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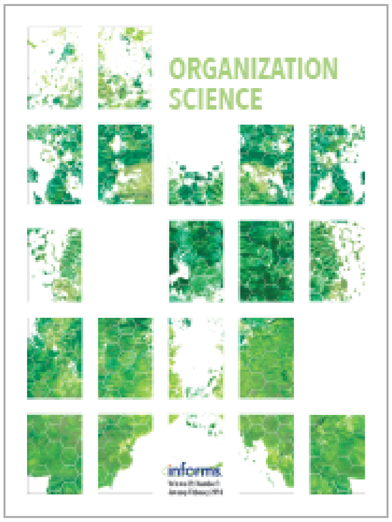

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Marco Tortoriello, Bill McEvily, David Krackhardt

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Being a Catalyst of Innovation: The Role of Knowledge Diversity and Network Closure

Marco Tortoriello
IESE Business School, University of Navarra, 28023 Madrid, Spain, mtortoriello@iese.edu

Bill McEvily
Rotman School of Management, University of Toronto, Toronto, Ontario M5S 3E6, Canada, bill.mcevily@rotman.utoronto.ca

David Krackhardt
Heinz College, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213, krack@cmu.edu

Whereas recent research on organizational innovation suggests that there is an ecology of roles supporting the innovation process, the majority of network research has concentrated on the role of inventors. In this paper, we contribute to research on organizational innovation by studying the social structural conditions conducive to individuals supporting, facilitating, and promoting the innovativeness of their colleagues—a role we refer to as *catalysts of innovation*. We consider an individual's network position and the type of knowledge available to her through her network as key enabling conditions. We argue that the unique configuration of having access to diverse knowledge through a closed network enables individuals to act as innovation catalysts. Based on a study of 276 researchers in the research and development division of a large multinational high-tech company, we find strong support for our prediction and demonstrate that catalysts make important contributions to the innovative outputs of other researchers in terms of their colleagues' patent applications.

Keywords: innovation; social networks; catalysts
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Introduction

Research on the social structure of innovation has advanced considerably in recent years and enriched our understanding of how the generation of new products, processes, and ideas in organizations is contingent upon the surrounding social context (Phelps et al. 2011). Most notably, social structures characterized by brokerage and closure have been shown to have independent and contingent effects on innovation processes and outcomes (Burt 2005, Fleming et al. 2007, Reagans and McEvily 2008, Tortoriello 2014). A key insight emerging from this stream of research is that an actor's network position influences that actor's own innovativeness. This observation is important because it identifies how patterns of informal social relations contribute to an actor's capacity to perform the role of innovator. At the same time, the primary focus on innovators and the extent to which they occupy advantageous network positions overlooks other important questions about the influence of social structure on organizational innovation. Indeed, implicit in the emphasis on the network position of innovators is the idea that their network contacts contribute to their innovativeness. Yet network contacts have largely been treated as homogeneous and undifferentiated in terms of their ability to contribute to innovators, and we know relatively little about the social structural conditions that are conducive to network contacts stimulating the innovativeness of others.

The broader literature on organizational innovation emphasizes that the generation of new products, processes, and ideas is often the result of collaborative efforts involving numerous parties who perform a variety of distinct roles. Along these lines, Hargadon and Bechky (2006) identify different innovation activities performed by individuals, including help giving, help seeking, reflective reframing, and reinforcing. Similarly, Ibarra (1993) differentiates administrative from technical innovation roles. And Obstfeld (2005) distinguishes among individuals acting as initiators of innovation, major contributors, and minor contributors. Taken together, these studies suggest that in addition to the primary role played by innovators, there are a number of supporting roles that contribute to the overriding objective of generating innovations in organizations (Hargadon 2002, Carlile 2004). Beyond a general recognition of multiple innovation roles, however, we know relatively little about the relationships and connections among these roles, the extent to which they are mutually supportive, and how they collectively form an ecology of innovation roles in organizations.

Although well suited to do so, previous research on the social structure of innovation has yet to systematically explore the pattern of connections that contributes to the emergence of different innovation roles in general and, in particular, the specific network configurations conducive to the formation of those roles that act

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in a supportive capacity to the role of innovators. Scholars who study organizational innovation from a network perspective have described the importance of supporting social structures to numerous high-profile breakthroughs. For instance, key to the invention of the electric light bulb was "the web around [Thomas] Edison ... thick with ties to other people, ideas, and objects that together made up his particular 'invention.' ... Ignoring these connections hides central insights into how innovations unfold" (Hargadon 2003, p. 7). Additionally, network scholars studying organizational innovation have implicitly focused on the type and content of relationships that trigger creativity (Sosa 2011). Although such observations do reflect a general recognition of supporting roles, they are less informative about the types of roles that may be critical to facilitating and enabling innovation in organizations and the extent to which social structural conditions are integral to the fulfillment of such roles.

In this paper we focus on one type of role through which organizational members support, facilitate, and promote their colleagues' innovativeness. We refer to this role as *catalysts of innovation*, defined as individuals who are able to stimulate and enhance the development of new ideas in their colleagues by providing them with relevant knowledge and who are recognized by their colleagues as key contributors to the process of generating innovations.

To gain a better understanding of the social structural conditions enabling individuals to act as catalysts of innovation, we draw on and extend research examining the influence of networks on the creation, dissemination, and use of knowledge in organizations (Borgatti and Cross 2003, Reagans and McEvily 2003, Cummings 2004, Obstfeld 2005, Haas 2006). According to this body of research, the role of innovators has been explained as a function of the position individuals occupy in social structure and by the type of knowledge available to them by virtue of their network position. For instance, individuals maintaining bridging ties between otherwise disconnected contacts have access to diverse knowledge (Burt 1992), which favors their ability to identify innovative solutions (Hargadon and Sutton 1997), develop good ideas (Burt 2004), and generate innovations (Reagans and Zuckerman 2001, Tortoriello and Krackhardt 2010). We extend this line of work to explain how individuals' positions in social structure and the diversity of knowledge accessed through individuals' networks combine to influence their ability to act as catalysts of innovation.

Second, we also explore the interplay between network position and knowledge diversity. Central to research on the social structure of innovators is the assumption of a strong correspondence between network structure and knowledge diversity. Specifically, a sparse network rich in bridging ties is thought to provide access to diverse, nonredundant knowledge, whereas a dense network of closure ties is argued to provide homogeneous and overlapping knowledge. Yet the degree to which an individual's position in network structure corresponds with the diversity of knowledge available to that individual may vary (Rodan and Galunic 2004). For instance, knowledge sourced from outside of the organization can substantially change the knowledge base of a focal individual irrespective of the configuration of her network of contacts inside the organization. To the extent that network structure is not strictly isomorphic with knowledge diversity, there may be a multitude of ways in which networks and knowledge are configured, and those different configurations may matter for furthering our understanding of organizational innovation. Given our interest in explaining the ability of individuals to act as catalysts of innovation and that, as described further below, a defining activity of this role is the sharing of relevant knowledge with others, we treat social structure and knowledge diversity as distinct. We further argue that the configuration of social structure and knowledge diversity conducive to performing the role of catalyst is fundamentally different from that for the innovator role. Specifically, we propose that being embedded in a closed network (e.g., overlapping ties to common third parties) within an organization and having access to diverse external sources of knowledge increase an individual's capacity to act as a catalyst of innovation. We refer to this configuration of internal social structure and external knowledge diversity as a "diverse knowledge clique."

To gain a better understanding of how internal social structure and external knowledge diversity combine to influence individuals' ability to act in the role of catalyst of innovation, we conducted a study of 276 researchers in the research and development (R&D) division of a large, multinational high-tech company. In addition to conducting preliminary field interviews, we surveyed the members of the R&D division to obtain information about their external sources of knowledge and their knowledge-sharing networks within the organization. As a complement to the survey data, we also drew on archival sources from the company to obtain details about respondents' background, research profile, and position in the formal organization. In addition, we collected data about the innovative outputs of the individuals in the company based on monthly reports that identified patent applications and that the company used to assess and reward individual performance.

