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Working Paper Nº 2014-02

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Connections Matter: How Personal Network Structure Influences Biomedical Scientists' Engagement in Medical Innovation

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Abstract: In this study, we analyze the determinants of biomedical scientists' participation in various types of activities and outputs related to medical innovation. More specifically, we argue that scientists occupying brokerage positions among their contacts will in a more favorable position to deliver medical innovation outcomes, compared to scientists embedded in more dense networks. However, we also theorize that beyond a threshold, the coordination costs of brokerage may surpass its potential benefits. In addition to that, we study the influence of two individual-level attributes as potential determinants of the participation in medical innovation activities: cognitive breadth and perceived beneficiary impact. We situate our analysis within the context of the Spanish biomedical research framework, where we analyze a sample of 1,292 biomedical scientists.

Keywords: Social Capital, Ego-Network Brokerage, Medical Innovation, Translational Research, Perceived Beneficiary Impact, Cognitive Breadth

JEL Codes: D85, Z13, O31

1 Introduction and research context

An increasing amount of research in the fields of sociology and management has centered on whether and how the position of actors in a social network influences their creativity and innovation (Baer, 2010; Burt, 2004; Obstfeld, 2005; Wu, Chang, & Chen, 2008). These studies have provided robust evidence about the existence of a strong relationship between network structure and innovation performance. However, the question about the particular characteristics of network structures that are most conducive to innovation remains an open debate. This issue is of particular importance in the context of biomedical research, where initiatives to foster translational research and cooperation between biomedical communities have become central ingredients of the policy agenda to foster medical innovation.

The question of how to accelerate the diffusion of research findings into clinical practice has become an important issue among academics, practitioners and public policy actors. The concern stems from the fact that few of the most promising biomedical discoveries effectively result in direct and tangible impacts on human health (Contopoulos-Ioannidis, Ntzani, & Ioannidis, 2003). For instance, the length of time from a basic discovery to approval of a new drug averages around 13 years and the failure rate exceeds 95% (Collins, 2011); or as pointed out by Wheling (2010), from 1991 to 2000 only 11% of drugs delivered to humans for the first time were successfully registered, with success rates varying dramatically among therapeutic areas. Additionally, this literature has highlighted the difficult transit from basic scientific findings to different types of medical innovation, such as drug development or new medical treatments.

In order to increase the health benefits of investing in biomedical science, a discussion around the concept of translational research has consistently proliferated

among leading scholars from the biomedical research community (Duyk, 2003; F. Marincola, 2003; E. A. Zerhouni, 2007). There is substantial agreement on the idea that the essential objectives of translational research should involve interventions to improve human health through the rapid progression of basic scientific knowledge to patient benefit. The rhetoric and terminology of translational research has permeated the policy agenda of the majority of public and private funding agencies worldwide. For instance the US National Institute of Health (NIH) made translational research a strategic priority by releasing in 2003 the *Roadmap for Clinical Research* (Zerhouni, 2003). In Europe, initiatives in this direction have been also presented (European Science Foundation, 2012).

Even though "translational research means different things to different people" (Woolf, 2008, p. 471), and the past few years have witnessed a flourish of theoretical models adopting a terminology to conceptualize the different steps through which biomedical knowledge moves forward from the "bench to the bedside", there are some common foundations about what is generally understood by translational research that provide the grounds for the following working definition. Translational research refers to a mode of research based on the dialogue and cooperation among multiple actors - basic scientists, clinical scientists, medical practitioners, patients, among others – that elicits a bi-directional flow of knowledge with the objective to improve healthcare. This two-way flow of knowledge involves feeding basic scientists with questions for research based on clinical practice, and facilitating the transfer of new theories of disease pathways into clinical practice (Marincola, 2003; Rey-Rocha & Martín-Sempere, 2012).

In this paper we propose two contentions. First, the critical role played by "brokers" or "connectors" as a particularly salient issue in the translational research model. As pointed out by Hobin et al. (2012), a successful translational research environment

demands a structure that promotes interaction between different people trained across different disciplines and working in different contexts. For instance, an effective communication between those who are specialized in fundamental biology and those who have experience in clinical methods becomes essential to move knowledge forward through the translational research pipeline. However, moving and spreading new knowledge in the biomedical context is particularly challenging since it involves an effective communication and interaction between many different professional groups. Evidence suggests the presence of strong social boundaries between each of the multiple professional communities involved in biomedical research and healthcare (Ferlie, Fitzgerald, Wood, & Hawkins, 2005; Gittelman, 2013). These distinct communities are reflected in different professional roles, identities and traditional work practices. Therefore, a major challenge for translational research is to bring together contrasting scientific paradigms based on the basic and applied logics of biomedical research. Our first contention is that those researchers who are capable to liaise and coordinate a diverse range of actors contributing to the biomedical research process, should be more likely to develop new medical technologies and innovations in healthcare.

Second, in addition to the structure of their personal research networks, the scientists' involvement in medical innovations is likely to be a function of certain individual-level attributes. Participation in translational research activities and outputs are a good expression of the scientists' capacity to identify clinical needs (Hobin et al., 2012) and to successfully exploit routes to move fundamental knowledge into clinical applications. This implies an explicit focus on the micro-level, individual abilities and motivations of scientists towards research. More specifically we contend that the scientists' heterogeneity in terms of their cognitive breadth and their perceived impact on

beneficiaries may explain differences in the scientists' likelihood to develop medical technologies and be involved in innovations associated to the delivery of healthcare.

Extant literature of innovation in the biomedical context has taken explicit account of the critical importance of knowledge brokers to overcome collaboration barriers and bridge translational gaps (Currie & White, 2012; Lomas, 2007). However, research has not addressed empirically so far the question of which is the most effective structural pattern of collaborations at the micro-level to facilitate biomedical scientists' identification and exploitation of potential opportunities for innovation. We propose to look at this process through a social capital perspective since biomedical scientists can widely differ in their personal network structures and content. We expect different types of personal networks to be linked to the degree of involvement in medical innovation outputs. As a way to explore this relationship, we account for different types forms of ego-network structures drawing insights from social capital and social network literatures. Our ultimate goal is to go one step further in the understanding of the role of interactions and knowledge flows between biomedical actors as enablers of medical innovation.

