Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

Community-Spanning, Network-Spanning, and Scientist Innovativeness

Martin C. Goossen
HEC Paris
Department of Strategy
martin.goossen@hec.edu

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Jelcodes:O31,D85

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This is an exploratory study on the innovativeness of intra-organizational community-spanning and network-spanning scientists. While a large body of the boundary-spanning literature deals with the role of employees crossing organizational, divisional or team boundaries, little is known regarding the effects of spanning communities and networks revolving around different scientific fields. In this study we focus on the medical devices industry where R&D is located at the intersection of medical and technical knowledge. We posit that scientists involved in both communities come across more recombinant opportunities, which increases their innovativeness. This effect will be stronger if they have strong professional connections in both communities, but knowledge diversity makes it questionable if they could successfully take advantage of brokering opportunities. Results from a longitudinal dataset of scientists indicate that community-spanning and network-spanning scientists are indeed more innovative, but that effect reduces with the size of their professional network. The findings of this study contribute to the research on boundary spanners, intra-organizational communities and networks, and recombinant innovation.

INTRODUCTION

This study asks how community-spanning and network-spanning positions influence scientists’ innovativeness. Extant literature on boundary spanners has shown how employees crossing team or firm boundaries gain access to different knowledge and resources (Marrone, 2010; Williams, 2002). In turn, these employees perform their roles better and are extraordinary beneficial for their team, division or organization (Marrone et al., 2007). However, little research has dealt with the effects of spanning different communities and professional networks present within the same department in the same organization.

Communities of practice and social networks are great sources of innovation (Hildreth & Kimble, 2004; Phelps et al., 2012). The role of professional connections for innovation has been subject of many studies (Amin & Roberts, 2008) and has shown that scientists with more and more diverse connections are more creative. Interactions among scientists lead to an exchange of more relevant and more recent information, which increases their recombinant opportunities and innovations (Paruchuri, 2010). The size and structure of professional networks therefore has a significant impact of scientist innovativeness (Carnabuci & Operti, 2013).

Communities of practice are groups of people sharing a similar professional interest who strengthen their knowledge and know-how about this topic via continuous social interactions (Wenger et al., 2002). Communities of scientists with a common interest are highly efficient in sharing, transferring and developing tacit knowledge. Members of such communities have access to more, novel and complex information related to their professional activities. Communities of practice provide information access and resource mobilization, which fosters innovation for its members (Brown & Duguid, 1991). But communities of practice may also create new boundaries that inhibit innovation (Amin & Robert, 2008; Roberts, 2006). Since communities revolve around scientific knowhow and expertise, novel information stemming from other scientific communities is easily disregarded. Strong communities of practice may therefore result in isolation and a lack of useful information for its members. The role of communities of practice is therefore arguable weaker in settings where knowledge from different professions and sciences is combined.

While most R&D departments in corporations are home to one community of practice and one professional network, we focus on a situation where this is different. The medical devices industry builds upon two complementary, though different scientific disciplines: medicine and engineering (Metcalfe et al., 2005). As a result, the R&D divisions in such groups have two scientific communities and two professional networks. On the one hand, the medical community is essential in correctly identifying medical issues and assessing the feasibility of new solutions. The technical community, on the other hand, has the knowledge required for coming up and implementing new solutions. Improvements in medical devices thus comprise knowledge from both communities.

In this study we have a closer look at individuals spanning both communities. We posit that individuals belong to both communities (e.g. ‘community spanners’) have better access to complementary knowledge. This increases the number and quality of their recombinant opportunities (Fleming, 2001). However, it remains questionable if being part of both communities is sufficient. The search-transfer theory has argued that complex technical knowledge can only be transferred via strong personal interactions (Hansen, 1999). Therefore we also examine the situation where community-spanning scientists have strong professional connections in both communities (e.g. ‘network spanners’). We argue that such networks will provide an additional positive effect on scientist’ innovativeness, particularly when the scientist has a larger and sparsely-connected ego-network.

The predications are tested on a longitudinal sample of all active scientists in five major medical device firms over the period 1994-2004. We track the scientific activities, collaboration networks, and innovativeness of over 5,000 experts for a period of five years, on average. The results indicate that scientists that are part of both the medical and technical communities (community spanners) in their firm are 1.5 times more innovative than their colleagues. If these scientists subsequently maintain professional connections in both networks (network spanners), their innovativeness increases 1.3 times further. Surprisingly, the effect of network-spanning decreases with the size of the scientist's ego-network.

The results of this study speak to research on boundary spanners. Different from traditional team or organizational boundaries, this study dealt with epistemic boundaries within a company's R&D units. Successful innovations integrate knowledge from separate scientific disciplines. Scientists that span different communities and networks developing around each discipline gain access to complementary knowledge. Their superior recombinant opportunities lead subsequently to more and higher-quality innovations.

The outcomes of this study also shed light on the role of communities and networks by disentangling their different effects for knowledge transfer. This study shows that being involved in a community provides direct positive benefits, but these effects are stronger for scientists that also main strong professional connections in both communities. Having strong professional connections, as the search-transfer theory argues, is thus no prerequisite, but still beneficial.

CONTEXT: THE MEDICAL DEVICES INDUSTRY

The medical devices industry is a fast-growing industry characterized by innovation-based competition. In this industry, new product development is strongly related to firm survival and financial performance (De Vet & Scott, 1992). Firms in this industry actively pursue technological innovation and R&D accounts, on average, for 7 to 13 percent of total firm expenses (Xerfi, 2011). Innovation in this intermediately concentrated market stems from existing firms, large and small, as well as new entrants (Chatterji, 2008). Since most innovations are based on technological advancements, the intellectual property rights of medical device firms are strongly protected via patents (De Vet & Scott, 1992). The industry consists of many smaller market segments based on the field of application[1], but all major medical firms are active in multiple fields (Xerfi, 2011).

