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Structural Microfoundations of Innovation: Relational Stars and Quality of Inventive Output

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Abstract

Applying social network theory, we attempt to uncover the role of individuals as drivers of organizational invention. Conceptualizing invention as a process of knowledge search and recombination, we go beyond the focus on productive individuals and emphasize the importance of individual relational capacities to effectively implement the process of invention. We rely on intraorganizational knowledge networks emerging through individual collaboration to identify actors who using their extreme collaboration behavior can positively influence the quality of their organization?s inventive output. We develop a taxonomy of three types of such relational stars: integrators, connectors, and isolates. We test our ideas in a sample of 106 pharmaceutical firms from 1974 to 1998. Our results suggest that all three individual role-sets have positive effects on their organization?s inventive quality and that the positive effects are much more pronounced for quality than quantity of inventive output. Connectors are the strongest drivers of quality followed by integrators and isolates. In addition, we show that relational stars compensate for each other and that the most effective internal configuration for inventive quality includes many integrators combined with many connectors and few isolates.

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ABSTRACT

Applying social network theory, we attempt to uncover the role of individuals as drivers of organizational invention. Conceptualizing invention as a process of knowledge search and recombination, we go beyond the focus on productive individuals and emphasize the importance of individual relational capacities to effectively implement the process of invention. We rely on intraorganizational knowledge networks emerging through individual collaboration to identify actors who using their extreme collaboration behavior can positively influence the quality of their organization's inventive output. We develop a taxonomy of three types of such relational stars: integrators, connectors, and isolates. We test our ideas in a sample of 106 pharmaceutical firms from 1974 to 1998. Our results suggest that all three individual role-sets have positive effects on their organization's inventive quality and that the positive effects are much more pronounced for quality than quantity of inventive output. Connectors are the strongest drivers of quality followed by integrators and isolates. In addition, we show that relational stars compensate for each other and that the most effective internal configuration for inventive quality includes many integrators combined with many connectors and few isolates.

Since Schumpeter (1942) we have known that innovation is a vehicle of economic growth and a source of firm performance heterogeneity. Research on the antecedents of innovation has extensively focused on the innovative capabilities that firms need to develop in order to initiate or respond to frequent technological change. Organizational scholars have convincingly argued that innovative organizations are those with superior routines (Nelson and Winter, 1982), capabilities (Kogut and Zander, 1992), competences (Henderson and Cockburn, 1994), or dynamic capabilities (Teece, Pisano, and Shuen, 1997) of transforming existing knowledge into something new. The simple observation that knowledge is the key raw material for innovation (Nonaka, 1994) combined with the recognition of individual actions and interactions as the realistic locus of knowledge creation (Felin and Hesterly, 2007), directed attention to the role of individuals as the microfoundations of the necessary capabilities (Felin and Foss, 2005). Indeed, research indicates that firms benefit from investments in individual expertise expressed as well above average research productivity (Zucker, Darby, Brewer, 1998; Lacetera, Cockburn, Henderson, 2004; Rothaermel and Hess, 2007). As a result, there is a significant degree of consensus that the so-called 'star scientists' positively affect innovative outcomes. However, we still have a gap in our understanding with respect to other individual roles and skills that are critical for innovation. Is individual productivity the only relevant skill for innovation?

Evidence suggests that innovation is a communal team-based endeavor (Wuchty, Jones, and Uzzi, 2007). Innovative performance depends on effective knowledge sharing (Hansen, 1999), search (Gavetti and Levinthal, 2000; Katila and Ahuja, 2002), transfer (Tsai and Ghoshal, 1998), recombination (Galunic and Rodan, 1998), reconfiguration (Henderson and Cockburn, 1994), diffusion (Zollo and Winter, 2002), and renewal (O'Reilly and Tushman, 2007). Individuals are responsible for implementing these knowledge sub-processes through their actions and interactions. Such interactions result in extensive knowledge networks, in which actors occupy various positions. Relying on the structural, cognitive, and affective benefits stemming from their positions (Nahapiet and Ghoshal, 1998), certain individuals emerge as more effective than others to execute the knowledge sub-processes and become highly consequential for the innovative performance of the network as whole. In this paper, we make an effort to identify them by looking for extreme patterns of individual collaborative behavior. Applying network thinking, we argue for the positive effect of three individual structural roles on the inventive output of their organizations. We refer to them as ‘relational stars’ to emphasize the social aspect of their skills and depart from traditional ‘productivity stars’. More importantly, we extend our current understanding of the effect of productivity stars on quantity of inventive output and provide our first contribution by highlighting the role of relational stars as the structural microfoundations of inventive quality. In essence, we argue that these actors can exploit their patterns of collaborative behavior to not only identify more opportunities for knowledge recombination but also select the most promising ones leading to knowledge of higher quality.