The paper is structured as follows. In the following section, we begin by discussing the importance of considering the ego-centric structural position as an antecedent for the scientists' engagement in medical innovation. Afterwards, we acknowledge the relevance of cognitive skills and perceived impact of beneficiaries as potential antecedents of translational research. Then, we contextualize our research and present the results. The last section ends by discussing the main theoretical and empirical findings from our study.

2 Theory and hypothesis

2.1 Network brokerage and medical innovation

A significant body of literature from multiple fields has explored how the position occupied by individuals in a social network can influence creativity and other performance-related outputs. A social network can be defined as a set of actors and the relations that connect the actors (Kilduff & Tsai, 2003). An ego-centric approach to social networks defines the structure of each individual network in terms of lack of connectivity between the contacts in the network. Research from the fields of management and innovation have used ego-centric social network approaches to evidence that certain network positions partly explains a range of individual-level outcomes such as job performance (Sparrowe, Liden, Wayne, & Kraimer, 2001), innovation (Obstfeld, 2005; Wu, Chang, & Chen, 2008) or creativity in organizations (Baer, 2010; Burt, 2004; Perry-Smith, 2006). Scholars studying the processes explaining the creation of knowledge have also emphasized the role of particular network structures in facilitating knowledge creation (McFadyen & Cannella, 2004; McFadyen, Semadeni, & Cannella, 2009).

Although research has demonstrated the importance of the structural position in the network for innovative-related outputs, there is less agreement on the underlying mechanism through which this structural advantage is gained. In this sense, research dealing with structural relationships and their impact indicates that two opposite network structures - structural holes and dense networks - both bear a potential to generate positive effects on innovation. These effects, however, operate through differentiated mechanisms in each case. On the one side, Burt (1995) suggested that the greater benefits

from a structural position are obtained through spanning structural holes. When a focal individual (*ego*) is connected to two individuals (*alters*) that are not connected between themselves, a structural hole exists. In the research network literature, an individual holding this network position is known as a 'broker' (Burt, 1995; Fernandez & Gould, 1994). Positive returns to brokerage positions are well documented (e.g.: Cross & Cummings, 2004; Lee, 2010; Soda, Usai, & Zaheer, 2004), and are commonly attributed to a privileged access to novel information and a greater control over its use. Having an egocentric network rich in structural holes provides access to more diverse, potentially novel information (Burt, 2004; Zhou, Shin, Brass, Choi, & Zhang, 2009). The underlying rationale is that alters that are not connected among themselves belong to different social and/or professional circles. This brokerage position enables the focal individual to gain access to heterogeneous perspectives and non-redundant knowledge. There is also a control advantage derived from occupying a brokerage position. Since actors in a brokerage position provide the only connection between two other actors, any flow of information or knowledge between these two actors necessarily passes through the broker (Burt, 1995; Lee, 2010). Controlling the flow of information between disconnected others may allow the focal actor to determine how this information will be used and which actors will be included or excluded in a brokered exchange (Rider, 2009).

On the other side, it has been argued that cohesive network structures, in which actors are densely linked to each other, are desirable for a number of reasons. First, networks formed by closely tied actors facilitate the emergence of mutual trust, common norms and a collective sense of reciprocity that, in turn, smooth the flow of knowledge among the members in the network and favor the creation of novel knowledge (Coleman, 1994). Because actors in dense networks are more able to rely on norms and sanctions against opportunism (Zaheer & Bell, 2005), misbehavior is less likely to arise and

coordination costs in the network are reduced. Dense networks can also increase actors' engagement in putting into practice the potential knowledge accessed through the network because it is easier to gain the cooperation of network members towards a common interest (Obstfeld, 2005; Phelps, Heidl, & Wadhwa, 2012). Some scholars have found that network density increases knowledge sharing and knowledge creation among network contacts (Morrison, 2002; Reagans & McEvily, 2003). Dense networks also appear to have positive influences on creativity. For instance, Amabile, Barsade, Mueller, & Staw (2005) suggest that closed networks promote positive affect between the network members, and this predicts higher levels of creative-related outcomes. From an ego-network perspective, dense networks are characterized by the existence of close triads between ego-networks' direct contacts. When two ego's contacts share a tie between them, a closed triad exists. Hence, dense ego-networks are measured as the existence of closed triads between ego and alters (Burt, 2004).

The theoretical discussion raised above has important implications for modeling the impact of specific ego-network structures on the participation of biomedical scientists in activities and outputs related to medical innovation. We expect that ego-networks rich in structural holes are particularly important predictors of the scientists' engagement in medical innovation. The rationale for this claim is that actors with the capacity to mediate between disparate communities may be in a more advantageous position to identify, locate and mobilize the resources and capabilities needed to get involved in medical innovation.

Holding an ego-network rich in structural holes reflect a mediating role between actors located in disparate communities. That means that the range of knowledge and resources available for the focal scientist will be comparatively higher compared to scientists embedded in dense networks (Rotolo & Messeni, Petruzzelli, 2012), who will

tend to rely on more homogeneous knowledge. Linkages to weakly connected actors means a greater exposure to different approaches, outlooks and interests, allowing the focal scientist to frame their research problems from a broader perspective and to align these problems to the reality of human disease and the needs of health care professionals from different social groups. Thus, keeping a sparse collaborative network makes additional cognitive material available for the focal scientist, increasing the recombining knowledge possibilities and the subsequent materialization in the development of novel therapeutic solutions.

We expect, however, that our predicted relationship between ego-network brokerage and the degree of participation in medical innovation is not lineal. Empirical evidence on ego-network research shows, for instance, that the benefits of weak ties for creativity-related outcomes is limited, and that there is an optimal level, rather than a maximum level, of weak ties where outcomes are maximized (Baer, 2010; A. McFadyen & Cannella, 2004; Zhou et al., 2009). Similar effects may be expected for the case of biomedical scientists occupying brokerage positions. Spanning structural holes entails costs for the broker in terms of time, energy and cognitive resources needed to cultivate and maintain these ties. Disconnected alters tend to belong to different social and professional circles (Burt, 1995) and be dissimilar among them in terms of cognitive frames and norms of conduct. Hence, the necessary egos' cognitive efforts to simultaneously communicate with alters may be higher compared to scientists embedded in more dense networks. Further, ego's capability to process and benefit from the diversity of knowledge and resources coming from the network is limited (Cyert & March, 1963; Ocasio, 1997; Simon, 1955). When the diversity of information accessible through the network is too large, individuals may experience information overload, which makes more difficult to make sense of it (Weick, Sutcliffe, & Obstfeld, 2005;

Zhou et al., 2009) and therefore use it to identify and exploit opportunities for medical innovation.