The medical devices industry combines two integral streams of science to develop and improve medical devices: medicine and engineering (Metcalfe et al., 2005; Ramlogan et al., 2007). On the one hand, firms need a profound understanding of the elements and functions of the human body. The origins of this knowledge rest in various medical disciplines, including life sciences, biology, physiology, and so on. Experts in this area are often trained as medical doctors and a substantial amount of research in this field is performed by universities and hospitals. Medical device firms need medical knowledge to properly understand the issues faced by their ultimate customers, i.e. the patients. Medical knowledge is also required to develop well-suited solutions for patients. Medical device developers working in the medical field often disclose their research findings via articles published in medical journals to share their accomplishments with colleagues in other organizations.

On the other hand, medical device firms need to have a full understanding of the technologies available to them to develop novel solutions. The origins of this knowledge stems from diverse specializations in the field of engineering, including mechanical engineering, electrical engineering, and materials science. Often trained as engineers, these experts draw upon their diverse knowledge to develop novel solutions for medical issues identified by doctors and medics. While scientists working the medical field use medical journals as outlet for their research, patents are more commonly used in the engineering field. Patents not only provide the ownership rights to a technical solution, but also a detailed

[1] Sub-markets for devices are spinal, cardiovascular, neuromodulation, diabetes, urology, dental, orthopedics, diagnostics, and surgery

description of the innovative idea. Therefore patents mean more than simply intellectual property rights for engineers.

Medical device firms are thus faced with a paradoxical situation. The fields of medicine and engineering are obviously highly complementary. Whereas the medical staff has the expertise to identify issues, the engineers have the expertise to develop novel solutions. However, both fields have different scientific origins, developed separate professions, and created different communities of practice (Amin & Roberts, 2008; Metcalfe et al., 2005). Medical device firms face the issue of integrating both groups of employees to develop novel products. The performance of individual employees in this industry will then depend on their ability to integrate both streams of knowledge.

SCIENTIST INNOVATIVENESS

To understand the innovative performance of individual scientists in the medical devices industry, we build upon three highly related streams of research: knowledge recombination, social capital, and the search-transfer problem. Literature on knowledge recombination has argued that innovations are ultimately the outcome a problem-solving process resulting in novel combinations of diverse components (Fleming & Sorenson, 2001). Components in our setting refers to different types of knowledge, both technical and medical, available to an employee. Employees can either innovate by creating new combinations of components or by combining existing components differently. The degree to which employees include new components or change the configuration of existing components determines whether they employ local or distant search strategies (Fleming, 2001; March, 1991). Local search requires fewer efforts results in solutions with a predictable and small positive effect. Distant search involves more extensive search process and provides uncertain, though potentially highly successful solutions (Fleming, 2001). Employees in the medical devices industry face a variety of options for recombination. The have a range of potential solutions for certain medical problems and each potential solution could be realized via different technical options.

Theory on social capital has shown that interpersonal connections are an important source of information (Tsai & Ghoshal, 1998). Employees receive new and different information via social connections within and outside the organization (Borgatti & Foster, 2003; Van Wijk et al., 2008). This increases their job performance and also increases their probability to develop novel solutions. The structures of their own professional network as well as the entire network influence the likelihood and speed by which they receive new information (Freeman, 1977; 1979). A secondary effect of social capital is related to resource mobilization (Ibarra, 1993). Employees having more and stronger professional connections face fewer hurdles when turning ideas into practice. Firstly because they can access more diverse resources via their larger social network and secondly because they can get people more easily aligned (Obstfeld, 2005). Again, both the structure of their social network and the strength of their connections matter for this purpose.

The search-transfer literature has dealt with the role of professional connections in learning simple and complex knowledge (Hansen, 1999). This theory confirms the idea that it are often weak ties providing novel information (Granovetter, 1973), but makes a proper distinction between identifying and acquiring useful information. If knowledge is straightforward and easy to understand, weak ties are a better source of information and more likely to lead to novel solutions (Hansen, 2002). On the contrary, employees can only access complex and tacit knowledge successfully via strong ties. Frequent and intensive communication creates a mutual understanding and increases the communication bandwidth (Aral & Van Alstyne, 2011). The knowledge required for new product development in the medical devices industry is often tacit and complex (Metcalfe et al., 2005). Companies can set up project teams that work intensively together for a period of time to facilitate recombination of complex knowledge. Professional connections in project teams enable knowledge transfer during the collaboration and thereafter (Singh, 2005).

Combining the literatures on knowledge recombination, search-transfer and social capital, scientist innovativeness will be strongly related to their boundary-spanning activities. Literature on boundary spanners has shown the importance of boundary-crossing individuals for generating novel ideas and insights (Marrone, 2010; Williams, 2002). Boundary spanners have connections to colleagues in different parts within or outside the organization. Their professional relations with these colleagues allow them to absorb diverse knowledge and enable their search activities. As a result, boundary-spanning individuals are more innovative than their colleagues. Most extant research focused on individuals spanning organizational or business unit boundaries and far less is known about the role of boundary-spanning employees within organizational units (Marrone, 2010). However, in the medical devices industry, boundary-spanning opportunities exist between different communities of practice: the medical and the technical.

Community-spanning by scientists

Communities of practice are loosely-defined social entities. They exist of experts bound together by a common professional interest and serve as a source of information and knowhow (Wenger, 1999). Since they are informal, emerging communities, there is no structure, hierarchy or formal purpose. But generally, they involve informal communication that may cross intra- and inter-organizational boundaries. Though informally organized, communities of practice are observed in many occasions and need to be taken into account since they can be strong drives of change or resistance within the organization (Wenger et al., 2002).

One of the major roles of communities of practice is efficient knowledge transfer and storage (Brown & Duguid, 1991). Since these communities consist of experts with a similar profession, their communication is often work-oriented. Because employees in similar jobs have a similar background (education, past experience, previous job), there is a strong mutual understanding among them. Combined with the physical proximity and in-person meetings, this facilitates the transfer of tacit knowledge among member of a community (Brown & Duguid, 2001). In addition, these professionals become more aware of each other's specialization and can easily turn to one another if they face a particular issue.