In particular, we focus on three types of relational stars: integrators, connectors, and isolates. Integrators are the actors who have a very large network of collaborators and therefore have the capacity to integrate and recombine knowledge from many different sources. Connectors are the individuals who collaborate across knowledge areas, operate as the linking pins among internally distant and otherwise unconnected clusters of knowledge and therefore have the capacity to engage in high risk and radical trials of knowledge recombination. Isolates are productive individuals that are relatively unconnected from their organization’s network and therefore have the capacity to infuse the knowledge base with diverse perspectives as they are the least affected from the organization’s knowledge directions. Conceptualizing invention as a search process of knowledge recombination (Fleming, 2001), the three types correspond to three alternative paths: local recombination, distant recombination, and independent knowledge production. Apparently, all three individual roles become important for the quality of inventive output not necessarily because they are extremely productive but mainly because their collaborative behavior facilitates effective recombinant search. It is important to note here that if these types of actors are defined relative to their peers in an organization's internal network, then every organization would have its own share of relational stars. Instead, we define relational stars relative to their counterparts in every competing organization's network looking for outliers in each of the three categories.

This approach follows existing research on 'star scientists' where stars are the actors at the top of the productivity distribution of all scientists across firms. More importantly, this approach allows us to provide an important contribution to the literature on internal networks. Research on networks has unveiled that an individual's position in the internal network may affect that individual's involvement in innovation (Obstfeld, 2005), creativity (Fleming, Mingo, and Chen, 07), and performance (Gargiulo, Ertug, Galunic, 2009). In addition, the structure of the knowledge network may affect the overall network's innovative performance (Brown and Eisenhardt, 1997; Reagans and Zuckerman, 2001; Reagans and McEvily, 2003). Much less is known with respect to the effect of nodes in certain positions on the overall network's performance. Authors of two recent reviews on networks conclude that it is imperative to address cross-level network phenomena and understand how micro-level network effects translate into macro-level network phenomena (Brass et al., 2004; Ibarra, Kilduff, and Tsai, 2005). With this study, we make an effort to document the mechanisms through which the mere presence of an individual position (that is, a certain pattern of individual collaborative behavior) may affect not only that individual's performance but also the performance of the network as whole. In particular, we show that individuals who are outliers in terms of their collaborative behavior in three meaningful dimensions can improve inventive quality of their organizations through identifying more promising, novel, or diverse knowledge recombinations.

Finally, we provide a contribution to the literature on social capital. In particular, our objective is to document how social capital can create human capital (Coleman, 1988) by looking at the interaction between human and social capital. Intraorganizational collaborative networks are built in order to transform a number of creative individuals into creative collectives (Hargadon and Bechky, 2006). Therefore, our relational stars in these networks do not try to exploit their position for their own benefit in a competitive environment (Burt, 2000); rather, they operate as relational experts to promote collective creativity in a cooperative context (Lingo and O'Mahony, 2010). Relational stars possess the right amount and type of social capital to foster invention at the network level but at the same time have the necessary human capital to generate knowledge and be part of the network at the first place. Therefore, their importance stems from the right blend of human and social capital. Building that social capital requires both opportunity and ability (Adler and Kwon, 2002). If we look at their collaborative ties as prisms (Podolny, 2001) we can safely assume that individuals in relational star positions possess unique skills, abilities, and capacities that make them particularly valuable for the inventive performance of their organization. In addition, we extend current understanding on the role of knowledge brokers by looking at individuals who not only span structural holes but also use their bridging ties to link distant knowledge clusters and access a wider share of the network. Further, we highlight the important role of individuals who may lack social capital but still positively affect the invention process by providing much needed knowledge diversity. Our main argument is that organizations with any type of relational stars have an invention advantage. We test our ideas in a sample of 106 large firms in the global pharmaceutical industry using a longitudinal research design spanning a 25-year period. We rely on co-patenting events to build extensive knowledge networks with over 550,000 observations at the individual level from 1974 to 1998 and employ network metrics to define the three types of relational stars. We use counts of these stars at the organizational level to predict how important they are for inventive quality. We compare the magnitude of the individual effects to identify the individual role that is the strongest driver of quality. In addition, we are able to document some very interesting interactions among the three types of relational stars and uncover the most effective internal configuration of relational stars. Overall, our sample allows us to investigate the extent to which incumbent firms can remain innovative and survive technological discontinuities by managing the inventive potential of their human capital resources (Tushman and Anderson, 1986; Anderson and Tushman, 1990).