While the current debate on translational research has provided insights into the critical role of brokers for the mobilization of basic knowledge into medical innovation, this literature has not empirically assessed this relationship. Furthermore, the potential costs of brokerage positions have not been considered, thus implicitly assuming positive, linear relations between brokerage positions and medical innovation outcomes. However, costs associated to brokerage positions are likely to operate in our context of analysis. For instance, basic scientists spanning structural holes between clinical researchers and patients' representatives need to be responsive to the distinct interests of both communities (Ferlie, Fitzgerald, Wood, & Hawkins, 2005). This requires the investment of a significant amount of cognitive resources and attention to achieve the innovation performance benefits associated to brokerage positions. Lacking common ground may limit the potential benefits from this structural position.

Thus, we can expect that an adequate balance between the benefits and the costs of brokerage will be obtained at intermediate levels of ego-network brokerage and therefore, the participation in medical innovation activities will be higher at that point.

Hypothesis 1: *Ego-network brokerage will have an inverted u-shaped relationship with scientists' degree of participation in medical innovation activities, which will be maximized at intermediate levels of brokerage.*

2.2 Individual determinants of biomedical scientists' participation in medical innovation

Some prior work on translational research has focused on the individual factors that are particularly critical for the adoption of translational-research practices among

biomedical scientists. For instance, research has noted that it is important to count with an interdisciplinary educational background (Feldman, 2008; Rubio et al., 2010). Research also suggests that there is a significant motivational factor behind the scientists' engagement in medical innovation activities. The desire to "make a difference" by ultimately improving human health may fuel the scientists' interests in searching for effective ways to make a positive impact. Testing basic models into clinical reality, for instance, may be viewed as a way to channel this interest (Hobin et al., 2012). These ideas led us to question the relevance of two blocks of individual-level features potentially related to the scientists' engagement in various forms of medical innovation.

Breadth of cognitive skills. An important challenge to bridge the gap between basic research and clinical practice is directly related to the biomedical scientists' skills and academic background. In the past, basic biomedical scientists were only assumed to develop research skills aimed to make their mark and gain reputation in their scientific field. However, the adoption of a translational research logic to the organization of medical research suggests that an adequate combination of basic and clinical skills is essential to maximize the scientists' participation in medical innovation activities. For instance, Hobin et al. (2012) indicate that there are three skills that biomedical scientists must learn to succeed when engaging in research projects with an explicit translational component. The first one is the ability to define a health need with the same precision as a basic science hypothesis. The second is about understanding how to develop inexpensive and robust assays applicable to humans. And the third skill is related to the conceptualization of a pathway to regulatory approval or clinical adoption. Although some specific training programs are increasingly covering these issues, basic research programs are normally focused on the specialization of one (or few) research topics. It is well documented that narrowly defined training trajectories represent a barrier that

complicates a smooth translation of basic knowledge into clinical practice (Cochrane et al, 2007). Other scholars have suggested that to cross the gap from lab bench to patient bedside, biomedical scientists should receive specific training in research methodology including clinical trial design and medical statistics (Homer-Vanniasinkam & Tsui, 2012; Kurpinski, Johnson, Kumar, Desai, & Li, 2014). Similar arguments apply for biomedical scientists performing biomedical research at the clinical side of the translational research continuum. It is increasingly acknowledged that clinical research and clinical practice should be fully based on empirical evidence (Ioannidis, 2004). This means that clinical scientists should be able to prioritize, for instance, those biological problems with a greater potential impact for clinical practice. Or they should be able to recognize when sufficient evidence has been accumulated for an intervention to be translated into a clinical guideline or a new treatment (Kelley et al., 2012; Ferlie et al., 2005). However, most training programs in biomedicine are still grounded on a strict separation between academia and health care (Borstein et al, 2011), which perpetuates the existing silos between theory and practice.

Taken together, the above arguments support the prediction that those scientists who have acquired a broader set of basic and clinical skills will be more capable to bridge the gap between basic research and clinical practice, and as a consequence they will be more susceptible to engage in a broader range of medical innovation activities, compared to peers with a narrower set of basic and clinical skills. This gives rise to the following hypothesis:

> **Hypothesis 2***: Breadth of cognitive skills will have a positive relationship with the scientists' degree of participation in medical innovation activities.*

Perceived impact on beneficiaries. Social psychology scholars have conceptualized *perceived impact on beneficiaries* as the degree to which individuals are

aware that their own actions have the potential to improve the welfare of others (Grant, 2008; Grant, 2007). Individuals reporting higher levels of perceived impact on beneficiaries are particularly conscious about the direct connection between their behavior and the outcome they can exert in other people or groups. It has been documented that the higher the perceived impact on beneficiaries, the greater the individual's engagement in actions and behaviors aimed to channel this perception into explicit outcomes (Aknin, Dunn, Whillans, Grant, & Norton, 2013). Thus, high levels of perceived impact on beneficiaries has been theorized to result in greater persistence and dedication (Grant, 2008), particularly towards those activities through which the action-result relation becomes more straightforward.

In our context, we expect that a higher perception of exerting a positive impact on patients and clinical practitioners will directly influence the scientists' engagement in actions and outcomes related to improvements on existing therapeutic treatments and discovery of new ones. One of the main tenets of the translational research debate lays on the idea that biomedical researchers should be more aware about patients and clinical needs (Marincola, 2011). This may lead to the generation of biomedical knowledge and research results with a greater potential to be translated into practice. Biomedical scientists may conceive their participation in medical innovation as a form to connect their research activities to patients and clinical staff needs, and thus may devote greater efforts to bridge the gap between basic understanding and healthcare delivery. For example, clinical guidelines have emerged as critical tools for improving healthcare practices, and represent a tool to strengthen connections between scientists, clinical practitioners and patients (Nigam, 2013). We contend that scientists particularly aware of the influence they exert on patients through their work will be more likely to embark in the identification of opportunities for translational research as well as in the exploitation

of such opportunities in various forms, such as in the design of clinical trials or the delivery of clinical guidelines. This idea is partially suggested by previous findings from the biomedical research community. In 2011, the Federation of American Societies for Experimental Biology (FASEB) conducted a survey addressed to basic and clinical scientists whose main objective was to explore the benefits for scientists to engage in translational research activities. Results from 1,770 collected responses showed that nearly three-quarters of the respondents initially decided to participate in translational research activities because they were motivated to exert a direct and positive impact on a particular disease or condition. Similarly, more than half of the respondents reported that they pursued to exert an impact on human health in general through their research activities (Hobin et al., 2012). This supports the idea that the greater the scientists' perception of impact on patients and clinical practitioners, the higher their capacity to identify and exploit potential opportunities to participate in medical innovation. Thus, we propose the following hypothesis:

> **Hypothesis 3***: Perceived impact on patients and clinical staff will have a positive relationship with the scientists' degree of participation in medical innovation activities.*

3 Methods

3.1 Research context

We situate our analysis within the biomedical research field in Spain. In the course of the last decade, 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 representative step towards this aim 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 as a mean to foster excellence in biomedical research as well as to improve the quality, value and effectiveness of the healthcare services delivered to the general population. A crucial part of the CIBER program was the development of a formal network structure to promote research cooperation among professional groups working on similar biomedical research areas, lending greater weigh to hospitals and clinical research groups. Thus, applicant biomedical groups could be placed at universities, public research organizations, hospitals, clinics and biomedical research foundations in Spain. Participant groups were selected through open calls, each call focused on a specific range of pathologies or diseases of strategic interest to the Spanish National Health System. The acceptance of research groups in the program was subjected to an evaluation process based on each groups' previous research excellence and contributions to healthcare. The selected groups were organized around nine biomedical research networks, each one related to a particular biomedical research area: 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).

3.2 Sample

The CIBER program provides us with a unique opportunity to study the collaborative networks of biomedical scientists, as well as their main individual characteristics and their degree of participation in a variety of translational research activities and outputs. Our research population comprised all biomedical scientists and technicians of every research group belonging to each of the nine CIBER networks. We

contacted CIBER' Scientific Directors to obtain explicit support for our research and collected e-mail addresses and complete names of scientists and technicians included in all CIBER networks. To develop the survey questionnaire, we conducted a number of interviews with Scientific Directors, research groups' principal investigators and biomedical scientists between June 2012 and March 2013. An extensive list of activities and outputs related to translational research was obtained from biomedical literature and validated through the interview process. The questionnaire was organized in multiple sections, with a particular focus on the structure and content of the scientists' personal network. The questionnaire also asked for the involvement of scientists in a range of medical innovation activities. Attitudinal and motivational questions were also included in the questionnaire, together with a series of questions on respondents' socio-demographic aspects, such as age, gender or educational level. In April 2013, the questionnaire was distributed to 4,758 biomedical scientists and technicians from all nine CIBER networks. In collaboration with the CIBER Scientific Managers, all scientists were encouraged to participate in a study aimed to explore the relationship between the scientists' collaboration network, their individual characteristics and their participation in medical innovation activities and outputs. 1,309 scientists responded the questionnaire, meaning an overall response rate of 27.5%, which is fairly similar to other surveys on academic scientists (Perkmann et al., 2013). The distribution of our sample is as follows: 31,9% of our respondents were affiliated to a University, 35,3% to a hospital, 28,9% to a public research institution and 4% were affiliated to private research bodies and other similar institutions. Regarding their role in the research group, 10,4% of our respondents are principal investigators of their research groups, 53,8% are post-doctoral scientists, 18,2% are pre-doctoral scientists and 14,2% are technicians or similar positions. Response rates across CIBER are fairly evenly distributed (see details in the Appendix).

We conducted a number of analyses to test for non-response bias. First, we compared response rates in terms of the institutional affiliation, the hierarchical position in the research group and the size of the group (archival analysis). Though we found significant differences in some aspects, the overall distribution of response rates is fairly homogeneous (see Table in the Appendix). Furthermore, we performed a wave analysis to check whether responses differ with regards of the date respondents completed the questionnaire. This study complements the archival analysis, since the response patterns of late respondents may be considered as a proxy for the response patterns of non-respondents (Rogelberg & Stanton, 2007). Our sample was classified 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 actual survey variables (participation in medical innovation activities, ego-network size). The hypotheses of differences in the means are all rejected, suggesting that our data does not suffer from major problems of non-response bias.

3.3 Variables

3.3.1 Dependent Variable: Degree of participation in medical innovation

To capture the scientists' degree of participation in different types of medical innovation, 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 forward and backward through different stages of the research pipeline. These breakthroughs include the discovery or invention stage, often associated with basic research on the root cause of diseases, and generally epitomized by the identification of a new molecular target for the discovery of new drugs or diagnostic

devices (*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 (Westfall, Mold, & Fagnan, 2007; Dougherty, 2008; Khoury et al., 2007; Sung et al., 2003). While dominantly based on a linear approach from 'the bench to the bedside', they provide a foundation to address the variety of indicators associated to medical innovation.

We end up with a list of 14 items reflecting this variety of medical innovations, which were further validated by biomedical scientists interviewed during the pilot phase of the survey. The full list is shown in Table 1 below, as well as a sample of academic references supporting the association between each category of items and the delivery of 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.* They were offered a drop-down menu where they could choose any number between 0 to 10 times, or more than 10 times. We conducted a principal components analysis (PCA), finding that 11 of our innovation-related outputs grouped into 4 factors. Following varimax rotation, results showed that Factor 1 explained 22% of the total variance in the items, comprising outputs related to invention and commercialization (*Product generation: invention and commercialization*). Factor 2 accounted for 16% of the variance in the items (*drug development*). Factor 3 explained

13% of variance, grouping outcomes associated with the development of guidelines for clinical practitioners and patients (*clinical guidelines*). Factor 4 accounted for 10% of the total variance in the items and groups all items related to the development of diagnostic devices and prevention-related activities (*Diagnostics and prevention*)[1].

Table 1. Grouping medical innovation items into categories.