Because of its knowledge-intensive nature, communities of practice are very common in R&D environments (Brown & Duguid, 1991). Researchers belonging to a similar scientific discipline can more easily exchange information because of their shared expertise. In addition, the benefits they obtain from the community are larger since knowledge is their key resource. Communities of practice are therefore an important source for firm innovativeness.

However, communities of practice also have a downside (Roberts, 2006). In many cases, they tend to be relatively inward looking and interactions focus only on the common scientific domain. As a result, information stemming from other disciplines may easily be disregarded by a community and communities can "lead to isolation of learners" (Brown & Duguid, 1991). In the medical devices industry, such consequences may be particularly strong since innovation often combines knowledge from both the medical and technical community.

Therefore we expect that scientists belonging to both communities are more innovative than their colleagues embedded in a single community. Community-spanning scientists gain knowledge advantages from communities. On the one hand, they remain up-to-date about developments in the medical field (new knowledge on the functioning of a particular body part, assessment of why certain medical devices fail to function, etc.). On the other hand, they are aware of new technologies developed within or outside the firm (new materials and technologies, new combinations of these, etc.). Since both are highly complementary, community-spanning scientists will be more innovative. Therefore we hypothesize:

> H1: Community-spanning scientists are more innovative than non-community-spanning scientists.

Network-spanning by scientists

While the literature on communities of practice argues that being part of a community provides a scientist with new knowledge and will increase his/her innovativeness, the search-transfer literature argued that simply being part of a community is insufficient. While communities may help a scientist to obtain simple knowledge, only strong relations and intense communication facilitate the transfer of complex knowledge in an R&D setting (Hansen, 1999). Therefore we also look at the role of professional ties within both communities.

Professional connections among employees are an important source of knowledge and information (Borgatti & Foster, 2003, Brass et al., 2004; Phelps et al., 2012). In fact, the network of professional relationship among scientists forms “the backbone of knowledge flows within the firm” (Paruchuri, 2010). The size and structure of a scientist’s ego-network as well as his/her position in the entire organizational network determine the amount, speed, and reliability by which s/he receives novel information (Burt, 1992; Freeman, 1977; 1979). Little is known, however, what the effects of two distinct and hardly overlapping networks are.

We argue that scientists spanning two professional networks gain brokerage-like advantages that increase their innovativeness. First, similarly to community-spanning scientists, they can take advantage of accessing diverse, complementary knowledge. Their social capital gives them access to the knowledge and knowhow of their colleagues. Second, they can obtain more complex knowledge since they have strong social ties required for such (Hansen, 1999). Third, their strong connection implies a strong mutual understanding that facilitates efficient communication and learning among them (Aral & Van Alstyne, 2011). Compared to community-spanning scientists, network-spanning scientists have the strong connections needed to learn the more valuable, more complex, and more tacit knowledge. Compared to non-network-spanning scientists with have all their professional connections in one community, network spanners have access to more diverse knowledge. Therefore we expect a positive effect of network-spanning, even after controlling for community-spanning and ego-network size:

> H2: Network-spanning scientists are more innovative than non-network-spanning scientists.

Past studies have also investigated the effect of network size on scientist innovativeness (Carnabuci & Operti, 2013; Paruchuri, 2010). Network size gives access to more knowledge and resources. In addition, it also increases the likelihood and speed of receiving new information. Therefore most studies found a strong relation between ego-network size and innovativeness (Phelps et al., 2012). We expect that ego-network size will also have a positive joint effect with network spanning: the benefits a scientist can obtain from having ties in both the medical and technical network will increase if s/he has more professional connections. More connections means that the scientists will receive not simply more information, but also more complementary knowledge. This increases the recombinant opportunities and will have a significant effect on scientist' innovativeness.

> H3: The positive effect of network-spanning on scientist innovativeness is stronger if *the scientist's ego*-network is larger.

Not only the size, but also the structure of the ego-network matters. According to Burt (1992), connecting two otherwise unconnected individuals provides a person with unique benefits: s/he is the only person that can combine the unique knowledge that the two alters possess. Being in such a brokerage position is strongly related with knowledge benefits and ultimately innovativeness. However, an opposing view provided by Coleman (1988) argues in favor of connected alters. Triads in the ego-network provide trust and mutual understanding, which together improve information-sharing (Obstfeld, 2005).

We expect that either effect may hold and may have a joint effect with network-spanning. Network spanners can access complex complementary knowledge via their professional connections in both the medical and technical network. Therefore they can gain advantages from knowledge brokering. However, brokering medics and engineers will be less successful if these scientists are already directly connected to one another. In that case, these experts will already exchange information with one another voluntarily to directly create a new innovation. So the positive effect of network-spanning will be stronger if the ego-network of a scientist is less dense.

> H4a: The positive effect of network-spanning on scientist innovativeness is stronger if *the scientist's ego*-network is less dense.

If network density has a positive effect on innovativeness, this may strengthen the effect of network-spanning. In settings where knowledge is tacit and where opportunism is hard to detect or prove, closed triads may work as a mechanism for trust and reciprocity (Ahuja, 2000; Coleman, 1988). This fosters knowledge-sharing among scientists and will increase innovation. If scientists are spanning multiple networks, trust and reciprocity are essential for gaining access to complementary knowledge held by scientists in both networks. Therefore we expect that ego-network density will strengthen the relationship between network-spanning and scientist innovativeness.

H4b: The positive effect of network-spanning on scientist innovativeness is stronger if *the scientist's ego*-network is denser.