Based on our analysis of the data collected, we make three key observations. First, consistent with our prediction, individuals having access to diverse sources of external knowledge through a closed network of contacts within the organization are well positioned to play the role of innovation catalysts. Second, the role of catalysts of innovation is distinct from the role of innovators. Third, having knowledge-sharing relationships with

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catalysts of innovation helps inventors generate innovations. We discuss the implications of these observations for research on organizational innovation and for research on social networks in the concluding section of the paper.

Enabling Conditions

Anecdotally, innovation catalysts appear to be prevalent in organizations. For instance, a number of companies have established specialized roles, or teams of individuals, primarily responsible for enabling and facilitating the innovative activities of their colleagues (Martin 2011). In other organizations, the role is less well defined and individuals informally fulfill the function of assisting their colleagues' innovative efforts (Obstfeld 2005, Hargadon and Bechky 2006). Regardless of the extent to which organizations structure the role, the general observation that certain individuals in organizations act as catalysts by supporting and facilitating their colleagues' ability to generate innovations appears to have some representative validity. At the same time, however, systematic evidence on innovation catalysts is rather limited, and little is known about the supporting conditions that enable individuals to perform this role.

By definition, catalysts share knowledge with others. What sets apart the catalyst from others who perform similar activities is the combination of the relevance of the knowledge shared with recipients and the generative influence of that knowledge for colleagues in terms of stimulating and enhancing the development of novel products, processes, and ideas. For knowledge to be relevant, individuals need to be aware of who in their network is likely to benefit from that knowledge. And for knowledge to be generative of novel outputs requires that it be diverse relative to a colleague's existing stock of knowledge. Thus, beyond just the *willingness* to share knowledge with others, we would argue that *awareness* of knowledge needs in one's network and *diversity* of knowledge shared constitute a minimal set of enabling conditions for individuals to perform the role of catalyst. As we further argue below, these three conditions emerge from closed social structures that also provide access to diverse pools of knowledge.

In structural terms, the willingness to help and assist others by sharing knowledge has been traditionally associated with being embedded in a closed network of dense and overlapping connections to mutual third parties. Individuals embedded in closed networks develop norms of cooperation, enjoy greater levels of trust, and are well positioned to pursue collective rather than individual gains (Coleman 1988). Individuals embedded in closed networks are also likely to develop a clear understanding of what their colleagues do and do not know, which provides them with an enhanced awareness of their colleagues' knowledge requirements (Uzzi 1997). Thus, in terms of both the willingness to do so and the awareness of others' needs, closed networks are conducive to the knowledge-sharing activities that are integral to the catalyst role. Yet to stimulate and enhance the development of new ideas by others also requires innovation catalysts to have access to diverse sources of knowledge. We suggest that it is this configuration of access to diverse sources of external knowledge through contacts within an organization that are embedded in a closed network structure (i.e., a diverse knowledge clique) that provides the explanatory power for predicting individuals' ability to act as catalysts of innovation. In the next section, we develop a theory of innovation catalysts that focuses on the enabling conditions emerging from diverse knowledge cliques: access to diverse external knowledge, awareness of colleagues' knowledge needs, and willingness to share knowledge.

A Theory of Innovation Catalysts

Although the combination of network closure and knowledge diversity is unique with respect to the traditional literature on networks and innovation, more recent research has decoupled the type of knowledge accessed from the structure of the network (Rodan and Galunic 2004). The implication is that while knowledge diversity and network structure are related, they are not perfectly overlapping (Fleming et al. 2007). We build on this insight by considering a specific driver of knowledge diversity that is likely to introduce heterogeneity into even closed networks: access to knowledge sources that are external to the organization.

Knowledge Diversity

We focus on external knowledge because the broader literature on organizational innovation has stressed its critical role in fostering innovation (Cohen and Levinthal 1990, Chesbrough 2003). Short of assuming that individuals inside an organization acquire the exact same type of knowledge from the same external sources, external knowledge presents elements of novelty with respect to the knowledge available inside the organization (Cohen and Levinthal 1990, Zahra and George 2002, Chesbrough 2003, Laursen and Salter 2006). It follows that the diversity of knowledge sourced from outside the organization makes the knowledge base of individuals inside the organization less homogeneous even in those cases in which the pressure toward knowledge homogenization is greater (i.e., in closed networks). Our contention is based on the premise that the diversity of knowledge introduced into the organization as a result of individuals internalizing external sources of knowledge represents one important condition through which even structurally redundant contacts can come to possess knowledge that is not entirely overlapping of one another. As noted above, previous research has

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shown that access to diverse sources of knowledge is an important precursor to the innovation process. Similarly, access to diverse knowledge is also a precondition to helping and assisting others in the process leading to the generation of innovations. In particular, individuals act as a catalyst of innovation when they share the diverse knowledge accessible to them with *others* who might benefit from it.

Absorbing knowledge and insights from external sources is an important input into the process through which organizations generate innovations (Chesbrough 2003). For research-intensive organizations, being able to acquire and leverage inputs developed outside of the organization is particularly critical for their innovativeness (Cohen and Levinthal 1990). For instance, searching outside of technological and organizational boundaries has been shown to have a positive impact on a firm's technological evolution (Rosenkopf and Nerkar 2001). And engaging in wide and deep searches for external knowledge by leveraging market, institutional, and specialized channels promotes companies' innovation performance (Laursen and Salter 2006). However, external knowledge can also be difficult to integrate and leverage into an organization's own operations, suggesting that its internal use cannot be taken for granted. Thus, although numerous members of an organization may access diverse sources of knowledge, they may not all have the awareness of who needs what type of knowledge.

Awareness

When the diversity of knowledge and perspectives in an organization increases as a function of the diversity of knowledge accessed from outside, individuals are less likely to have a common knowledge base to understand and integrate the newly acquired knowledge (Ellis 1965, Simon 1985, Cramton 2002). This lack of common knowledge base could partially, or completely, prevent the further diffusion of external knowledge throughout the organization by increasing the difficulties associated with its transfer (Reagans and McEvily 2003) and acquisition (Tortoriello et al. 2012). Closed network structures, however, tend to facilitate the development of shared languages, frames of reference, and eventually a common knowledge base (Carlile and Rebentisch 2003).

In addition to facilitating the development of a common knowledge base, the frequent and repeated interactions that are characteristic of closed structures promote fine-grained information sharing and allow individuals to recalibrate their understanding of a contact's skills and knowledge (Borgatti and Cross 2003). Frequent interactions observed in cliques favor the formation of individuals' expertise associations so that individuals interacting with one another learn about the content and depth of each other's knowledge. In this way, it is easier to develop an accurate understanding of what colleagues know, what kind of problems they are currently working on, and what type of knowledge and expertise could be of help to them given their specific knowledge needs (Huber and Lewis 2010).

The preceding arguments suggest that when individuals inside an organization source different types of knowledge from outside, network closure is critical to explaining individuals' ability to perform the role of innovation catalyst. On the one hand, network closure promotes the development of a common language and shared frames of reference. On the other hand, individuals embedded in closed structures develop a capacity for understanding what their colleagues know (or do not know) so that they become better able to identify their colleagues' specific knowledge needs. Thus, individuals embedded in a diverse knowledge clique should have an enhanced awareness of their colleagues' knowledge requirements.