Medical Innovation Categories (Factors)	Items	Key references
Product Generation (invention and commercialization)	Patent applications for new drugs Licenses granted from patents Participation in spin-offs	(Ding et at., 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[2]	(Duyk, 2003; Khoury et al., 2007; Westfall, et al. , 2007)
Clinical Guidelines	Clinical guidelines for health practitioners Clinical guidelines for patients	(Cochrane et al., 2007; Dougherty & 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 & Lorenzi, 2011; Khoury et al, 2007)

Table 2 shows the rate of scientists that have participated at least once in a particular type of medical innovation category, according to the institution they are affiliated. The results reported in Table 2 reflect that the most widespread medical innovation is the development of clinical guidelines. About 23% of scientists had participated in the development of clinical guidelines during the year 2012. Activities related to diagnostics and prevention were the least frequent form of medical innovation. Only a 10% of scientists have been involved in such type of activities. A deeper analysis of the results reflects that there are significant differences in the level of involvement in medical innovation categories across respondents' affiliation. Scientists affiliated to

[1] Details of the PCA analysis can be found on Annex 1

[2] 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"

hospitals and clinics have participated more frequently in all range of medical innovation categories, except for the 'invention and commercialization' category.

Table 2: Involvement of scientists in the four medical innovation categories, according to institutional affiliation (% of scientists engaged at least once over the year 2012 in any of the items included in each of the four medical innovation categories).

	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
Other organizations	15.2	8.8	12.0	7.2	125
Total	15.5	19.0	22.8	10.2	1261

We developed an indicator to assess the degree of participation in different forms of medical innovation. To do so, we coded scientists from 0 to 3. If scientists reported no participation in any of the four categories defined below, we coded 0 (56.3% of our sample). If they had engaged at least once in one category, we coded 1 (25.3%). Similarly, if they had participated at least once in two of the defined categories, we coded 2 (14.2%). Finally, if they had participated at least once in three or in all four categories, we coded 3 (4.2%). Our dependent variable was further rescaled between 0 and 1, as we explain in the section on the econometric results.

3.3.2 Independent Variables

Ego-network brokerage. We used an ego-centric network approach (e.g.: Baer, 2010; Smith, Collins, & Clark, 2005) to capture each scientist' network of critical contacts. Our survey allowed each respondent (ego) to list the names of up to ten contacts (alters) from outside their research group whom they considered critical 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 was chosen because we were particularly interested in capturing the network of contacts that were important for each scientist' research purposes. In response to this name-generator question, respondents provided an average number of 3.57 unique contacts outside their research group. Then the survey asked respondents for information on each alter-alter relationships (Burt, 1992; Podolny & Baron, 1997). Although ego-network data is based on individual perceptions, it has been shown that measures from ego-network data are highly correlated with measures collected from whole-network data (Everett & Borgatti, 2005) as well as from data collected from both members of the dyadic relationship (Battilana & Casciaro, 2013). Building on previous literature, we calculated ego-network brokerage by counting the number of structural holes for each ego-network (Everett & Borgatti, 2005). That is, the absence of alter-alter ties between each ego-network contact. This sum was then divided by the total number of possible alter-alter ties, $n\ (n - 1) / 2$. The maximum brokerage score occurs when there are no connections between alters in the scientist personal network (ego-network). 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 on ego-network brokerage. Since the ratio of structural holes is sensitive to ego-network size, we controlled for the effect of size in our regression model.

Breadth of cognitive skills. Our literature review indicated that key barriers to the participation of biomedical scientists in medical innovations were directly related to the (lack of) specific skills and the highly specialized academic training of scientists (Arar & Nandamudi, 2012; Coller, 2008). We identified a pool of biomedical-related skills and abilities that were critical for an effective two-way transit between the "bench

and the bedside[3]". These skills were completed and validated with preliminary interviews with biomedical scientists. Finally, we included in the questionnaire a list of nine skills and specific abilities: *development of clinical trials, clinical guidelines, state of the technology, clinical pharmacology, biostatistics, molecular biology; experimental methods, animal experimentation and studies with control groups*. To elicit how many of those skills were possessed by the respondents, the following question was asked: "*Have you received, through your career, training on one or more of the following activities?"*. We pointed that this training could have been received in the form of face-to-face lectures, on-line courses or any other mode. We operationalized the variable as a direct count of the number of different skills indicated by each respondent.

Perceived impact on beneficiaries. To capture the perceived impact of scientists' research results into social agents from a clinical context, we used a seven-point Likert scale adapted from the *beneficiary impact* scale proposed by Grant (2008). Since all our respondents were involved in biomedical research, we explicitly consider the perceived impact of their research activities on three different groups: patients, clinical practitioners and vulnerable social groups. Specifically, our question asked: "*Please, indicate the extent to which the following collectivities benefit more directly from the results obtained from your research activities"*. We averaged the responses to the three items to create a composite indicator of the perceived clinical impact of the research activities (Cronbach's Alpha = 0, 78).

Control variables. Several factors that are outside the scope of our hypotheses could influence the respondents' degree of participation in medical innovation. We controlled for these factors in the statistical analysis. We accounted for control variables

[3] Journals considered for the literature review include: Journal of the American Medical Association (JAMA), Nature Medicine, Translational Research, Journal of Translational Medicine, British Medical Journal and Clinical and Translational Science (among others).

at the individual level and at the research group level. To control for the effect of accumulated learning and experience in the propensity to engage in TR activities, we controlled for the age of the respondents (*Age*). Similarly, we also used a dummy variable to account for those respondents who have a PhD, taking value of 1 if the respondent reported to have a PhD degree, zero otherwise (*PhD*). Given that the number of contacts may affect the number of structural holes to which each respondent can access we effectively controlled for the size of each scientist' ego-network. We included a dummy variable which was coded 1 for those respondents having a large ego-network (more than 4 contacts reported by the respondent). Selecting this threshold allowed us to capture the top 30% of our respondents having larger personal networks. Respondents with 4 or less contacts were coded 0 (*Ego-network external size*). In addition, we defined nine dummy variables to control for the scientific field of each respondent, leaving CIBER-BBN as the default group. Depending on the type of institution where each respondent belongs there may be few or many opportunities to engage in medical innovation activities. Accordingly, we controlled for that by including 4 dummies reflecting the type of institution of the respondent. Specifically, the type of institution can be *university*, *hospital/clinic*, *public research organization* and *other type of institution* (the latter being the reference category in the econometric analysis). Finally, we resorted to the CIBERs' scientific reports to retrieve information about the number of scientists working in each research group (*Group size*).

4 Results

4.1 Descriptive analyses and correlations

Table 3 provides the descriptive statistics and correlations for the variables used in the model. The average ego-network brokerage score was 0.63 (SD=0.33). For the

purpose of this study, we are particularly interested in the heterogeneity of the respondents' ego-network structure. The histogram displayed below (Figure 1) shows that biomedical scientists' exhibit significant variability in terms of their ego-network structure, reflected as their brokerage scores. We observe that the proportion of cases at the extremes of the score-range distribution is particularly high. The high frequency of 1's indicates that, for a significant proportion of scientists, none of the egos' contacts are connected among them, while the high number of 0's corresponds to those egos whose contacts are all connected among them.