METHODOLOGY

Data collection and community and network construction

For this study we looked at all active scientists in a sample of five larger North-American pure medical device firms, which was based on four considerations. First, the method used to observe the medical and technical networks within a firm cannot differentiate if a scientist is working for the medical device division or another business unit. Therefore firms with less than 90% of their revenues in medical devices (SIC 3841-45,3851) are excluded. Second, we only choose larger corporations to observe real community and network effects. Small organizations normally have form one community with a fully connected network, so there are no boundary spanners. Third, we selected the firms that were active in the medical devices industry for the full observation period from 1990 till 2004. Since some variables are constructed over a longer time period, some variables can only be calculated if employees remain in the same firm for a longer period of time. Though this may introduce a survival bias at the firm level, it is unlikely to affect the performance of community-spanning scientists. Fourth, we only included North-American firms to prevent biases in data collection: better data availability for US firms reduces potential biases in several measures. The final sample consists of C. R. Bard, Bausch & Lomb, Medtronic, St. Jude Medical, and Stryker.

Data for these five firms were collected from four different sources. First, Compustat North America was used to select the sample and to collect data regarding several control variables. Second, 10K statements were used to identify firm family trees of all its subsidiaries. Third, we combined the firm family trees with the updated NBER patent dataset

(Hall et al., 2001) and the Harvard Patent Dataverse (Lai et al., 2011). Finally, we combined the firm family trees with journal publication data in the field of 'life sciences' in Elsevier Scopus.

Because details regarding individual employment are not available, we used patent and publication data to identify all productive R&D scientists in these organizations.[2] As explained earlier, technical scientists often rely on patents as a source of knowledge and as a way to publish their new inventions while medical scientists often rely on medical journals to learn or diffuse new information. Therefore, a scientist is classified as 'engineer' if s/he appears as an inventor on a patent and is classified as a 'medic' if s/he appears as an author on an article. We use five-year moving windows to classify each scientist as a medic or an engineer.

The medical and technical networks have been operationalized via co-inventorship and co-authorship. When engineers collaborate in project teams on novel solutions, they interact intensively for a continued period of time (Paruchuri, 2010). Moreover, they often remain in touch after the collaboration has finished (Singh, 2005). Strong ties and mutual understanding established while collaborating facilitate the transfer of complex knowledge among these engineers. Therefore we observe the intra-firm technical network via the firm co-inventor network, similar to earlier studies (Carnabuci & Operti, 2013; Paruchuri, 2010). Similarly, when medical scientists work together on an experiment or assessment, they also communicate frequently during that period and will remain in contact if they share a similar professional interest. To ensure that co-authorship is a valid measure of collaboration and strong ties, articles with over ten authors were excluded during network composition. The intra-organizational medical network is therefore observed via co-authorship networks,

[2] For publications, each individual author can be linked to his/her home institution. For patents, I assume that each inventor is working for that particular company.

similar to earlier research (Murray, 2002). Disambiguation of variation in author and inventor names is based on simple matching of the first initial and family name.[3]

The final longitudinal sample contains 5,727 scientists observed in 27,606 scientist-years. Community spanners are those scientists that are simultaneously classified as medics and engineers. Network spanners are those scientists with connections to both medical and technical scientists. For the network analysis, the technical and medical networks have been collapsed into a single network. Figure 1 below shows a graphic representation of the intra-organizational communities and networks of Bausch & Lomb in 1994. As can be seen, community-spanning and network-spanning are inter-related: while some community-spanners do not have professional connections in both communities, most do.

INSERT FIGURE 1 HERE

Measurement

Dependent variable

Scientist innovativeness is measured as a citation-weighted patent count. Patents are a common measure of scientist innovativeness (Carnabuci & Operti, 2013), particularly in the medical devices industry where corporations tend to protect all their innovations via intellectual property rights (De Vet & Scott, 2002). To correct the number of patents for their individual quality (Trajtenberg, 1990), we correct for five-year forward citations.

Independent and moderating variables

Community spanner is a dummy variable taking the value of one if the scientist is part of both the medical and technical community in the firm. As explained earlier, scientists are classified to the medical or technical community according to their involvement in either

[3] Lai et al. (2011) provide a more complex algorithm reducing the number of false positives. A manual examination of my sample, however, revealed a substantial number of false negatives. Therefore I applied this method.

journal publications or patent applications in the past five years. So when a scientist authored both publications and patents, they are involved in both scientific communities and thus communing-spanning scientists.

Network spanner is a dummy variable taking the value of one if the scientists has professional connects to both medical and technical scientists. The intra-organizational network consists of two types of actors (medical and technical) and two types of connections (co-authorship and co-inventorship). If a community-spanning scientist has collaborated with fellow scientists for both medical articles and technical patents, s/he has a network-spanning position within the firm.

This measure is potentially biased since a new scientific discovery could have led to both a patent and a publication. This would create 'clusters of network spanners' in the network, without actually bridging both communities. However, a simple analysis on network spanning scientists shows that, on average, only 1.3 out of 10.8 connections is also a network spanner.

Ego-network size is simply the number of alters in the intra-organizational network, calculated as the number of unique co-authors and/or co-inventors within the organization during the past five year.

Ego-network density is simply the density of the ego-network of each scientist, calculated as the number of ties among a scientist's alters divided by the potential number of ties. Ego-network density in co-authorship and co-inventorship networks is traditionally high because of the two-mode to one-mode network conversion.

Control variables

Control variables have been added at three different levels: the individual, the community and network, and the organization. At the individual level, we included Past patents and Past publications to control for past productivity of the scientist. This measure also corrects for the scientist's individual innovativeness and creativity. Additionally, R&D budget, calculated as the firm's total R&D expenses divided by the number scientists, was included to control for varying means and resources between firms and over time.

At the network level, we controlled for many alternative explanations. First, the percentage of ties that are medical and technical scientists (Ego-net % medical/technical) is included to control for the effects of alter types. Since community-spanning scientists are both medical and technical, both measures are included. Second, Component size was included to control for network fragmentation at the individual level and measured via the size of the two-step ego-network. Third, Network size was computed as the total number of scientists within a firm. It is therefore similar to the size of medical and technical communities combined. Fourth, Network density was calculated as the total number of ties within a firm divided by the potential number of connections.