RELATIONAL STARS AND INVENTIVE QUALITY

Organizational research on the antecedents of organizational innovation has been dominated by the notion of 'routines' (Nelson and Winter, 1982). The knowledge-based conceptualization of the firm as a social community guided by higher-order principles that are irreducible to individuals (Kogut and Zander, 1992) spurred significant research efforts linking capabilities directly to organizational innovative outcomes (Kogut and Zander, 1992; Henderson and Cockburn, 1994; Teece, Pisano, and Schuen, 1997; Zollo and Winter, 2002). However, early research in the knowledge-based paradigm emphasized the importance of accounting for individuals in order to clearly understand the formation of such organizational capabilities (Nonaka, 1994; Conner and Prahalad, 1996; Grant, 1996). Macro-level explanations that link capabilities with outcomes without considering individuals as their microfoundations open the door for alternative micro-level explanations (Abell, Felin, and Foss, 2008).

Theoretical support of individuals as the realistic locus of knowledge (Felin and Hesterly, 2007) channeled some research towards the role of human capital in driving organizational innovation. Evidence suggests that firms are generally more innovative when they employ highly productive individuals with the capacity to generate scientific knowledge. The so-called ‘star scientists’ are instrumental for knowledge sensing (Lacetera, Cockburn, and Henderson, 2004), renewal (Zucker and Darby, 1997), knowledge capture (Zucker, Darby, and Armstrong, 2002), and adaptation to radical discontinuities (Rothaermel and Hess, 2007). Therefore, we have a deep understanding of the innovative benefits provided by individual knowledge productivity.

However, individual creativity has an apparent social side and is affected by the working environment (Amabile et al. 1996; Perry-Smith and Shalley, 2003). Organizations have an advantage over individuals because they can internally develop intellectual capital based on social interactions among their members (Nahapiet and Ghoshal, 1998). Early research on the emergence of industrial R&D suggested that the advantage of the industrial research laboratory was that “it could take several men, each lacking the necessary qualifications for successful independent research, and weld them into a productive team in which each member compensated for the others’ shortcomings” (Beer, 1959: 71). Hence, apart from individual productivity there is a set of social and collaborative skills that is at least as important for fostering innovation. This importance is even more pronounced in the innovation literature which suggests that innovation is an outcome of a socially intensive process of knowledge transformation. Individuals innovate by searching for potential knowledge recombinations between familiar and new components (Fleming, 2001). Socialization (Fleming, 2002) and intraorganizational persuasion and conflict (Gavetti and Levinthal, 2000) are important components of successful search outcomes. Firms need to integrate disparate pieces of knowledge (Henderson and Cockburn, 1994) and dynamically reconfigure their existing knowledge stocks as markets evolve (Galunic and Eisenhardt, 2001). Knowledge should be reused, recombined, and accumulated to result in innovation (Murray and O'Mahony, 2007). To effectively implement these processes, individuals collaborate within firms and form extensive internal collaborative networks.

The importance of these networks has not been neglected. For instance, there is research documenting the effect of individual position on a host of meaningful individual outcomes (Brass, 1984; Ibarra, 1993; Morrison, 2002; Cross and Cummings, 2004) and research supporting the effect of the network's overall structure on network-level outcomes (Tsai, 2002; Argyres and Silverman, 2004; Lazer and Friedman, 2007; Yayavaram and Ahuja, 2008). However, although there is some evidence that actors in certain positions may affect organizational outcomes as for instance, central actors shape their firms' future technological capabilities (Nerkar and Paruchuri, 2005), research on the role of individuals in these networks as drivers of network-level outcomes remains sparse. Authors of recent reviews echo this statement by calling for more research addressing cross-level network phenomena (Brass et al., 2004; Ibarra, Kilduff, and Tsai, 2005). In this study, we make an effort to do that by introducing the concept of 'relational stars'. Relational stars are actors whose patterns of collaborative behavior make them valuable for the inventive performance of the network as a whole. Their value comes from the structural, cognitive, and relational benefits associated with their position in the intraorganizational collaborative network (Inkpen and Tsang, 2005). To identify them, we compare the collaborative behavior of all individuals across firms in the same industry and select the outliers in three dimensions that we believe positively affect the inventive performance of the system. Our logic is quite simple: we argue that if certain patterns of collaboration are more impactful than others for invention, then individuals with the capacity to express these patterns are the best positioned ones to exploit their positions and explore opportunities for new knowledge of higher quality.