Figure 1: Histogram of ego-network brokerage scores

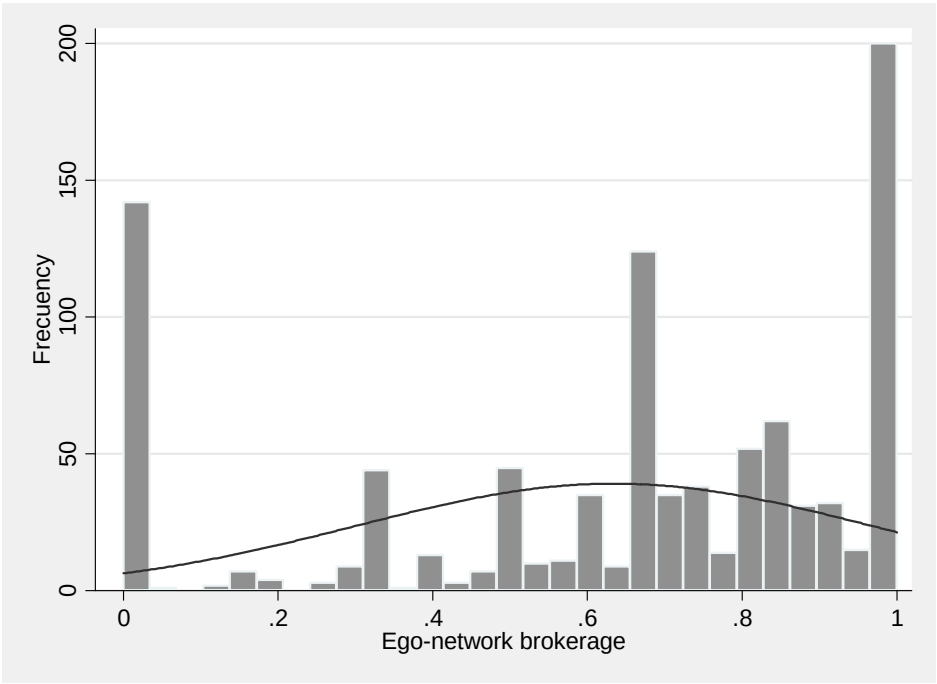


Table 3: Descriptives and Correlations

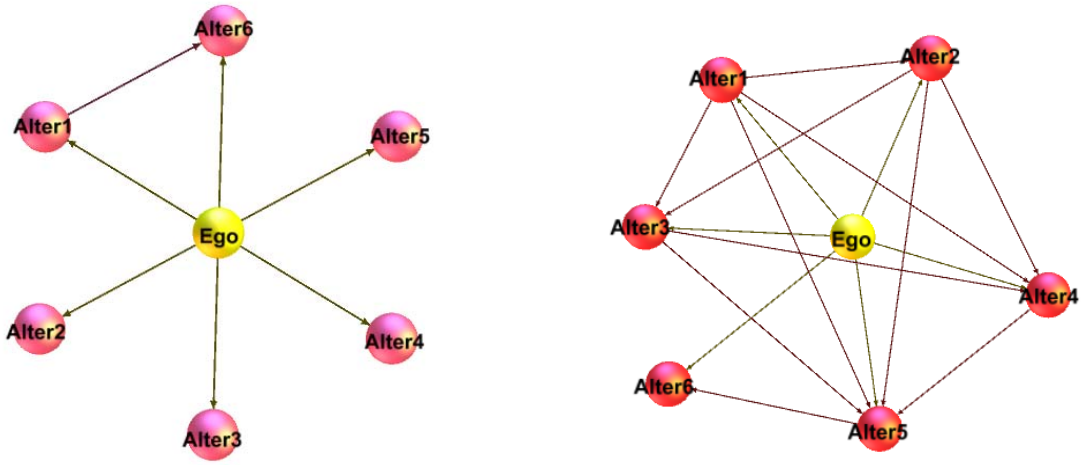
	Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1.	Engagement in Medical Innovation	0.221	0.290	0.000	1.000	1.000										
2.	Ego-network brokerage	0.634	0.333	0.000	1.000	-0.010	1.000									
3.	Cognitive breadth	2.711	1.882	0.000	9.000	0.213***	0.002	1.000								
4.	Perceived beneficiaries	4.437	1.455	1.000	7.000	0.266***	-0.111**	0.181***	1.000							
5.	Large ego-network[a]	0.310	0.463	0.000	1.000	0.124***	0.185***	0.155***	0.108***	1.000						
6.	Age	41.894	10.651	23.000	78.000	0.282***	0.054	0.096	0.062*	0.129***	1.000					
7.	PhD[a]	0.628	0.484	0.000	1.000	0.134***	0.058†	0.192***	-0.010	0.137***	0.410***	1.000				
8.	Group size	18.248	10.457	2.000	79.000	-0.038	-0.042	-0.131***	-0.031	-0.031	-0.193***	-0.096**	1.000			
9.	University[a]	0.306	0.461	0.000	1.000	-0.151***	0.036	-0.109***	-0.150***	0.005	-0.039	0.076†	0.135***	1.000		
10.	Hospital[a]	0.324	0.468	0.000	1.000	0.362***	-0.042	0.187***	0.232***	0.038	0.188***	0.032	-0.055†	-0.460***	1.000	
11.	Public Research Organization[a]	0.270	0.444	0.000	1.000	-0.165***	0.013	-0.050†	-0.100***	-0.067*	-0.112***	-0.089*	-0.077**	-0.404***	-0.422***	1.000

†10% (p<0.10); *5% (p<0.05); **1% (p<0.01); ***0.1% (p<0.001).
[a] Dummy variables

Illustrating the ego-networks of two scientists from our sample is useful to visualize how their personal network structures differ and, therefore, how different are the potential sources of information they can tap into when facing a research problem. To do so, we selected two respondents from the same CIBER network (CIBER-NED: neurodegenerative diseases) and with the same external network size (six alters). Despite the identical size of their external networks, , they exhibit a significant difference in their brokerage score. The scientist on the left side (*Ego 1*) reported that only two of the mentioned alters (*alters 1 and 6*) were connected among them, while all other alters do not known each other. That implies that the only connection between alters is provided through their mutual relations with the ego. As outlined above, disconnected contacts are more likely to operate with different ideas and practices. It is this broader exposure to variation that provides the ego an opportunity to develop different ways of looking at medical problems and access to a diverse range of resources and knowledge. The ego-network brokerage score for this respondent is comparatively high: 0.933 (one reported connection among alters, over fifteen possible). In contrast, the second scientist reported to have a much more densely connected network. The closure benefits of ego-networks are related to more efficient coordination of alters as trust is more easily elicited in this case. However, it is likely that much of the information and resources accessible through these contacts will be redundant, since it will be much more homogeneous compared to the previous case. In this case, the brokerage score is comparatively low: 0.267 (eleven reported connections among alters, over fifteen possible).