Willingness

Although access to diverse knowledge and awareness of others' knowledge requirements are important preconditions, assisting others' innovative efforts also requires the willingness to share knowledge that may be relevant and valuable to others. In closed networks, prosocial behaviors such as the willingness to share knowledge are enabled because of the ease of creating and enforcing cooperative norms. Since behaviors in closed networks are more "public," news of one person's actions quickly spreads to mutually connected third parties. As a result, reputational considerations and encouragement to engage in cooperative behaviors act as powerful inducements to, for instance, share diverse knowledge with colleagues who might be in a better position to exploit it. The norms of reciprocity and cooperation that develop in a close-knit social system (Coleman 1988) increase the likelihood that individuals embedded in that system would help and assist others when they are in need (Granovetter 1983, Reagans and McEvily 2003). By talking about common past experiences when interacting with a particular colleague, different individuals contribute to creating, maintaining, and disseminating that colleague's reputation in the broader social network. To the extent that such a reputation is positive, it facilitates interactions with others because of the greater availability of information about the focal party's trustworthiness. In the specific case of catalysts, their positive behaviors helping and supporting others' efforts toward the generation of innovations increase the degree of trust their colleagues have in them and contribute to maintaining and projecting their reputation as catalysts throughout the network.

To summarize the foregoing arguments, we propose that being embedded in a diverse knowledge clique creates the conditions conducive to individuals acting as catalysts of innovation. When the external knowledge

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sourced by an individual's internal contacts is diverse, we expect closure in the individual's network to be positively associated with the individual's ability to contribute to her colleagues' innovativeness because of the individual's increased awareness of colleagues' knowledge requirements and to the individual's increased willingness to collaborate by sharing it with others. Based on this reasoning, we predict the following.

Hypothesis 1 (H1). *Embeddedness in a diverse knowledge clique is positively related to being a catalyst of innovation.*

Data and Methods

Research Setting

To test our theory of innovation catalysts, we collected data on 276 scientists, researchers, and engineers in the R&D division of a large, multinational high-tech company. The R&D division consists of 16 research centers located in 10 countries around the world: 4 in the United States, 10 in Europe, and 2 in Asia. The R&D division's activities deal with a broad range of products, such as microelectronic components (e.g., memories, transistors, wireless applications, integrated circuits amplifiers, microprocessors), and develop specific applications targeting markets such as digital consumer electronics, wireless communications, storage, security, etc. The R&D division's personnel is further assigned to 1 of 21 different areas of technological expertise. Each area of technological expertise is focused on the development of a distinct technology. Examples of such areas/technology include Bluetooth data transfer, low power devices, and imaging/rendering. Interviews with lab personnel prior to data collection revealed the importance of informal interactions for knowledge sharing within the R&D division. For instance, a senior engineer in one of the largest labs explained that "keeping relationships with a lot of different people helps you ask the right questions. It also improves your understanding of their problems." This general statement about the relevance of informal relationships to facilitate knowledge sharing and understanding was further confirmed by another quote offered from a mid-career researcher at a different lab who reflected on his network as follows: "I think it is important to spend a lot of time with technicians, listening to their problems, understanding exactly what they need. I call this active listening. At the same time it is also important to go back and talk with people in your group with knowledge more similar to yours."

Data Sources

In addition to preliminary interviews, data for this paper came from survey and archival sources. In particular, we surveyed the members of the R&D division to obtain information about their external sources of knowledge and their knowledge-sharing networks within the organization. To complement survey data, we obtained data about respondents' backgrounds (gender, level of education), position in the formal organization (job grade, tenure, laboratory), and research profile (areas of technological expertise) from archival sources provided by the company.

The survey was administered using a password-protected website. Questionnaire items were developed after extensive field interviews with the company's senior managers and several researchers and engineers at different R&D labs. The survey was then pretested prior to the beginning of the actual data collection process. Only personnel with active research and development duties (e.g., no administrative or support staff) participated in the study. The survey yielded a response rate of 91% (249 actual respondents out of 276 potential respondents). Even though a minority of individuals did not respond, we tested for nonresponse bias looking at lab location, organizational tenure, organizational job grade, age, and gender, obtaining no statistically significant differences. The survey asked respondents different questions about the type of external sources of knowledge they systematically relied upon to accomplish their tasks in the innovation process (discussed in more detail below) and their knowledge-sharing network.

To collect network data, we used a sociometric approach, presenting respondents with a list of all the people working in the R&D division organized by lab and asking them to check the names of those with whom they have worked in the past two years on one or more projects or who represented an important source of knowledge for them even though they did not work on a project together. This process generated a unique list of contacts for each respondent that was then interpreted through specific questions about frequency of interaction with each contact and the extent to which each contact facilitated his or her own innovativeness. To address concerns about construct validity and accuracy of network data, we implemented Marsden's (1990) recommendations. For instance, we pretested the instrument used and, in the definition of specific question items, focused on long-term patterns of relationships rather than interactions limited to specific situations or narrowly defined periods of time (Freeman et al. 1987, Borgatti and Cross 2003).

Dependent Variable

Catalysts of Innovation. The extent to which an individual fulfils the catalyst role by helping his or her contacts to generate new creative solutions and ideas is the dependent variable in this study. Focusing on the supporting role of catalysts, we followed the same measurement strategy implemented by previous research emphasizing the diversity of innovation roles in which individuals engage during the innovation process (Ibarra 1993,

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Obstfeld 2005, Hargadon and Bechky 2006). In our particular case, we took into account relational assessments of individuals' contributions to the innovation process, considering the extent to which a given individual is recognized as a catalyst of innovation by his or her colleagues. Respondents assessed the extent to which each of their contacts was considered instrumental in supporting and developing their own innovativeness by answering the following survey item: "When I interact with this person it is easy for me to generate new creative solutions and/or ideas" (measured on a 5-point Likert scale). We entered the responses to this question into a squared matrix (i.e., catalyst matrix **C**) that reports individuals' evaluations of their colleagues ability to facilitate the generation of new solutions and ideas. We used this matrix to derive the extent to which each person was considered a catalyst of innovation by his or her contacts.

Since our intention was to capture the extent to which the catalyst's role was instrumental in promoting the innovativeness of others, we weighted the scores reported in the **C** matrix by each respondent's innovativeness. In particular, we weighted a respondent's assessment of his colleagues as catalysts of innovation by multiplying the entries in the **C** matrix by the log-transformation of the number of patents the respondent applied for in a 24-month period. Accordingly, the catalyst assessments reported by researchers who applied for patents increased with the number of applications, whereas the catalyst assessments reported by researchers who applied for no patents remained unchanged.[1] We calculated our dependent variable as the normalized in-degree centrality of the weighted **C** matrix.

This measure of innovation catalysts is particularly appropriate for our purposes for several reasons. First, it is consistent with the relational nature of the phenomenon studied. We conceptualized the role of innovation catalyst as an individual's contribution to other researchers' innovativeness, and our measure reflects each researcher's assessment of the extent to which each of his or her contacts enhanced his or her own innovativeness. Second, by weighting catalysts' evaluation by the actual innovativeness of the evaluators, our measure takes into account variation in the extent to which individuals are effective in their role as catalysts. For instance, our measure allows us to discriminate between someone who catalyzes prolific innovators versus someone who is indicated to be a catalyst by individuals who are not very prolific innovators. Third, being based on everybody's evaluation of all the contacts in their network, this measure takes into account multiple perspectives. This makes our measure more robust than, for instance, a simple supervisor's ratings where one individual provides evaluations of all his or her subordinates. Fourth, since this measure is based on the evaluations of ego made by his or her alters, it has the additional advantage of not being a self-reported measure. This allows for mitigating possible issues of common method variance in the analysis since the other independent variables of interests (e.g., exchange of information, type of knowledge sourced from outside) are based on self-reported measures.[2] Taken together, we believe that our measure for catalyst of innovation is consistent with our theoretical conceptualization.