The intraorganizational collaborative network is an instance of a creative collective (Hargadon and Bechky, 2006) and a social structure characterized by cooperation rather than competition (Tsai, 2002). Individuals work together to enhance the organization's knowledge base. Nodes in the network are individuals participating in the knowledge co-production process. Ties reflect instances of direct collaboration with the purpose of knowledge co-creation. They can be viewed as strong ties (Hansen, 1999), which are necessary for effective knowledge transfer (Singh, 2005) or recombination (Galunic and Rodan, 1998), and play a dual role at they facilitate both inflows and outflows of knowledge (Borgatti and Foster, 2003). They can also be viewed as prisms to allow us make inferences about the characteristics of the nodes (Podolny, 2001). Therefore, we look at both the type of collaborative relations and the utility coming from these relations to deduce the value of individuals in certain positions (Kilduff and Brass, 2010). We posit that relational stars are very valuable sources of human capital because they have the capacity to utilize superior structural, cognitive, and relational benefits associated with their collaborative behavior (Nahapiet and Ghoshal, 1998).

The main mechanism underlying our hypotheses is the value of human capital. However, we emphasize the role of social capital in the creation of that necessary human capital (Coleman, 1988). Relational stars are defined as the ones having the 'right' type and amount of social capital. However, the acquisition of that social capital reflects unique abilities and skills on their end (Adler and Kwon, 2002). In addition, relational stars possess unique blends of human and social capital. Looking at knowledge as both an action and a possibility (Hargadon and Fanelli, 2002), these individuals have not only the human capital to co-develop knowledge and be part of the network but they also have the relationships to explore for future knowledge possibilities. Further, they rely on social interactions to generate possibilities for knowledge recombination (Felin and Zenger, 2009). They use their position to shape the network, access and diffuse knowledge stocks (Borgatti and Foster, 2003). Relational stars emerge because their alters have a positive representation of their skills; a ‘star’ position in the network emerges through interpersonal collaboration and is the result of continuous adjustments (Kilduff, Tsai, and Hanke, 2006). The previous discussion suggests that relational stars develop superior human capital through their social capital endowments. In what follows, we link individual behavioral patterns and organizational outcomes. In reality, a behavioral pattern has two components: what the individual can do with that position and what the individual is (derived from the position) although the two are closely intertwined. It is important to note that these patterns have certain origins beyond individual skills and abilities. Actors emerged in their positions because they were also appropriately motivated to collaborate and were provided with the opportunity to do so by their organization’s structures, incentives, or strategies. These other origins are out of this paper’s scope and are briefly addressed in the discussion section. Here, it is important to emphasize that a network position is an organizational product as much as it is a product of individual skills. Relational stars have the capacity to alter the organization’s knowledge base with high quality inventive output by utilizing their skills and capacity to use the structural, cognitive, and relational features of their ties.