At the firm level, we controlled for factors that could potentially influence the R&D strategy. Ln sales (the log value of firm sales) controls for the effects of firm size while Return on sales (EBIT divided by the sales) controls for firm profitability. The firm's ability to absorb and integrate knowledge is related to its R&D expenses (Cohen & Levinthal, 1990), and therefore R&D intensity (R&D expenses divided by firm sales) was included. Finally, knowledge resources present within the firm may drive the integrative ability of individual scientists and therefore the number of patents and publications during the past five years (Patent stock and Publication stock) have been included.

Analysis

The dependent variable of our analysis, citation-weighted patent count, is a non-negative count variable. Following earlier research (Carnabuci & Operti, 2013; Paruchuri, 2010) we employ a negative binomial regression. This regression is similar to a Poisson regression, but does not put any restrictions on the mean/variance ratio (which are not met in our case).

To avoid simultaneity issues, the dependent variable is lagged by one year (t_{+1}). All independent variables are either based on the focal year (t_0) or based on a five year observation period (t_{-4}-t_0). To overcome potential multicollinearity issues in our regressions, the moderating variables (ego-network size and density) are mean-centered.

Finally, we control for unobserved heterogeneity at the firm and individual level. To account for this issue, I used firm-fixed effects and scientist-level random effects. The Hausman test regarding fixed effects at the level of the scientist was inconclusive. In addition, using random effects allowed us to keep the full sample size.

RESULTS

Table 1 shows the descriptive statistics and correlations among all variables. The average scientist in our sample has a citation-weighted patent count of 3.2 each year. However, the distribution follows a Poisson distribution with a mode of 0 (77.6%). In the sample 7.3% of all scientists are part of both the medical and technical community, and 5.3% have connections in both scientific networks (i.e. 73% of all community-spanning scientists is also a network-spanning scientist). Since the large majority does not span between communities, the average patents and publications per scientists (2.4 and 0.4 respectively) are evidence that the technical network is much larger than the medical network.

INSERT TABLE 1 HERE

Results of the negative binomial regression analysis are included in Table 2 and the incident rate ratios (multiplier ratios) are in Table 3. Model 1 only includes the control variables. Past scientific performance, both in patents and publications, is a significant, though weak predictor of scientist innovativeness. Ego-network characteristics of the scientist have a much stronger effect, particularly its size, percentage engineers and percentage medics. Density has a negative effect, indicating support for the idea of brokerage. Component and network characteristics have little effect, just like most firm characteristics. Firm dummies, however, have a strong significant effect: as the incident rate ratios show, scientists at St. Jude Medical are twice as innovative as those at C.R. Bard (the base level).

INSERT TABLE 2 AND 3 HERE

Model 2 provides support for hypothesis 1: community-spanning scientists are more innovative than non-community spanning scientists. These scientists are almost twice as productive as scientists that are only active in one of both communities. However, this effect also includes the effect of network-spanning scientists, since the large majority of all community spanners are also a network spanner. We disentangle this effect in Model 4, where both community- and network-spanning are tested simultaneously. The results sustain hypothesis 1 and also provide proof for hypothesis 2: having strong connections in the medical and technical community provides benefits in addition of being active in both communities.

Models 5 to 7 test the network moderation of the next two hypotheses. In model 5 and 6, we tested the moderating effects separately for fear of multicollinearity. In model 7 both hypotheses are tested together. Both VIF statistics as well as stable coefficients indicated no real problem. The results provide strong and robust evidence contradicting hypotheses 3: the number of connections significantly weakens the positive relationship between network-spanning position and scientist innovativeness. Neither hypotheses 4a nor 4b, arguing in favor of closure or brokerage, is supported: the density of the ego-network does not significantly change the positive effect of network-spanning.

DISCUSSION

The study examined the role of community-spanning and network-spanning positions on scientist innovativeness. Professional communities and networks among scientists are valuable sources of new knowledge and information and increase scientist productivity (Brown & Duguid, 1991; Paruchuri, 2010). In many occasions, an R&D department of one corporation comprises one community revolving around a specific scientific discipline and similarly one professional network of scientists. In such occasions, being part of the community and network has a direct positive effect on productivity. This effect is even larger if a scientist has a more central or brokerage position (Carnabuci & Operti, 2013; Paruchuri, 2010).

However, none of the extant literature has dealt with the issues that arise when corporations build upon two different scientific disciplines. In such cases, the presence of two communities of practice and two professional networks may in fact reduce innovation: strong community boundaries and disconnected networks will inhibit knowledge recombination. In such occasions, innovators are not the more central or brokering scientists, but those that span the different communities or networks. Similar to boundary-spanning employees (Marrone, 2010; Williams, 2002), community- and network-spanning tap into different types of knowledge. In cases where this knowledge is highly complementary, like in our study, spanning scientists are more innovative, independent of their position in each individual community. The results indicate that being a member of both communities strongly increases scientists' creativity. This effect is even stronger when scientists maintain professional connections in both communities.

Past studies have also shown how ego-network size and structure play an important role for knowledge recombination (Carnabuci & Operti, 2013; Guler & Nerkar, 2012; Ibarra, 1993; Paruchuri, 2010). More connections give access to more knowledge and resources present in other scientists. This increases the scientist's opportunity and ability to realize innovation. However, this effect is weaker for network-spanning inventors: our analysis has revealed a strongly significant negative effect. So while ego-network size and being a network spanner independently have positive effects, their joint effect is negative. One potential explanation for this effect is the limited cognitive explanations of scientist. Zhou et al. (2009) already argued that ties also put a mental burden upon an individual. At a certain point, the benefits of having additional connections are no longer outweighed by the efforts one has to do to maintain the tie. In addition, many ties lead to an information overflow and cognitive overload for an individual (O'Reilly, 1980). Since network-spanning scientists continuously face situations where knowledge is more diverse and more complex, having more connections may actually not provide the expected benefits. In fact, fewer professional ties may be more beneficial: this allows them to interact more intensely and create an understanding of both scientific disciplines (Aral & Van Alstyne, 2011). As a result, while more connections may be better for scientists within a single community, scientists spanning multiple communities are better off with fewer connections in each community.