In addition to determining the theoretical consistency of our catalyst measure, we also thought it was important to assess the measure's empirical properties. To our knowledge, the concept of the innovation catalyst is novel, and certainly, our proposed indicator of the catalyst role is heretofore untested in its psychometric properties. Although in-depth psychometric analysis of this measure is beyond the scope of this paper, we did explore two properties of this measure that are generally considered critical in measurement theory: convergent and discriminant validity (Campbell and Fiske 1959; Urbina 2004, p. 180). That is, we explore the question of whether our measure of innovation catalysts converges on independently measured indicators that being a catalyst *should* predict, and we explore whether our measure of catalysts adequately discriminates from other potentially confounding but different constructs.

Discriminant Validity. A catalyst is one who inspires others toward innovation. One could argue, though, that innovators themselves are seen as fountains of ideas, that these ideas inspire others to be innovative. Perhaps being a proficient innovator is both necessary and sufficient to be a catalyst. If this were the case, then being a catalyst would add nothing more than being an innovator; the concept of the catalyst would provide little insight into the innovation process. Although it is possible that some catalysts may be innovators, our argument about the role of the catalyst does not require the person to be an innovator him- or herself. Thus, we would expect that some, but not all, innovators would be catalysts. Conversely, we would expect that some, but not all, catalysts will be innovators. Thus, the extent to which identification as a catalyst and identification as an innovator are relatively unrelated to each other is an indication that the two roles are distinct concepts and provides evidence to support the discriminant validity our measure of catalyst relative to innovation itself.

Table 1 shows the relationship between the roles of catalysts and innovators. Of the 276 researchers, 39 (14%) are designated as catalysts; 21 (8%) are designated as innovators. As can be seen, the overlap between catalysts and innovators is minimal (1.5%, or 4 individuals out of 276 are both innovators and catalysts). The majority of innovators are not catalysts (i.e., 17 out of 21, or approximately 81% of innovators, are not catalysts), and the majority of catalysts are not innovators (i.e., 35 out of 39, or approximately 90% of catalysts, are not

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Table 1 Comparing Catalysts' and Innovators' Roles

	Catalysts		
Innovators	Low score	High score	Total
High score	17 (6.2%)	4 (1.5%)	21 (7.7%)
Low score	220 (79.6%)	35 (12.7%)	255 (92.3%)
Total	237 (85.8 %)	39 (14.2%)	276 (100%)

Note. "Low" and "high" are defined as smaller than and greater than mean plus standard deviation, respectively.

innovators). More telling, the proportion of innovators who are catalysts is 19% (4 of 21), which is not substantially higher than the proportion of *non-innovators* who are catalysts (14%, or 35 of 255). A similar account is found if we look at the proportion of catalysts who are innovators: 10% (4 of 39) of the catalysts are also innovators, only slightly higher than the 7% (17 of 237) of *non-catalysts* who are innovators. The point biserial correlation between these two constructs is 0.13. This is safely below the commonly used threshold of 0.8 to establish discriminant validity between two constructs (values above 0.8 are often interpreted as suggesting a lack of discriminant validity). Indeed, a chi-square test of independence ($\chi^2 = 0.12$, $p > 0.7$) indicates there is no significant relationship at all between these two measures. Being a catalyst is clearly distinct from being an innovator.

Convergent Validity. Perhaps even more important, though, is whether the instrument adequately assesses the underlying construct it purports to measure. Several types of convergence of the measure with its underlying construct are typically used to evaluate how good the measure is. We have access to two types of convergent validity tests. First, a construct has "face validity" if, by virtue of its specific wording on a questionnaire, it appears to be related to the underlying construct. The face validity is evident in our case since respondents are asked directly whether the target is a catalyst in innovation.

A second, more critical test of convergent validity, however, is whether the measure empirically is associated with what it is theoretically supposed to capture—that is, whether it has what Anastasi and Urbina (1997) refer to as "criterion-prediction validity" (p. 188). If an individual colleague is truly a catalyst, then those researchers who are connected to that catalyst should be more innovative than those researchers who have no direct tie to such a catalyst. To test this, we examined the innovative productivity of researchers who were directly connected to a catalyst in their network, comparing this to the productivity of researchers who had no such catalyst in their local network.

The results of this comparison are reported in Figures 1(a) and 1(b). Figure 1(a) uses the patent-weighted specification of the catalyst measure as described above,

Figure 1(a) (Color online) Effect of Catalysts on Other Researchers' Patent Applications (Weighted Dependent Variable to Identify Catalysts)

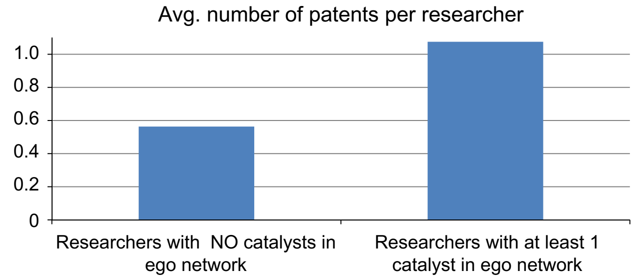
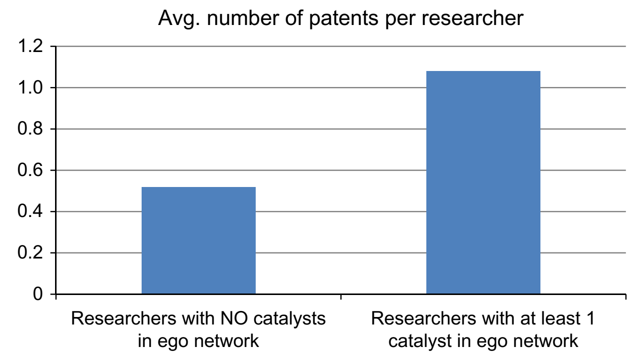


Figure 1(b) (Color online) Effect of Catalysts on Other Researchers' Patent Applications (Unweighted Dependent Variable to Identify Catalysts)



and Figure 1(b) identifies catalysts as simple in-degree of the **C** matrix (i.e., without patent weighting). For ease of exposition, we refer below to the patent-weighted specification of the catalyst measure; results obtained considering the unweighted specification of catalysts are substantially similar. Although the number of catalysts in the R&D division was relatively small (less than 15% of the sample in either specification), each of these catalysts connected to a number of researchers. Thus their catalytic benefits spread to a larger number of colleagues than their small numbers would imply. Of the 276 researchers, 185 (67%) enjoyed the benefit of having at least one catalyst in their local network. The remaining 55 (33%) were not connected to any catalysts. The difference between these two sets was substantial. As shown in Figures 1(a) and 1(b), those who were connected to a catalyst were almost twice as productive as those who had no catalysts in their local network. This difference is significant as well as substantial ($t = 2.19$, $p < 0.015$, one-tailed).[3]

Independent Variables

The social network measures used as independent variables in the analysis are based on knowledge and information exchange relationships. The following two questions were used to capture information exchange relationships: "Please indicate how often you generally go to this person for information or knowledge

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on work-related topics" and "Please indicate how often this person generally comes to you for information or knowledge on work-related topics." Respondents were asked to answer these questions on a 1 to 5 scale (where 1 ="seldom" and 5 ="very frequently"). Following Krackhardt (1990),[4] we derived a matrix of *confirmed* information exchange relationships based on the combination of entries in the "go to for information" matrix with the transpose of the "come to you for information" matrix. This allowed us to retain only those relationships for which both parties involved agree that one goes to the other for knowledge or information.

Network Redundancy. In general terms, network redundancy refers to the situation in which ego's alters are also themselves connected. To measure redundancy in our particular case, we used the algorithm implemented in UCINET 6 (Borgatti et al. 2002), computed on the confirmed exchange of information matrix described above. As described in detail in Borgatti (1997), for each ego in the network, this measure represents the average within ego-network degree of alters and expresses the extent to which each of ego's alters are tied to ego's other alters. Network redundancy can be expressed as $2t/n$, where t is the number of ties in the network (not counting ties to ego) and n is the number of nodes excluding ego. Greater values of redundancy indicate that the individuals' ego network is mostly composed of contacts that are themselves connected to each other, whereas lower levels of redundancy indicate that the individuals' ego network is mostly composed of contacts that are not connected to each other. We entered these values into a squared matrix (i.e., the redundancy matrix, **R**).