Integrators

Integrators are individuals with an extraordinary amount of collaborative ties in their organization's network; normally, these actors occupy a highly central position in the network. The positive effect of such a central position on individual level outcomes has been widely documented. Centrality is associated with an individual's promotions (Brass, 1984), exercise of power (Ibarra, 1993), supervisor ratings (Mehra, Kilduff, Brass, 2001), socialization (Morrison, 2002), innovative performance (Cross and Cummings, 2004), involvement in innovation (Obstfeld, 2005), and performance bonus (Gargiulo, Ertug, and Galunic, 2009). However, much less is known with respect to the role of such individuals on the performance of the network as a whole. Here, we make an effort to link the presence of integrators in an organization's collaborative network with the inventive quality of its output. To do that, we define integrators as universal outliers; integrators are the individuals whose collaborative behavior involves a number of alters which is large not relative to their peers in their organization's network but relative to all individuals in all competing organizations. We argue that organizations employing such collaborative outliers enjoy a quality advantage in their inventive output. The tools through which integrators drive inventive quality are the knowledge inflows and outflows embedded in their collaborative ties. The mechanisms through which flows result in quality are three: conceptualizing invention as recombinant search, integrators rely on knowledge inflows coming from many different sources to identify not only more potential knowledge recombinations but also select the most promising ones among them. Outliers have an advantage in this respect because every additional tie has an exponential effect on the number of potential recombinations. Second, integrators use their outflows to diffuse a constantly updating knowledge base for further recombination. Third, the mere presence of these actors creates the conditions for invention to occur. We choose the term 'integrators' to illustrate their main knowledge function, that is, knowledge integration; the term has been previously used to describe actors who bring people together and fill structural holes (Xiao and Tsui, 2007). In addition, we prefer this term over central actors to emphasize the outlier status of these individuals. Integrators are not just central in their firm's network; their number of collaborative ties puts them at the top of the distribution when compared with all individuals from all competing organizations.

In particular, integrators through their inflows have the capacity to observe a large number of alters, understand who knows what (Borgatti and Cross, 2003), and follow the most promising local recombinations. This view is consistent with evidence that knowledge recombined by central actors is more likely to be found in their firm's future technological capabilities (Nerkar and Paruchuri, 2005). Their commanding position allows them to scan the environment, understand where relevant knowledge lies, familiarize themselves with a number of different knowledge stocks, and experiment with alternative combinations to identify the most valuable ones. On the other hand, through their outflows integrators have the capacity to effectuate diffusion of a changing knowledge base to initiate further cycles of knowledge refinement. Evidence suggests that integrators should be able to diffuse knowledge easier than others as they exert significant influence on their peers (Brass, 1984). Eventually, integrators become the organization's 'enabling bureaucracy' (Adler, Goldoftas, and Levine, 1999).

As importantly, the presence of integrators creates some necessary conditions for invention to occur. They operate as the glue that increases the network's density and makes it promising for knowledge sharing and learning. Centralized R&D structures have been shown to generate more impactful innovations (Argyres and Silverman, 2004) and cohesive structures positively affect individual motivations for knowledge sharing (Reagans and McEvily, 2003) and knowledge transfer (Reagans, Zuckerman, McEvily, 2004). In addition, integrators play the role of a coordinating mechanism. Their collaborative behavior results in strong ties, shared norms, communication codes, trust, and clan-fostering initiatives which are all necessary conditions for invention and learning to occur (Tsai and Ghoshal, 1998, Kang, Morris, and Snell, 2007). Finally, invention includes significant levels of uncertainty for the individuals involved and central actors are the ones sought after by peers under uncertainty (Tushman and Romanelli, 1983). Arguably, that is because their position also exists at the minds of their peers and signifies competence (Kilduff, Tsai, and Hanke, 2006). Therefore, integrators take over decision making, reduce uncertainty for peers, and encourage high quality knowledge creation. Overall, integrators have the capacity to integrate knowledge locally for high quality recombinations, diffuse the updated knowledge base, and create the conditions for further high quality invention to occur.

Hypothesis 1: The quality of a firm's inventions is a positive function of the number of integrators in its internal collaborative network.

Connectors

Extensive evidence suggests that individuals who span structural holes in a knowledge network are more likely to come up with better ideas (Burt, 2004), are more creative (Fleming, Mingo, and Chen, 2007), and can adapt better to changes in the task environment (Gargiulo and Benassi, 2000). Such knowledge brokers enjoy informational advantages which increase their own social capital (Burt, 2000) but may hurt the creation of communal social capital under conditions of competition (Ibarra, Kilduff, and Tsai, 2005). However, in a cooperative structure as is the case in a firm's internal collaborative network (Hargadon and Bechky, 2006), brokers are more likely to play the role of relational experts who bring together unconnected knowledge stocks to promote the innovative performance of the system (Obstfeld, 2005, Lingo and O'Mahony, 2010).