Contributions and limitations

This study aims to contribute towards the literature on boundary-spanning and the literature on communities and networks. With regard to earlier, this study has looked at two less-investigated boundary-spanning positions. By exploring the effects of community-spanning on scientist innovativeness, this study has shown that communities of practice provide both advantages and disadvantages for organizations. Communities of practice stimulate information exchange among community members (Brown & Duguid, 1991; Wenger, 1999). In fact, in our setting these communities are essential in advancing our knowledge in the respective scientific fields. But communities of practice are also inwardly-focused and tend to isolate themselves from external knowledge flows (Amin & Roberts, 2008; Brown & Duguid, 1991). This study has shown that this effect is very likely: even in an industry where innovation is at the intersection of two scientific disciplines, only a meager 7% of all scientists were actively involved in both. As a consequence, this minority has access to more diverse knowledge and is far more innovative than their counterparts that are only part of one community of practice.

Second, this study aimed to disentangle the effect of two highly related and similar concepts: communities versus networks. While communities are more informally created, without a clear structure or purpose, they are essential in storing and sharing information. Novel information may quickly diffuse via a community of practice, but it remained questionable if complex knowledge can also be shared in such a loose structure (Hansen, 1999). Networks on the other hand are more strictly defined via either the absence or presence of professional connections among scientists. The absence of such a connection may mean they still belong to the same community and exchange brief information, but they will lack the ability to transfer complex knowledge. This study has shown that, in case knowledge is embedded in multiple communities with different networks, both are useful sources of information. The effects of community-spanning are significant, but even stronger if community-spanning scientists also have strong professional connections in each community.

The results of this study should be considered in the light of its limitations. We point out two major limitations. First, many studies have argued that network position is not exogenous, but may in fact represent individual ability. This may imply that community-spanning and network-spanning scientists are significantly different from other scientists in the organization. Though we cannot find support for that in our dataset, we cannot disregard this concern.

The second limitation is related to the use of archival data to identify scientists and measure their innovativeness. By using patent and publication data, we certainly do not observe all scientists working in the five medical device firms. In fact, we may only observe a fraction. This would include a bias towards the more productive and innovative R&D employees. Also, by using patents as a measure for innovativeness we tend to overlook non-patented innovation or non-patentable discoveries by these scientists.

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FIGURE 1 – COMMUNITIES AND NETWORKS IN BAUSCH & LOMB (1994)