External Knowledge Diversity. External knowledge sources were defined after extensive interviews with senior researchers at the company prior to data collection and were subsequently approved by a panel of senior managers. The final set of knowledge sources include conferences, scientific journals, patents, collaboration with research institutions, relationships with clients, relationships with suppliers, funded projects, and standardization committees. Respondents were asked to rate "the extent to which each item represented for them an important source of scientific and/or technological knowledge for their professional activity at <name of the company>" on a scale from 1 to 7 (where 1 = "not at all" and 7 ="to a very large extent").

A principal component factor analysis with varimax rotation performed on the external knowledge items identified two distinct factors with eigenvalues greater than 1: scientific external knowledge and industrial external knowledge.[5] As shown in Table 2, industrial external knowledge is defined by four items with a Cronbach's alpha of 0.77, and the first principal component explained 63.2% of the variance. Scientific external knowledge is also defined by four items with a Cronbach's alpha of 0.81, and the first principal component explained 58.4% of the variance.

Table 2 Sources of External Knowledge: Item Loadings

External knowledge variables	Mean	S.D.	Loading on scientific knowledge	Loading on industrial knowledge
Funded projects	4.23	1.85	0.46	**0.61**
Standardization committees	4.68	1.82	0.37	**0.67**
Collaboration with clients	4.11	1.92	0.15	**0.84**
Collaboration with suppliers	3.43	1.83	−0.03	**0.87**
Conferences	4.67	1.84	**0.81**	0.11
Scientific journals	5.01	1.65	**0.84**	0.00
Patents	3.71	1.82	**0.55**	0.45
Collaboration with research institutions	5.06	1.79	**0.78**	0.28

Note. The question asked was "For each item please indicate the extent to which it represents an important source of technical and/or scientific knowledge for your professional activity at <name of the company>." Items were measured with a 7-point Likert scale, ranging from "not at all" to "to a great extent." Loading factors > 0.5 are in bold. Loadings are based on varimax rotation.

We captured heterogeneity in the type of knowledge sourced from outside the organization based on the combination of scientific versus industrial sources of knowledge accessed by individuals in our sample.[6] We measured the diversity of knowledge available in each ego network i as composed of two parts.

First we identify the diversity of external knowledge sources between each pair of individuals in our sample by computing the matrix **D**:

$$D = \sqrt{(S_i - S_j)^2 + (I_i - I_j)^2}, \quad i \neq j, \tag{1}$$

where S_i (S_j) is the reliance of individual i (j) on scientific sources of external knowledge and I_i (I_j) is the reliance of individual i (j) on industrial sources of external knowledge.[7] The term d_{ij} in the **D** matrix in Equation (1) expresses for each possible dyad similarity (or differences) in the combination of external knowledge that the members of that dyad access from outside the organization.

The next step was to measure the diversity of external knowledge available in each ego network by taking the average of alter–alter knowledge differences for all the contacts available in that ego network. We entered these values in the **K** matrix. The generic element k_{ij} in the matrix **K** is described in Equation (2) and reports for each alter in a given ego network i the average knowl-

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edge differences among alter j and all the other alters q in the ego network i:

$$k_{ij} = \frac{2}{N_{\text{ego}}(N_{\text{ego}}-1)} \sum_{j,\, q \in \text{ego}_i} d_{jq}, \quad j < q. \tag{2}$$

Finally, to obtain the measure of external knowledge diversity for each ego network i (based on the alter–alter knowledge differences described above), we summed the values k across all the j's in i's ego network and divided by the number of alters:

$$\textit{External\_Knowledge\_Diversity\_in\_Ego}_i = \frac{1}{N_{\text{ego}}} \sum_j k_{ij}. \tag{2a}$$

R-K Index (Diverse Knowledge Clique). In the theory section, we argued that being embedded in a diverse knowledge clique is positively related with the extent to which individuals are recognized as catalysts of innovation by their colleagues. To test this hypothesis, we created a measure to indicate the extent to which knowledge diversity and network redundancy coincide in the dyads of an individual's ego network. In particular, if **R** is the matrix with dyadic redundancy values (i.e., expressing the extent to which each alter represents a redundant contact for ego) and **K** is the knowledge diversity matrix composed of the elements described in Equation (2) (i.e., expressing the amount of external knowledge diversity that each alter brings to the ego), we obtained a newly defined matrix, **B**, by performing an element-wise multiplication of the values reported in the matrices **R** and **K**. In this way, we adjusted the redundancy score of each alter in a given ego network by the amount of knowledge diversity he or she provided to ego. Summing the values reported in the **B** matrix across all alters in i's ego network, we obtained a measure describing the extent to which each ego in our sample is embedded in a redundant structure that is, at the same time, rich in diverse external knowledge. In the analyses that follow, we refer to this measure as the *R-K Index*, formally defined as

$$b_i = \sum_j B = (R \times K). \tag{3}$$

A possible objection to this approach is that instead of Equation (3), which weights each alter's redundancy by the diversity of knowledge he or she provides, our theory could be tested with a simple interaction term between the two "main effects," network redundancy and knowledge diversity considered at the ego-network level. Although a conventional interaction term obtained by multiplying the overall network redundancy and overall knowledge diversity measured at the ego-network level of analysis has the virtue of simplicity, it also has the disadvantage of producing ambiguous values for our purposes.[8] Specifically, an interaction term defined at the ego-network level of analysis clouds the extent to which contacts that are redundant are also characterized by diverse knowledge among themselves—the very distinction we seek to highlight. For instance, an interaction term between network redundancy and knowledge diversity considered at the level of the ego network could yield the same result for an ego network in which the most redundant contacts provide the most diverse knowledge and an ego network in which the most redundant contacts provide the least diverse knowledge. However, based on our theorizing, the extent to which redundant contacts provide diverse knowledge to the ego is more accurately captured at the level of the specific dyads and then aggregated up at the level of the ego network (Reagans and Zuckerman 2001, pp. 508–509) rather than obtained through an ego-network interaction between overall redundancy and overall knowledge diversity.

Implicit in our theory and prediction is the assumption that knowledge diversity and network redundancy are distinct rather than isomorphic as much previous social network research has treated them. To validate this assumption, we calculated at the dyadic level the correlation between knowledge diversity and network redundancy. We calculated the dyadic correlation using the quadratic assignment procedure (Krackhardt 1988) and found a very modest and not statistically significant association ($p = 0.079$, n.s.). We find similar results computing a standard Pearson correlation between dyadic-level knowledge diversity and network redundancy ($r = 0.014$, n.s.). These results suggest that it is not only appropriate but also more precise to treat knowledge diversity and network redundancy as distinct.

Controls. In each model we control for several covariates that might provide alternative explanations for the hypothesized effect of external knowledge and social structure on individual's contribution to the innovation process. In particular, we use organizational *seniority* (i.e., days since hiring/100) to control for individuals with longer tenure having had more time to "prove themselves" useful in the innovation process relative to someone newly hired. Members of the organizations with more *seniority* might also have more "network leverage" than those newly hired. We also control for the highest *level of education* received (1 to 4 scale, where 1 = high school diploma, 2 = bachelor's degree, 3 = master's degree, 4 = Ph.D. degree), since individuals with doctorates likely have a higher research potential than people with less advanced degrees, and this might translate into a higher potential for contributing to the generation of innovations independent of the social network in which they are embedded. Organizational *job grade* could also be an alternative explanation for the relationship hypothesized in our model. Individuals with higher positions in the organization presumably have a record of being successful in the field of research and development that

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led to their career advancement, and individuals with higher positions in the organization are also often tasked with mentoring and assisting junior colleagues in their research efforts, which is akin to being a catalyst. Here, we use the nine-point scale adopted in the company to identify nine different formal levels. We also control for confounding effects provided by contextual features. For instance, the *size of the laboratory* (number of people) is an important covariate of networking opportunities: bigger laboratories offer more contacts and afford greater visibility than do smaller ones. Similarly, we use dummy variables to control for differences in labs and individuals' areas of technological expertise. Finally, we control for the type of external knowledge sourced by ego, distinguishing between *scientific* and *industrial* external knowledge, and for the number of contacts in each ego network based on out-degree in the knowledge-sharing network (*network size*) since individuals with more contacts might have more opportunities to access knowledge and information that could increase their ability to act as catalysts of innovation independent of the proposed theoretical mechanisms.