In an organization's knowledge network, individuals are often organized around their knowledge domains. As a result, knowledge clusters emerge with their boundaries defined by the nature and relatedness of knowledge. Such molecular units within firms are expected to form as a disaggregation effect of recent innovations and high-powered incentives (Zenger and Hesterly, 1997). Bridging ties across these units represent collaboration across knowledge clusters. We extend current understanding on the role of brokers by introducing the concept of connectors in the collaborative networks. Connectors are actors who span structural holes but at the same time connect distant clusters of knowledge. While not necessarily productive or highly collaborative, connectors operate as the linking pins among otherwise unconnected and distant knowledge stocks. There are not only rich in structural holes; their spanning of such holes also allows them to access a large share of the broader collaborative network in which they are embedded. In a sense, they are very efficient knowledge brokers; their collaborative behavior bridges knowledge silos within their firm's network. Similarly to what we did for integrators, we define connectors as actors who span structural holes in their network and access the highest share of their network compared to brokers in all other competing organizations' networks. With this term, we capture individuals who are the best in collaborating across knowledge domains and utilize a very large share of their organization's knowledge base. The main mechanism through which connectors can increase their organization's inventive quality is through novel knowledge combinations of diverse knowledge stocks.

Research suggests that individuals are more likely to come up with such novel recombinations when their ego-networks span boundaries across technologies (Fleming, 2002), disciplines (Henderson and Cockburn, 1994), locations (Singh, 2008), or divisions (Kleinbaum and Tushman, 2007). Here, we define connectors as actors whose collaborative behavior spans clusters and silos in the knowledge space. Connectors use their ties' inflows to access diverse sources of knowledge and are therefore more likely to identify potentially novel and high quality recombinations. Their capacity to collaborate across knowledge boundaries allows them access to heterogeneous knowledge stocks and engagement in high risk inventive trials. In addition, they have a broad view of the knowledge landscape and are therefore more likely to guide their experiential learning efforts towards more promising knowledge areas. Through their outflows, connectors rapidly diffuse new knowledge to distant clusters of knowledge for further quality recombinations. Although actual transfer of knowledge through brokerage may be hampered because of several complexities (Obstfeld, 2005; Fleming, Mingo, and Chen, 2007), still the capacity of connectors to communicate new knowledge across distant knowledge domains increases the opportunity for others to engage in high quality recombination.

In addition, the presence of connectors in an organization's collaborative network creates the conditions for high quality invention. Connectors promote relaxed structures facilitating improvisation (Brown and Eisenhardt, 1997), network heterogeneity facilitating learning (Reagans and Zuckerman, 2001), network range supporting knowledge transfer (Reagans and McEvily, 2003), and decrease the path length between any two actors in the network thus improving its overall performance (Cowan and Jonard, 2003). The presence of connectors in an organization's network reflects a knowledge base which is nearly decomposable, a characteristic which has been linked with inventive quality (Yayavaram and Ahuja, 2008).

Hypothesis 2. The quality of a firm's inventions is a positive function of the number of connectors in its internal collaborative network.

Isolates

The process of knowledge recombination, especially within intraorganizational knowledge networks, can be viewed as a pursuit for local optima (Gavetti and Levinthal, 2000). Actors collaborate to generate improvements based on a given set of knowledge resources. This process can be self-sustaining and result in significant similarities of knowledge among the actors of the collaborative network as recombinations are communicated through diffusion. Therefore, internal collaborative networks are vulnerable to falling into competency traps (Levitt and March, 1988), a tendency to rely on inferior knowledge spaces when superior alternatives exist. As a result, these networks can greatly benefit from individuals who can infuse some knowledge diversity into the system of knowledge recombination. Such actors should participate in the development of knowledge but be relatively unconnected from the rest of the network to avoid overembeddedness and the risk of social capital (Adler and Kwon, 2002). Actors remaining uncoupled from an organization's network have been characterized as isolates (Tichy, Tushman, and Fombrun, 1979). We build on this notion and in an effort to describe how such actors may positively affect an organization's inventive quality, we define isolates as individuals who are almost unconnected from the internal network but at the same time are more productive than their counterparts in all of competing organizations' networks.