Figure 2: Graphical representation of two ego-network structures

Ego 1 **Ego 2**



4.2 Econometric analysis and results

Given that our dependent variable takes non-negative integer values (ranging between 0 and 3), standard regression techniques, such as OLS, are not fully appropriate for modelling this type of variables. To accommodate the bounded nature of our dependent variable, we conduct a Fractional Logit regression by rescaling the original scores within the range between 0 and 1.[4] Fractional Logit regressions are particularly suitable for dependent variables that are bounded (such as proportions and percentages) or for constructed variables crafted to take values within a specified range (such as Likert scales) (Fossett et al., 2012). The results of the Fractional Logit regression are reported in Table 4, together with OLS results that serve as a point of reference. In both cases, we provide the results for three Models. Models 1 and 2 include our full sample. However, as some of the researchers reported having zero or only 1 relevant contact, they cannot play any type of brokerage role by definition. In these cases, recognizing that the absence

[4] We rescale the scores of the original variable Y_i into a proportion P_i, such as: $P_i = (Y_i - Y_{min}) / (Y_{max} - Y_{min})$, where Y_{min} e Y_{max} are the extreme values of the original variable Y_i.

of contacts is qualitatively different from a zero score for brokerage, we have included a dummy variable (i.e. Dummy Ext. Contacts < 2), to indicate that a score of zero for this individuals reflects having less than two critical external contacts. While Model 1 includes only the control variables, Model 2 shows the results for the full model. Our Model 3 is the one including only those researchers (i.e. 853 observations) who report at least two critical external contacts.

In Hypothesis 1 we predicted a quadratic (inverted U-shaped) relationship between the ego-network brokerage score and the involvement in medical innovation. The coefficient for the ego-network brokerage is positive and significant, while the coefficient for the ego-network brokerage squared is negative and significant, in our full models. Figure 3 shows the quadratic association between ego-network brokerage score and the degree of participation in medical innovation. The shape of the relationship is consistent with the hypothesis. Thus, Hypothesis 1 was supported.

Hypothesis 2 predicted that the breadth of cognitive skills was positively associated to the involvement in medical innovation. The coefficient is always positive and significant, which provides support for hypothesis 2. Hypothesis 3, which proposed that scientists' perceived impact on patients and clinical practitioners would be positively related to their involvement in medical innovation, was also supported. The coefficient is positive and significant in all our specifications.

Among the control variables, we found that scientists working at hospital settings are more likely to participate in medical innovation. Further, we found that age also predicts the engagement in medical innovation.