Analysis and Results

Descriptive statistics and correlations among all variables are reported in Table 3. We used a set of ordinary least squares (OLS) regressions to evaluate the effects of internal social structure and external knowledge sources on individuals' ability to help their colleagues generate new ideas and creative solutions. Table 4 presents regression coefficients, standard errors, R-squared values, and adjusted R-squared values. Model 1 estimates the effects of the control variables. Among the controls, job grade, scientific external knowledge (only marginally so), and network size are significantly associated with our dependent variable. Occupying a high position in the formal organization of the R&D division, accessing scientific knowledge from outside the organization, and having a large network of contacts are positively associated with being recognized as a catalyst of innovation.

In Model 2 we introduce external knowledge diversity, which is positively and significantly associated with being recognized as a catalyst of innovation. This suggests that there are direct benefits of having relationships with contacts that source diverse types of knowledge from outside the organization. Model 3 introduces internal network redundancy, which is negatively and significantly associated with being recognized as a catalyst of innovation. The negative effect of network redundancy is consistent with prevailing theoretical accounts for the "vision" advantage (Burt 1992, 2004) associated with nonredundant network structures, or conversely, that there are limited informational and knowledge advantages associated with redundant network structures. In Model 4, we include both external knowledge diversity

Table 3 Correlation Table and Descriptive Statistics

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
1 *Catalyst of innovation*	1.17	0.80											
2 *Job grade*	13.67	2.28	0.4718***										
3 *Sex*	0.90	0.30	0.1056	0.0596									
4 *Level of education*	2.95	0.49	0.0204	0.1198*	−0.0565								
5 *Size of the laboratory*	24.51	14.02	0.1078	−0.097	−0.0646	−0.035							
6 *Seniority*	18.25	16.77	0.2199***	0.5394***	0.0688	0.0042	0.0675						
7 *External scientific knowledge*	4.60	1.39	0.1722**	0.1186	−0.0409	0.1151	0.2479***	−0.0219					
8 *External industrial knowledge*	4.23	1.50	0.0688	0.0907	−0.0608	−0.0019	0.0425	0.015	0.3843***				
9 *Network size* (no. of alters)	11.00	6.71	0.3192***	0.2117***	0.0193	0.1006	−0.0873	0.1222*	0.0821	0.0915			
10 *Network redundancy*	0.29	0.19	−0.3187***	−0.3184***	0.0362	−0.0783	−0.1155	−0.2846***	−0.0572	−0.0114	−0.2041**		
11 *External knowledge diversity*	22.80	12.60	0.3132***	0.1228	0.0601	0.0095	−0.091	0.0937	−0.1149	−0.0128	0.8268***	−0.0928	
12 *R-K Index*	4.52	2.85	0.0179	−0.1482*	0.1072	−0.1256	−0.244***	−0.227***	−0.171*	−0.067	0.157*	0.553***	0.383***

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

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Table 4 Effects of External Knowledge Diversity and Network Redundancy on Being a Catalyst of Innovation

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6 (unweighted scores)
Job grade	0.170*** (0.02)	0.179*** (0.03)	0.165*** (0.02)	0.176*** (0.03)	0.155*** (0.02)	0.343*** (0.05)
Sex	0.042 (0.15)	0.015 (0.15)	0.118 (0.15)	0.098 (0.15)	0.004 (0.15)	−0.002 (0.331)
Level of education	0.04 (0.10)	0.085 (0.10)	0.082 (0.09)	0.086 (0.09)	0.179 (0.10)	0.369† (0.22)
Size of the laboratory	0.008 (0.02)	0.011 (0.02)	0.01 (0.02)	0.013 (0.02)	0.001 (0.01)	−0.003 (0.03)
Seniority	0.001 (0.00)	0.001 (0.00)	0.003 (0.00)	−0.001 (0.00)	0.003 (0.00)	−0.001 (0.01)
External scientific knowledge	0.073† (0.04)	0.07† (0.04)	0.066 (0.04)	0.06 (0.04)	0.048 (0.04)	0.11 (0.09)
External industrial knowledge	−0.032 (0.03)	−0.022 (0.03)	−0.036 (0.03)	−0.027 (0.03)	−0.009 (0.03)	−0.012 (0.07)
Network size (no. of alters)	0.037*** (0.01)	0.002 (0.02)	0.032*** (0.01)	−0.007 (0.02)	−0.015 (0.02)	−0.031 (0.04)
External knowledge diversity		0.020* (0.01)		0.021* (0.01)	0.007 (0.01)	0.014 (0.02)
Network redundancy			−0.642* (0.27)	−0.741** (0.27)	−2.486*** (0.38)	−5.45*** (0.84)
R-K Index					0.100*** (0.02)	.221*** (0.05)
Constant term	−2.516* (0.99)	−3.133** (1.07)	−2.366* (1.07)	−1.566 (0.93)	−1.526 (1.03)	−3.405 (2.27)
Laboratory dummy	Yes	Yes	Yes	Yes	Yes	Yes
Area of technological expertise dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.525	0.539	0.549	0.561	0.647	0.643
Adjusted *R*-squared	0.429	0.44	0.448	0.46	0.554	0.548
No. of observations	245	245	237	237	237	237
Model *F*-test	5.469***	5.459***	5.440***	5.532***	6.930***	6.8***

Notes. The dependent variable is *catalysts of innovation*. Standard errors are in parentheses.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

and internal network redundancy in the same equations obtaining the same results. Finally, Model 5 introduces the effect of the R-K Index in which the redundancy of each contact is weighted by the heterogeneity of external knowledge provided by that contact. As predicted in our main hypothesis, being embedded in a redundant structure in which individuals have access to diverse sources of knowledge is positively and significantly associated with being identified as a catalyst of innovation. In particular, comparing the effect of network redundancy with the effect of the R-K Index, we observe that the effect of the latter is more than half the size of the effect of the former. A one-standard-deviation increase in network redundancy translates into a 0.56-standard-deviation decrease in an individual's ability to act as an innovation catalyst, whereas a one-standard-deviation increase in the R-K Index translates into a 0.42-standard-deviation increase in an individual's ability to act as a catalyst of innovation. As a further check, we estimate Model 6 using the unweighted specification of the catalyst measure as a dependent variable (i.e., the simple in-degree centrality of matrix **C**). The fact that the results are virtually identical to those reported in Model 5 suggests that the patent weighting used to identify catalysts of innovation does not appear to be biasing our results in any direction.

Robustness Checks

In addition to the OLS models presented in Table 4, given the potential for nonindependence of observation within labs or within areas of technological expertise, we reran all the analysis-clustering observations by lab and by area of technological expertise. Since social interactions among individuals are more likely within rather than across organizational or technological boundaries, it is possible that social network data provided by individuals located in the same lab or working in the same technological area do not satisfy the requirement of independence of observation imposed by OLS estimation techniques. Individual responses about their networks'

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ties and about their colleagues' role as facilitators in the generation of new ideas and solutions might in fact be more similar within than across laboratories or areas of technological expertise, and this can potentially bias the results of traditional OLS models. A two-way clustering (by laboratories and by areas of technological expertise in our case) provides robust variance estimates that adjust for within-cluster correlation and thus controls for the potential nonindependence of observations (Cameron et al. 2011, Kleinbaum et al. 2013). Adopting this modeling technique, we obtained the same results as those presented in Table 4. This provides important evidence for the robustness of the findings presented in this paper. In addition to two-way clustering, our findings are also robust to other modeling techniques such as robust regression and regression with robust standard errors.