Organizations with the most productive isolates have an increased opportunity for knowledge diversity in their system. In turn, this diversity promotes identification of even more promising knowledge recombinations which are free from risks of competency traps. The most productive isolates remain unaffected by the knowledge directions of the network and have the capacity to provide it with additional insights at a high production rate. As importantly, isolates produce that knowledge at minimum coordination costs. Therefore, we shift attention to actors who are important for their organization not because of their ties but exactly because of the absence of such collaborative ties. In addition, evidence suggests that isolates are more willing to share their knowledge (Thomas-Hunt, Ogden, and Neale, 2003). Isolates should not be confused with just independent inventors who have been shown to generate both more impactful (Dahlin, Taylor, and Fichman, 2004) and less impactful inventions (Singh and Fleming, 2010). Our isolates actively participate in their organizations efforts to invent new knowledge and their independent but productive collaborative behavior protects their organizations from knowledge homogenization at a steady productive rate, thus increasing the chances for the network to generate inventions of higher quality.

Hypothesis 3. The quality of a firm’s inventions is a positive function of the number of productive isolates in its internal collaborative network.

The three types of relational stars will more than likely coexist in an organization’s collaborative network. Although all three have their own direct effects on inventive quality, it is important to explore for the effect of their interaction on the system’s output. Existing literature reflects a debate on whether the types of relational stars should complement or substitute each other in driving inventive quality. On one hand, the short run performance of the network requires efficiency in dissemination of information, while the long run performance requires inefficiencies and knowledge diversity (Lazer and Friedman, 2007). Knowledge of low complexity diffuses through distant ties, while knowledge of moderate complexity requires social proximity (Sorenson, Rivkin, and Fleming, 2006). High risk inventive trials should always be followed by intense socialization (Fleming, 2002). Distant ties enable knowledge search while local ties facilitate knowledge transfer (Hansen, 1999). Network cohesion and range together encourage knowledge transfer (Reagans and McEvily, 2003). A small world structure characterized by high clustering and bridging ties is more effective for collective invention (Cowan and Jonard, 2003). Local ties promote coordination while bridging ties increase flexibility (Gargiulo and Benassi, 2000). Finally, there is evidence that nearly decomposable knowledge bases with both dense networks and bridging ties generate more useful inventions (Yayavaram and Ahuja, 2008). Taken together, these studies suggest that the three types of relational stars play different but complementary roles in the path towards inventive quality.

On the other hand, researchers have emphasized that knowledge production through interpersonal collaboration entails significant costs. The presence of different individual roles with extreme heterogeneity of collaborative behaviors may reflect a serious coordination burden for their organization. Coordination can become the most important source of knowledge production costs and inefficiencies (Langlois and Foss, 1999). Gibbons (1999) asserts that firms are not well-oiled machines and suffer greatly from these coordination costs. Felin, Zenger, and Tomsik (2009) argue that any social process of knowledge co-creation includes costs and productivity losses. Further, Lavie (2006) notes that internal reconfiguration of capabilities, a role that relational stars play, consists of major risks and costs. Finally, O'Reilly and Tushman (2007) suggest although the pursuit of knowledge recombination simultaneously through local and distant ties may be beneficial, it also involves major challenges because of differences between the respective skill sets. Perhaps, the most illustrative case against complementarity is evidence by Burt (1997), which suggests that the value of social capital decreases as more people do the same work. Therefore, if integrators, connectors, and isolates are just alternative paths to knowledge of increased quality then we should observe a substitute relationship among them. Taken together, these studies suggest that the three types of relational stars may be inconsistent with each other and greatly increase coordination costs. Therefore, we proceed by juxtaposing two competing hypotheses:

Hypothesis 4a (b): Integrators, connectors, and isolates complement (substitute) each other in the invention process and thus their interactions are positively (negatively) associated with their organization's inventive quality.

METHODS

To test the developed hypotheses, we followed a longitudinal research design in the global pharmaceutical industry. Firms in this industry are under constant pressure to continuously innovate. In addition, they had to face the emergence of biotechnology as a new paradigm in product development, a discontinuity that increased existing pressures to keep innovating in order to survive. As a response, pharmaceutical firms engaged in a wide array of alternative strategies to remain innovative; they took on alliances, acquisitions, heavy investment in internal research, and in human capital to build or maintain innovative capabilities (Rothaermel and Hess, 2007). Therefore, the pharmaceutical industry is an ideal setting for this paper to explore for the role of relational stars in driving inventive output above and beyond the mentioned innovation levers. Our observation period is from 1974 to 1998. Our sample consists of 106 pharmaceutical firms that were active in the production of human in-vivo therapeutics and were founded before 1974. This sample is largely representative of the overall industry as it accounts for the vast majority of global sales of pharmaceutical products. We tracked these 106 firms forward until 1998. Horizontal mergers are a common incident in this industry; when a merger occurs we combine the data of the merging firms into one entity, we continue tracking it forward, and we create an indicator variable to capture a merged entity.