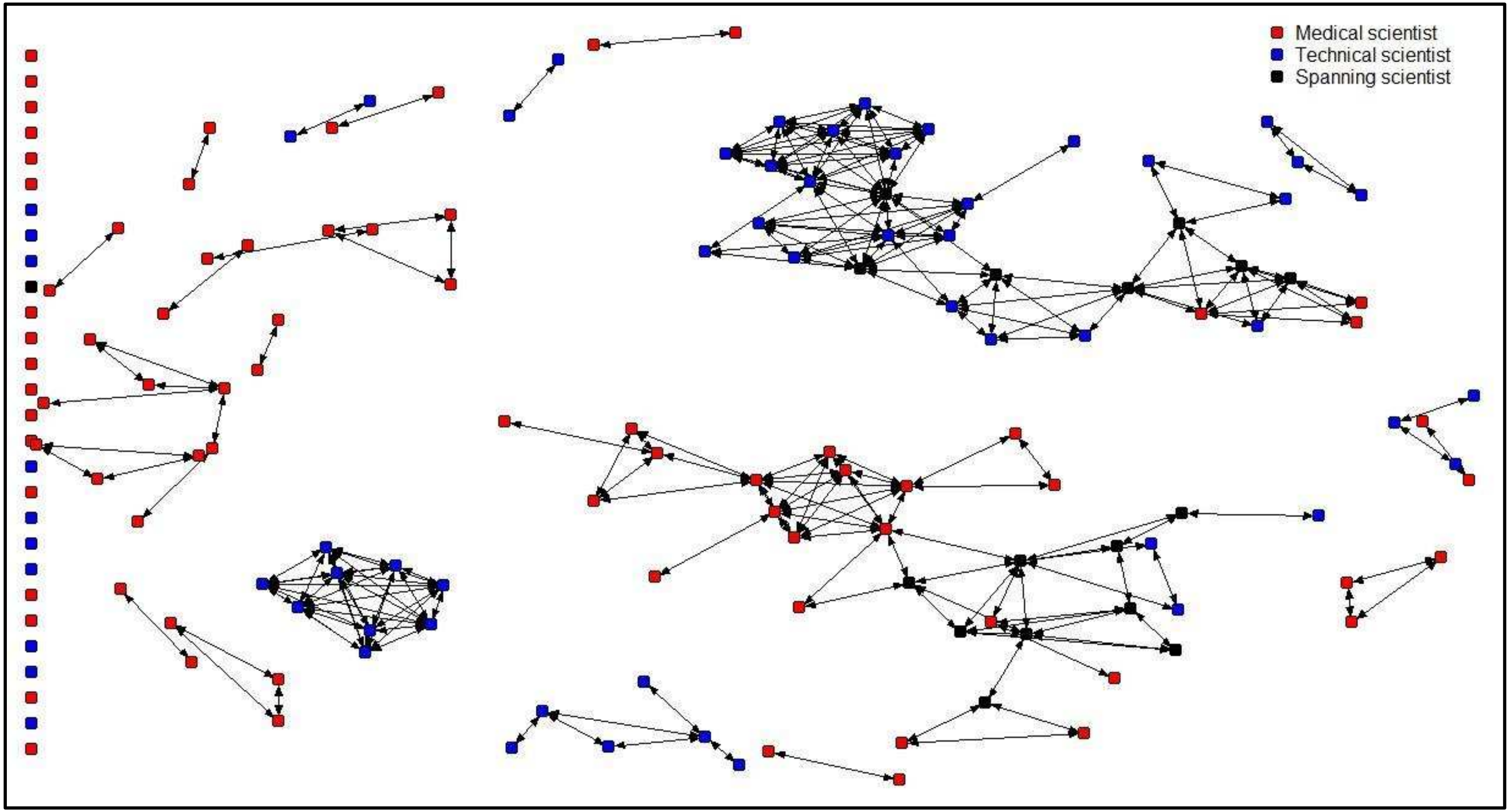

TABLE 1 – DESCRIPTIVE STATISTICS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
[1] Innovativeness	1.000																	
[2] Community span.	0.111	1.000																
[3] Network spanner	0.109	0.875	1.000															
[4] Ego-net size*	0.253	0.306	0.331	1.000														
[5] Ego-net density*	-0.067	-0.106	-0.108	0.067	1.000													
[6] Past patents	0.312	0.252	0.252	0.665	-0.163	1.000												
[7] Past publications	0.057	0.480	0.471	0.208	-0.140	0.084	1.000											
[8] R&D budget	-0.007	0.029	0.026	0.045	-0.017	0.030	0.045	1.000										
[9] Ego-net % tech.	0.083	-0.078	-0.092	0.212	0.265	0.247	-0.438	-0.024	1.000									
[10] Ego-net % med.	-0.060	0.155	0.173	-0.009	0.051	-0.193	0.494	0.023	-0.737	1.000								
[11] Component size	0.198	0.271	0.283	0.773	0.003	0.530	0.141	0.091	0.189	-0.046	1.000							
[12] Network size	0.013	0.045	0.039	0.217	0.047	0.087	0.008	0.233	0.040	-0.005	0.349	1.000						
[13] Network density	-0.064	-0.039	-0.032	-0.144	-0.034	-0.059	-0.002	-0.150	-0.038	0.011	-0.232	-0.776	1.000					
[14] Ln sales	-0.004	0.045	0.036	0.196	0.047	0.073	0.029	0.341	0.032	-0.001	0.311	0.933	-0.781	1.000				
[15] Return on sales	0.082	0.047	0.043	0.175	0.028	0.080	-0.003	0.206	0.026	0.006	0.284	0.828	-0.805	0.744	1.000			
[16] R&D intensity	0.098	0.057	0.059	0.100	-0.013	0.072	0.013	0.429	-0.025	0.048	0.171	0.338	-0.370	0.174	0.533	1.000		
[17] Patent stock	0.010	0.049	0.044	0.222	0.044	0.096	0.012	0.240	0.034	0.001	0.361	0.994	-0.755	0.916	0.827	0.377	1.000	
[18] Publication stock	-0.005	0.049	0.042	0.217	0.044	0.089	0.021	0.271	0.033	-0.001	0.351	0.985	-0.741	0.946	0.773	0.288	0.985	1.000
Mean	3.248	0.073	0.057	4.592	0.619	2.398	0.383	0.414	0.768	0.147	19.430	1007	0.026	8.046	0.259	0.099	959	214
Std. Dev.	13.028	0.261	0.232	4.666	0.418	3.760	1.086	0.094	0.409	0.338	26.804	738	0.015	0.796	0.084	0.033	722	167
Min	0	0	0	0	0	0	0	0.170	0	0	0	81	0.012	5.888	0.067	0.033	56	5
Max	304	1	1	65	1	117	26	0.763	1	1	376	2208	0.077	9.216	0.390	0.216	2146	535

N = 27,606

All correlations larger than |0.013| are significant at the 5% level.

All correlations larger than |0.015| are significant at the 1% level.

*Descriptive statistics based on absolute values, correlation based on mean-centered values of the independent variables

TABLE 2 – NEGATIVE BINOMIAL REGRESSION FOR SCIENTIST INNOVATIVENESS

	(model 1)	(model 2)	(model 3)	(model 4)	(model 5)	(model 6)	(model 7)
Community spanner		0.650***		0.483***	0.386***	0.458***	0.389***
		(0.048)		(0.082)	(0.082)	(0.082)	(0.082)
Network spanner			0.679***	0.237***	0.658***	0.424***	0.630***
			(0.054)	(0.091)	(0.096)	(0.099)	(0.101)
Network span × Network size					-0.051***		-0.053***
					(0.004)		(0.005)
Network span × Network density						0.794***	-0.165
						(0.179)	(0.193)
Past patents	0.022***	0.020***	0.020***	0.020***	0.031***	0.021***	0.031***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Past publications	0.069***	0.015	0.022**	0.012	0.067***	0.023**	0.066***
	(0.009)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
R&D budget	0.804*	0.756*	0.737	0.744*	0.759*	0.748*	0.759*
	(0.453)	(0.452)	(0.452)	(0.452)	(0.451)	(0.452)	(0.450)
Ego-net size (mc)	0.032***	0.031***	0.030***	0.030***	0.037***	0.031***	0.037***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ego-net density (mc)	-0.466***	-0.425***	-0.430***	-0.423***	-0.400***	-0.445***	-0.394***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
Ego-net % technical	1.030***	0.964***	0.981***	0.964***	0.921***	0.976***	0.916***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
Ego-net % medical	-0.330***	-0.524***	-0.555***	-0.559***	-0.742***	-0.591***	-0.741***
	(0.092)	(0.096)	(0.098)	(0.098)	(0.101)	(0.099)	(0.101)
Component size	0.004***	0.004***	0.004***	0.004***	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Network size	0.002***	0.002***	0.002***	0.002***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	0.423	0.191	0.400	0.259	0.437	0.279	0.429
	(2.617)	(2.614)	(2.615)	(2.614)	(2.597)	(2.614)	(2.597)
Ln sales	-0.087	-0.099	-0.090	-0.096	-0.086	-0.091	-0.088
	(0.132)	(0.132)	(0.132)	(0.132)	(0.131)	(0.132)	(0.131)
Return on sales	2.137***	2.185***	2.192***	2.194***	2.366***	2.157***	2.379***
	(0.764)	(0.763)	(0.763)	(0.763)	(0.763)	(0.763)	(0.763)
R&D intensity	-1.224	-1.011	-0.954	-0.968	-1.145	-0.979	-1.150
	(1.575)	(1.572)	(1.573)	(1.572)	(1.570)	(1.573)	(1.570)
Patent stock	-0.002***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Publication stock	0.003***	0.003***	0.003***	0.003***	0.003**	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bausch & Lomb	0.088	0.067	0.075	0.069	0.083	0.063	0.084
	(0.141)	(0.141)	(0.141)	(0.140)	(0.140)	(0.140)	(0.140)
Medtronic	0.479**	0.406*	0.414*	0.402*	0.405*	0.406*	0.405*
	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)
St. Jude Medical	0.847***	0.794***	0.804***	0.793***	0.761***	0.789***	0.761***
	(0.140)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
Stryker	0.257**	0.257**	0.257**	0.257**	0.267***	0.253**	0.269***
	(0.102)	(0.102)	(0.102)	(0.101)	(0.101)	(0.102)	(0.101)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	-3.711***	-3.576***	-3.662***	-3.600***	-3.692***	-3.644***	-3.681***
	(0.960)	(0.958)	(0.958)	(0.958)	(0.952)	(0.958)	(0.952)
Observations	27,606	27,606	27,606	27,606	27,606	27,606	27,606
Number of scientists	5,727	5,727	5,727	5,727	5,727	5,727	5,727