Additional analyses not reported here show that multicollinearity does not affect our results. As a rule of thumb, multicollinearity is an issue when a predictor has a variance-inflation factor (VIF) larger than 10 (Belsley et al. 1980). In the final model of Table 4, the average VIF is 2.03, with the largest value of 4.28 for the effect of external knowledge diversity. We also checked for heteroscedasticity using a Breusch–Pagan test. The results of the test confirmed the constant variance of residuals ($\chi^2 = 1.38$, $p = 0.24$).

In one last set of analyses not reported here, we control for the possibility that catalysts' evaluation might be due to homophily/similarity between the parties involved and/or to individuals' previous track record as innovators. Regarding the first point, for instance, there might be a tendency to recognize as catalysts individuals from the same occupational cohort, within the same job grade, or with the same educational degree. To dispel the possibility of biases in catalyst evaluations due to homophily-based explanations, we computed for each ego network similarity measures for each of the three attributes discussed above (seniority, job grade, and level of education). Our results are unchanged when adding these additional controls in our models. With regard to the second point, to capture individuals' previous track record as innovators, we also controlled for the number of patents generated by individuals in the sample in the three years before the collection of network data. Consistent with the discriminant validity analysis presented above, this covariate is not statistically associated with our catalyst measure ($p = 0.581$), and our results remain unchanged when this variable is introduced.

Endogeneity and Reverse Causality

Because of the cross-sectional nature of the data, the potential for endogeneity and reverse causality are two important concerns. Individuals that play a critical role in enhancing their colleagues' innovativeness may have idiosyncratic characteristics (experience, talent, abilities, expertise, etc.) that could explain their ability to generate innovations and could also explain, at the same time, their position in the overall social structure. For instance, more skilled/knowledgeable individuals might be more helpful in the innovation process and might also end up occupying network positions that further their ability to help their colleagues in the innovation process. Within the limitations of a cross-sectional design, we took all possible actions to reduce the potential risks of endogeneity. Consistent with previous research on social networks and knowledge management (Reagans and Zuckerman 2001, Reagans and McEvily 2003), we used individual-level covariates to control for unobserved differences in individuals' knowledge, ability, experience, and expertise, which may affect their capacity to contribute to the generation of innovations. That the effects of the network variables persist and remain statistically significant with the inclusion of these controls enhances our confidence in the validity of the results. At the same time, though, it is important to acknowledge that without the ability to lag our dependent variable or to instrument our explanatory variables (Wooldridge 2002, pp. 50–51), we cannot definitively rule out the possibility that unobserved variables might affect our results.

In addition to exploring the possibility of unobserved heterogeneity, we also attempted to address the issue of reverse causality. Indeed, given our cross-sectional design, one might argue that the hypothesized effect of social structure and knowledge diversity on an individual's ability to act as a catalyst of innovation runs in the opposite direction to what we predicted (i.e., being a catalyst of innovation affects an individual's position in the social structure and access to diverse knowledge). If this were the case, the frequency of interactions should be biased toward individuals widely recognized by their colleagues as catalysts of innovation, since there should be a tendency to favor interactions with those who have a positive reputation for their role as catalysts of innovations versus those who do not enjoy such reputation. To address this issue, as a robustness check, we computed a version of our dependent variable based only on a *subset* of the relational evaluations used to derive the original measure. In particular, for each ego in the analysis, we recomputed our dependent variable after removing the evaluations received from those alters who frequently interact with ego.[9] The results obtained with this different operationalization of our measure of catalyst of innovation are exactly the same as those obtained with the original specification of the dependent variable. This provides some indication that reverse causality does not appear to affect the results of the analysis in terms of biasing frequency of interaction in favor of more innovative individuals.

One last element that mitigates concerns of reverse causality is given by the pattern of results obtained. In Table 4 we observe that the direct effect of network

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redundancy is negative, whereas the effect of the R-K Index is positive. The change in the sign of the coefficients between network redundancy and network redundancy adjusted for knowledge diversity would appear to be difficult to explain based on reverse causality. If reverse causality were operating in our analysis, it is not clear why taking into account the type of knowledge exchanged through network ties would change the sign of the network redundancy measure. In fact, if reverse causality were operating in our context, we would expect the relationship between network redundancy and being a catalyst of innovation to be the same *independent of* the type of knowledge exchanged among individuals.

Discussion

Being able to support and inspire others' innovativeness is critical because it is at the core of the social and collective nature of the innovation process. Yet research on social structure and innovation has primarily focused on the role of innovators and on the knowledge and structural conditions that promote and support the development of this role.

Although a considerable body of research on organizational innovation has focused on the role of innovators and the conditions affecting their productivity, we join a growing stream of research suggesting that in addition to innovators, there is an ecology of roles supporting the innovation process that are seldom considered (Ibarra 1993, Obstfeld 2005, Hargadon and Bechky 2006). Among those, the role of catalyst is particularly important because it gets at the core of the social and collective nature of the innovation process, which has highlighted that the myth of the lone inventor is, to a certain degree, just that (Hargadon 2003). Ironically, though, although acknowledging that innovators are not alone in the pursuit of the innovation process, the majority of research in this area has remained relatively silent about the supporting roles that exist and under what conditions such supporting roles are more likely to emerge.

Catalysts of innovation are one specific example of the "less visible" but still critical role that individuals play in the process leading to the generation of innovations in organizations, and therefore it deserves to be explicitly studied. Clearly, different roles might require different enabling conditions in terms of access to knowledge and position in the social structure. For instance, previous network research has suggested that brokers are ideally positioned to act as innovators since they benefit from access to diverse sources of knowledge (Burt 2004, Perry-Smith 2006) and, at the same time, enjoy relative freedom to pursue their own goals and objectives thanks to their network positions rich in bridging opportunities (Burt 1992). Catalysts of innovation, however, while still requiring access to diverse knowledge and information to inspire creativity in others, differ from brokers in that rather than pursuing independently the generation of innovation, they are willing to provide knowledge inputs to help their colleagues be more innovative. In structural terms, we identified the condition of being embedded in a diverse knowledge clique as being associated with an individuals' ability to successfully act as a catalyst of innovation.

Our research further provides evidence for the fact that innovation catalysts are distinct from innovators, not just in terms of knowledge and structural positions but most importantly in terms of actual innovative output generated. Identifying innovators based on the number of their patent applications, our analysis shows that innovators and catalysts are two distinct roles, such that there is no statistically significant overlap between these two categories in the empirical context studied. Finally, our analysis also shows how the role of innovation catalysts is consequential for innovators' ability to generate patent applications. In particular, being connected to a catalyst is associated with researchers applying for a greater number of patents.

In addition to introducing the role of catalysts and distinguishing it from that of innovators, our study also suggests the importance of treating as distinct the type of knowledge individuals access through their contacts and the structural configuration of the contact network in which individuals are embedded. For instance, when the type of knowledge flowing through network ties is not explicitly considered, our results suggest that being embedded in a cohesive network structure has a negative impact on individuals' ability to act as innovation catalysts. This result is consistent with previous research on social networks and organizational innovation that have observed a negative association between being embedded in redundant social structures and various indicators of innovation in organizations (Models 3–5). When considering the impact of the R-K Index, we observed a positive effect on an individual's ability to contribute to the innovation process by helping others be more innovative (Model 5). Thus, although the assumption of isomorphism between the distribution of network ties and the type of knowledge has been widely accepted by social network and organizational scholars, we join an emerging line of research that has begun to explore the extent to which this assumption holds uniformly (Rodan and Galunic 2004, Fleming et al. 2007). We complement this stream of research by examining a different innovation outcome (i.e., playing the role of catalyst) and by considering a different element of knowledge diversity (i.e., external knowledge). Taken together, these studies along with the present research suggest that the degree of correspondence between network structure and knowledge diversity may vary across different empirical contexts and should not be assumed to be perfectly aligned in all circumstances. Future research in this area could evaluate how unusual configurations of knowledge and networks, such as diverse knowledge cliques, affect other

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innovation-related outcomes or innovation-related roles in addition to individuals' ability to act as catalysts.

