	0.249** (0.12)	0.032 (0.12)
neuroticism	0.033 (0.13)	-0.062 (0.09)	0.162* (0.09)	0.437*** (0.12)	-0.131 (0.09)	-0.214 (0.13)	-0.065 (0.12)	0.069 (0.09)
openness to experience	-0.249 (0.15)	-0.104 (0.11)	-0.021 (0.09)	-0.025 (0.13)	-0.055 (0.11)	0.078 (0.12)	0.225** (0.11)	0.254** (0.11)
extraversion	-0.082 (0.15)	0.010 (0.08)	0.122 (0.08)	-0.009 (0.10)	0.069 (0.11)	0.294** (0.13)	0.353*** (0.11)	-0.130 (0.10)
agreeableness	-0.034 (0.17)	0.190 (0.14)	-0.212* (0.12)	0.210 (0.16)	0.169 (0.13)	0.376* (0.22)	-0.266 (0.17)	0.112 (0.14)
academic position (6)	Included	Included	Included	Included	Included	Included	Included	Included
institution_dummy (4)	Included	Included	Included	Included	Included	Included	Included	Included
CIBER_dummy (9)	Included	Included	Included	Included	Included	Included	Included	Included
net_less_two (<2 contacts)	-0.115 (0.47)	-0.048 (0.25)	0.307 (0.23)	0.057 (0.34)	0.217 (0.30)	0.583* (0.32)	-0.295 (0.31)	-0.222 (0.30)
Gender (Female)	-1.383*** (0.40)	-0.226 (0.24)	-0.504*** (0.19)	-1.070*** (0.29)	-0.621*** (0.21)	-1.087*** (0.29)	0.064 (0.29)	-0.125 (0.24)
PI_top papers	0.007 (0.03)	0.002 (0.02)	0.038*** (0.01)	0.017 (0.02)	-0.019 (0.02)	-0.046* (0.02)	-0.023 (0.02)	-0.017 (0.02)
PI_patents	0.014 (0.05)	0.008 (0.05)	0.004 (0.05)	-0.517** (0.23)	0.186*** (0.04)	0.138*** (0.05)	0.014 (0.06)	0.027 (0.04)
PI_coauthors	-0.463** (0.22)	0.019 (0.16)	0.158 (0.16)	-0.061 (0.21)	0.014 (0.16)	0.443*** (0.16)	-0.153 (0.17)	-0.114 (0.14)
PI_pp_companies	-0.852 (3.56)	3.220** (1.57)	-0.828 (1.54)	1.629 (2.08)	-0.369 (1.52)	8.858*** (1.74)	-1.571 (1.93)	0.417 (1.49)
PI_pp_hospitals	-0.394 (0.94)	0.515 (0.59)	1.098* (0.58)	-1.856** (0.76)	-0.729* (0.44)	2.202*** (0.59)	3.052*** (0.51)	0.781* (0.42)
Constant	-1.696 (2.21)	-2.132 (2.19)	-4.989*** (1.72)	-4.371** (2.22)	-2.824 (1.79)	-11.659*** (2.49)	-6.769*** (1.75)	-4.990*** (1.60)
Observations	363	364	364	364	646	646	646	646
Pseudo-R2	0.251	0.226	0.267	0.256	0.259	0.255	0.261	0.144

Note: * p < 0.1; ** p < 0.05; *** p < 0.01