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 3 – INCIDENT RATE RATIOS FOR SCIENTIST INNOVATIVENESS

	(model 1)	(model 2)	(model 3)	(model 4)	(model 5)	(model 6)	(model 7)
Community spanner		1.916***		1.621***	1.471***	1.581***	1.475***
		(0.092)		(0.133)	(0.120)	(0.130)	(0.121)
Network spanner			1.973***	1.268***	1.930***	1.529***	1.877***
			(0.107)	(0.116)	(0.185)	(0.152)	(0.190)
Network span × Network size					0.950***		0.949***
					(0.004)		(0.004)
Network span × Network density						2.212***	0.848
						(0.396)	(0.164)
Past patents	1.022***	1.020***	1.021***	1.020***	1.031***	1.021***	1.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Past publications	1.071***	1.015	1.022**	1.012	1.069***	1.024**	1.068***
	(0.010)	(0.012)	(0.011)	(0.012)	(0.013)	(0.012)	(0.013)
R&D budget	2.235*	2.131*	2.089	2.104*	2.136*	2.114*	2.137*
	(1.011)	(0.963)	(0.944)	(0.951)	(0.963)	(0.955)	(0.963)
Ego-net size (mc)	1.033***	1.032***	1.030***	1.031***	1.038***	1.032***	1.038***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ego-net density (mc)	0.627***	0.653***	0.650***	0.655***	0.670***	0.641***	0.675***
	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.024)	(0.026)
Ego-net % technical	2.801***	2.623***	2.666***	2.623***	2.511***	2.653***	2.499***
	(0.199)	(0.187)	(0.190)	(0.187)	(0.179)	(0.189)	(0.179)
Ego-net % medical	0.719***	0.592***	0.574***	0.572***	0.476***	0.553***	0.477***
	(0.066)	(0.057)	(0.056)	(0.056)	(0.048)	(0.055)	(0.048)
Component size	1.004***	1.004***	1.004***	1.004***	1.003***	1.004***	1.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Network size	1.002***	1.002***	1.002***	1.002***	1.001***	1.002***	1.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network density	1.526	1.210	1.491	1.295	1.548	1.322	1.536
	(3.993)	(3.164)	(3.899)	(3.387)	(4.020)	(3.456)	(3.988)
Ln sales	0.917	0.906	0.914	0.909	0.917	0.913	0.916
	(0.121)	(0.120)	(0.121)	(0.120)	(0.120)	(0.120)	(0.120)
Return on sales	8.475***	8.887***	8.957***	8.971***	10.653***	8.648***	10.793***
	(6.478)	(6.779)	(6.836)	(6.844)	(8.127)	(6.596)	(8.236)
R&D intensity	0.294	0.364	0.385	0.380	0.318	0.376	0.317
	(0.463)	(0.572)	(0.606)	(0.597)	(0.500)	(0.591)	(0.497)
Patent stock	0.998***	0.997***	0.997***	0.997***	0.998***	0.998***	0.998***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Publication stock	1.003***	1.003***	1.003***	1.003***	1.003**	1.003***	1.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bausch & Lomb	1.092	1.070	1.078	1.071	1.086	1.065	1.088
	(0.154)	(0.150)	(0.152)	(0.151)	(0.152)	(0.150)	(0.153)
Medtronic	1.614**	1.500*	1.512*	1.495*	1.499*	1.501*	1.499*
	(0.374)	(0.346)	(0.349)	(0.345)	(0.346)	(0.346)	(0.346)
St. Jude Medical	2.332***	2.213***	2.235***	2.210***	2.141***	2.201***	2.141***
	(0.325)	(0.308)	(0.311)	(0.308)	(0.297)	(0.306)	(0.297)
Stryker	1.293**	1.293**	1.294**	1.293**	1.307***	1.288**	1.308***
	(0.132)	(0.131)	(0.131)	(0.131)	(0.132)	(0.131)	(0.132)
Year dummies	(included)	(included)	(included)	(included)	(included)	(included)	(included)
Constant	0.024***	0.028***	0.026***	0.027***	0.025***	0.026***	0.025***
	(0.023)	(0.027)	(0.025)	(0.026)	(0.024)	(0.025)	(0.024)
Observations	27,606	27,606	27,606	27,606	27,606	27,606	27,606
Number of scientists	5,727	5,727	5,727	5,727	5,727	5,727	5,727

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: these are multiplier rates! Values below 1 indicate a negative effect, above 1 a positive effect.