In addition to other innovation-related outcomes, we also see the relationship between the catalyst role and other organizational outcomes as an interesting avenue to pursue. Emphasizing the variety of roles that support the innovation process is also an important way of gaining a better understanding of the underlying causal mechanisms linking social networks and innovation in a way to inspire new managerial practices and improve on current ones. For instance, one practical implication of our study could be in the redesign of team composition in a way to promote closer interactions among individuals with different knowledge orientation. Perhaps investing in the formation of such teams might not immediately result in the generation of innovations per se but would likely promote the emergence of the catalysts' role that could help, indirectly, the process leading to the generation of innovation. Moreover, in this study we exclusively studied the catalyst role in the context of organizational innovation. We believe, however, that the role potentially extends to other critical organizational processes and outcomes such as change (Battilana and Casciaro 2013), growth (McEvily et al. 2012), and performance (Galunic et al. 2012) and that the way to improve individuals' ability to get things done in different organizational realms could pass through the development of supporting roles that emerge out of close interactions among individuals with different knowledge and skill sets.

Limitations and Future Directions

The implications of this research should be considered within the confines of the study's limitations. One limitation is the measure used for the outcome variable. Although the measure is consistent with the theory proposed, it is based on a single item, which might raise questions about the precision of the instrument. Future studies could advance our understanding of the potentially multifaceted role of innovation catalysts.

A second limitation concerns our measure of knowledge heterogeneity. Although we have measured knowledge heterogeneity in terms of differences between external sourcing of scientific and industrial knowledge, knowledge diversity could also be operationalized in other ways. The distinction adopted here is both very general and context specific. It is context specific because although distinguishing between industrial and scientific knowledge could be important in R&D divisions of large organizations, it might not be as salient in different organizational units (e.g., manufacturing). This distinction is also very general because within both realms of scientific and industrial knowledge, there are obviously several distinct content areas that introduce additional elements of heterogeneity that we are not capturing. Even though we considered it encouraging to observe the hypothesized effects on catalysts' roles when using two broad dimensions such as scientific and industrial knowledge, taking into account additional specifications of knowledge diversity would help to generalize the validity of our findings.

Finally, although we focused on the structural drivers of individuals' ability to fulfill the role of innovation catalysts, it would be valuable to consider the extent to which there are different types of catalyst roles and the extent to which the effectiveness of each role varies across different contexts. For instance, individuals in organizations can help their colleagues improve on their performance by inspiring and encouraging them to pursue certain directions, by offering them tangible resources and inputs, or by constantly criticizing and finding problems in what they do. Our goal with this paper was to bring attention to the role of catalysts with the hope of inspiring future research to further our understanding of the contingencies and mechanisms that drive the effectiveness of different catalyst roles.

Conclusions

Organizational innovation is increasingly coming to be understood as a collective rather than exclusively individual activity. Research on the social structure of innovation has contributed greatly to advancing our understanding of the collective nature of the innovation process. Apart from considering the different network configurations and positions that are central to the generation of innovations in organizations, we would stress the importance of identifying and understanding the ecology of roles involved in this essential organizational activity. This study provides an initial effort in this respect by focusing on catalysts and the social structural conditions conducive to performing this role. We hope that future research will build on these insights and further advance our understanding of the collective nature of organizational innovation.

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Endnotes

[1]The exact transformation is $\ln(e+p)$, where e is a constant and $p=$ the number of patent applications. Thus, a researcher who applies for zero patents and assesses a particular colleague as a 5 on the catalyst scale would yield a rating of 5, a researcher who applies for one patent and assesses a particular colleague as a 5 on the catalyst scale would yield a rating of 6.57, a researcher who applies for two patents and assesses a particular colleague as a 5 on the catalyst scale would yield a rating of 7.76, etc.

[2]As a robustness check, we ran several additional analyses based on catalyst measures that were calculated in different ways. One possible objection to the use of our catalyst measure is that in-degree only considers local (i.e., direct) connections and does not take into account the general perceptions of an individual as a catalyst that is prevalent in the broader social structure of the organization studied. To address this concern, we used Bonacich's centrality (Bonacich 1987) to measure the extent to which individuals are recognized as catalysts of innovation. One of the advantages of Bonacich's centrality is that in addition to evaluations made by direct connections, it also takes into account catalysts' evaluations provided by indirect connections through the *beta* parameter. When using Bonacich's centrality computed on the transpose of the catalyst matrix **C**, we obtained substantively similar results to those presented in Table 4. In addition, we also estimated our models using unweighted in-degree centrality to measure catalysts, which also produced results that are consistent with those reported in Table 4.

[3]Results reported in Figures 1(a) and 1(b) are further corroborated by more comprehensive regression models in which, to establish the relationship between having catalysts in the ego network and the number of patents generated, we controlled for individuals' job grade, gender, level of education, seniority, network size, size of the laboratory, and size of area of technological expertise in which the focal node belongs. In particular, while controlling for these covariates, we observed that having at least one catalyst of innovation in the ego network is significantly associated with patenting output at $p < 0.019$ level.

[4]This confirmation technique is commonly used in network research to increase the reliability of relational measures (Krackhardt 1990, Hansen 1999). Because both matrices are valued, the exchange of information matrix considers, for each confirmed relationship, the average of the go-to and the (transposed of) the come-to matrices. Unconfirmed relationships are set equal to zero. In a series of robustness checks, we obtained substantively similar results when calculating network redundancy based on unconfirmed ties (i.e., ties reported in the go-to matrix only).

[5]The same results were obtained using an oblique rotational strategy.

[6]In the reported analysis we use the average of the respective four items to identify scientific and industrial external knowledge. Our results do not vary when using factor scores instead of averages to measure scientific and industrial external knowledge.

[7]In additional analyses not reported here, we obtained the same results adjusting the d_{ij} term for the total amount of external knowledge available in each dyad (i.e., multiplying each term d_j in the **D** matrix by the term $t_{ij} = S_i + S_j + I_i + I_j / \max(S_i + S_j + I_i + I_j)$).

[8]Running the analysis with a simple interaction term computed at the node level of analysis yields a positive but not significant coefficient ($p = 0.698$). The lack of significance is consistent with our view that a node-level interaction term does not discriminate ego-network effects due to network redundancy versus knowledge heterogeneity.

[9]We categorized as high frequency those interactions among ego and alters that were rated greater than 3 on the 1 to 5 scale for information sharing.

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Marco Tortoriello is an associate professor of strategic management at IESE Business School. He received his M.S. and Ph.D. from the Tepper School of Business at Carnegie Mellon University. His research focuses on the impact of intra- and interorganizational networks on individuals’ and organizations’ ability to generate, leverage and share knowledge.

Bill McEvily is a professor of strategic management at Rotman, where he teaches courses on social networks, strategy implementation and organizational theory. His research explores social capital as an organizational and strategic resource. He has served as a senior editor at *Organization Science* and as guest editor for special issues of *Management Science* and *Organization Science*. He earned his Ph.D. in strategic management and organization from the University of Minnesota.

David Krackhardt is a professor of organizations at Heinz College and at the Tepper School of Business, Carnegie Mellon University. He received his Ph.D. from the University of California, Irvine. He studies the causes and consequences of social networks in organizations. He also develops methodologies designed to help organizational scholars pursue social network research.