Figure 3: Ego-network brokerage and engagement in medical innovation

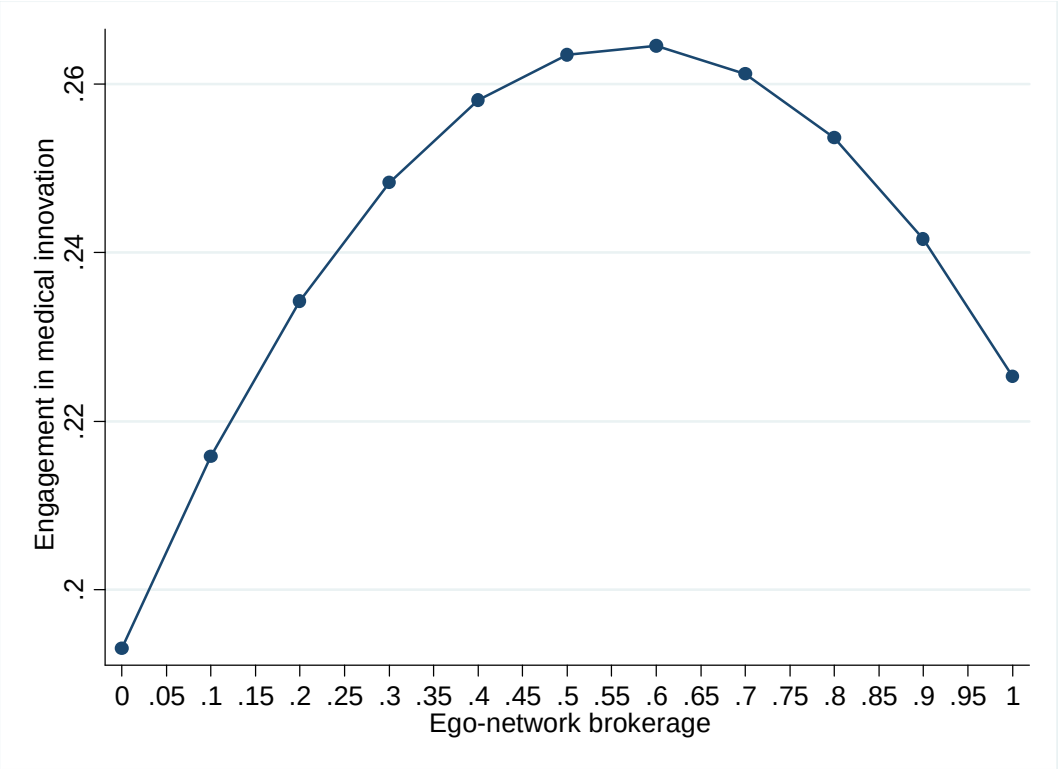


Table 4. Results for Fractional Logit and OLS Regression Analyses

	Fractional Logit			OLS		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Predictor variables						
Ego-net. brokerage	---	1.604**	1.721**	---	0.247**	0.249**
		(0.739)	(0.704)		(0.101)	(0.104)
Ego-net. brokerage^2	---	-1.259*	-1.320**	---	-0.220**	-0.217**
		(0.694)	(0.661)		(0.094)	(0.098)
Cognitive breadth	---	0.114***	0.125***	---	0.018***	0.021***
		(0.033)	(0.036)		(0.005)	(0.005)
Perceived benefic.	---	0.289***	0.323***	---	0.034***	0.039***
		(0.041)	(0.048)		(0.006)	(0.007)
Control variables						
Age	0.033***	0.034***	0.036***	0.005***	0.005***	0.005***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Large ego-network	0.258**	-0.023	-0.043	0.040**	0.001	-0.003
	(0.126)	(0.145)	(0.139)	(0.182)	(0.019)	(0.020)
PhD	0.157	0.190	0.015	0.020	0.018	0.004
	(0.126)	(0.132)	(0.155)	(0.018)	(0.018)	(0.022)
Group size	0.005	0.008	0.011*	0.001	0.001	0.002*
	(0.006)	(0.006)	(0.007)	(0.001)	(0.001)	(0.001)
University	0.057	0.050	-0.155	-0.001	0.010	-0.005
	(0.197)	(0.206)	(0.223)	(0.028)	(0.028)	(0.033)
Hospital	1.150***	0.982***	0.924***	0.189***	0.169***	0.168***
	(0.202)	(0.211)	(0.228)	(0.029)	(0.029)	(0.034)
Public Res. Org.	0.124	0.082	0.051	0.018	0.025	0.024
	(0.200)	(0.209)	(0.229)	(0.029)	(0.028)	(0.034)
Dummy Ext. Contacts (< 2)	-0.273**	0.111	---	-0.028	0.014	---
	(0.135)	(0.195)		(0.019)	(0.027)	
Constant	-3.330***	-5.168***	-5.029***	-0.082**	-0.294***	-0.310***
	(0.314)	(0.399)	(0.438)	(0.045)	(0.054)	(0.065)
Dummy CIBERs (8 dummies)	Included	Included	Included	Included	Included	Included
Adjusted - $R^{2\,(1)}$	0.193	0.235	0.230	0.182	0.226	0.219
Observations	1157	1157	853	1157	1157	853

* $p < 0.1$, ** $p < 0.05$, *** p 0.01

(1). For OLS, we report Adjusted R^2. For Fractional Logit, our R^2 is the square of the correlation between predicted and original values of our dependent variable.

5 Conclusions and implications

Our study aimed to theoretically and empirically analyze the medical scientists' personal network structures and individual attributes that are particularly conducive to their participation in a range of medical innovation activities. The majority of the discussion around the relevance of translational research and innovation in healthcare has emphasized the importance of promoting collaborative links between biomedical agents belonging to different communities of practice, but much less has been discussed around the potential costs associated with the development and maintenance of brokerage positions. Combined with the fact that medical scientists also differ in their capacity and willingness to establish effective research networks, this suggest room to a deeper analysis on the consequences of occupying brokerage positions in the medical context. .

Thus, this study elucidates the theoretical link between ego-network structure and participation in medical innovation activities. It investigates what types of personal networks are most conducive to innovation in biomedicine. While existing social capital research generally recognizes that innovation is a socially embedded endeavor, significant gaps remain in understanding whether there is an optimum level of personal network brokerage in which scientists' engagement in medical innovation is maximized. Our results show that there is an inverted U-shape relationship between scientists' ego-network brokerage scores and their participation in innovation. We see this as a reflection of the theorized trade-off between sparse and dense personal networks. On the one hand, results support the logic that the information and control advantages associated with brokerage positions (Burt, 1995, 2004) operate to facilitate scientists' participation in various forms of medical innovation activities. From a normative perspective, our results suggest that scientist devoting more time and efforts in cultivating and maintaining a

sparse network of contacts and interactions outside their formal research group would be in an advantageous position to deliver higher levels of medical innovation. On the other hand, our data confirmed that potential brokerage benefits do not come without a cost. Beyond a threshold, costs of building and maintaining a sparse network may surpass its potential benefits and ultimately be detrimental for the scientists' participation in medical innovation activities. These costs might be reflected in the form of higher coordination needs or a decreasing trust among network members, which may difficult the flow of knowledge around the network or cognitive costs related to the utilization of disparate pockets of knowledge. Further, actors connecting disparate others are subjected to different sets of role expectations, which may be sometimes in conflict (Soda & Zaheer, 2012). Therefore, our results show that both facets of brokerage's potential actually operate in the medical context, indicating that the most effective personal network structure lays at an intermediate level between a dense network (where most of the contacts know each other) and a sparse network (where most of the contacts do not known each other).

This study also identifies two individual-level variables that exert a significant impact on the participation in medical innovation, namely cognitive breadth and perceived beneficiary impact. We presented a pool of skills associated with basic biomedical and clinical research. Those scientists who reported to have a wider knowledge about the proposed skills were more likely to participate in innovation. This suggests the need to formalize and promote translational research studies and courses as a way to facilitate communication and integration between biomedical agents. These findings provide empirical evidence to recent claims from the biomedical community (e.g.: Kurpinski et al., 2014; Rubio et al., 2010), which have suggested that bridging the gap from lab bench to patient bedside requires a unique set of skills that are not typically

offered by traditional degree programs. Finally, we found that scientists that are particularly aware of the positive impact they exert over patients and clinical practitioners are more prone to engage in different forms of medical innovation. These results seem to be aligned with previous findings reported in organizational behavior and social psychology literature, which have highlighted that when individuals perceive that their actions have an impact on beneficiaries, they are likely to engage in the pursuit of making a positive difference in these beneficiaries' lives (Grant, 2007). Our results indicate that biomedical scientists may conceive the engagement in innovation activities as a way to channel such interest. Therefore, this suggests that developing and implementing mechanisms to increase the scientists' awareness of their direct impact on patients and clinical staff might enable scientists to participate more frequently in medical innovation activities.

To sum up, our use of the social capital discussion between dense and sparse networks is valuable in addressing the increasing interest among the medical community on the importance of knowledge brokers. Through this analysis, we have proposed a personal network perspective to examine the mechanisms through which different network structures may lead to different levels of medical innovation, and we offered a theoretical framework to deeply explore the interactions between different actors in the biomedical context. By adopting an individual perspective, we also bring onto our study two potential individual-level antecedents to explain differences in medical innovation engagement: cognitive breadth and perceived beneficiary impact.

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Appendix

Table: 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).