We constructed the key dependent and independent variables relying on patents granted to these firms by the USPTO. Despite some problems, patents have been extensively used to measure a firm's innovative activities (e.g. Ahuja, 2000; Henderson and Cockburn, 1994). In addition, the pharmaceutical industry is the industry which relies most on patents when it comes to intellectual property protection compared to all other manufacturing industries (Cohen, Nelson, Walsh, 2000). We used the NBER patent data file (Hall, Jaffe, and Trajtenberg, 2001) to create the patent portfolio for each one of our firms from 1974 to 1998. We tracked all different names under which firms patent (including spelling mistakes in the patent dataset) and collected patent data for those firms' subsidiaries to make sure that we have the full patenting activity for each firm. From resulting patent portfolios, we kept information regarding dates of applications, citations received, claims made, inventors listed, and assigned technology classes. Many firms in our sample are dedicated pharmaceutical firms. However, there is also a number of large diversified conglomerates that are also active in other industries. We argue that knowledge possessed by inventors in unrelated industries has little to do with our knowledge-based arguments. Therefore, we sampled on the resulting patent portfolio for every firm and we relied on information from technology classes to keep only patents that are assigned to classes with a clear chemistry or biology component and thus are more likely to be related to the technologies underlying human therapeutics.

Dependent Variables

To measure the quality of a firm's inventions, we used the number of citations that a firm's patents in year t received in subsequent years until 2006. Note that although our sample period ends in 1998, we track citations until 2006. We relied on the application date for the patents because it is much closer to the actual time of invention than the granting date. Evidence suggests that citations received by a patent is a significant predictor of its market value (Hall, Jaffe, and Trajtenberg, 2005) and has already been used to measure the usefulness of inventions (Yayavaram and Ahuja, 2008). In addition, we used the number of claims made by a firm's patents to capture a different dimension of their quality. Claims are arguably a measure of a patent's technical quality and have been used in prior research to measure the quality of a firm's inventive activities (Singh, 2008). As a robustness check, we also used simple patent counts to see if our independent variables have an effect on quantity of inventive output.

Intrafirm collaborative networks and independent variables

To identify relational stars and create the independent variables for this paper, we developed intrafirm co-inventing networks for each firm from 1974 to 1998. We relied on the NBER database inventor file and assigned a unique ID to each individual inventor based on a combination of last name, first name, and middle name. When there was still a conflict, we expanded our matching criteria to include city and state of residence for each inventor. The resulting dataset was a file for each firm with unique inventors IDs assigned to each patent from 1974 to 1998. As a next step, we used UCINET 6 to develop intrafirm co-inventing networks. Nodes of our networks were individual inventors and ties were co-patenting events among them. Our main argument is that these ties involve knowledge flows and thus, we proceeded by characterizing knowledge through a tie which is older than five years as obsolete. Therefore, we developed the knowledge networks using a five-year rolling window and assigned the resulting values to the last year of each time window (e.g. 1982-1986 values to 1986, 83-87 values to 87, etc.). We analyzed our network and kept a wide array of ego-network metrics to define the three types of relational stars. Then, we developed three variables at the inventor level:

Integrator. This is an indicator variable with a value one if the inventor's direct collaborative ties are two standard deviations more than the mean number of direct ties of all inventors of all firms during the same 5-year window **and** the inventor has more than two patents in the same period (to avoid one-time inventors that contribute little to their firm). Therefore, we captured inventors with a great number of alters as collaborators.[1]

Connector. In the theoretical part of the paper, we emphasized that connectors are not only knowledge brokers in terms of spanning many structural holes, but they are also individuals who connect distant clusters of knowledge and therefore have access to a large share of their firm's collaborative network. Therefore, to capture connectors we relied on a combination of two network metrics. First, we selected inventors with more than two patents and more than the mean number of collaborative ties in the firm's network. In this way, we retained only inventors who were not one-time inventors and who had enough ties to have a meaningful connecting impact. Second, we kept inventors whose ego-network density was lower than .333. Hence, we sampled on inventors who span structural holes; this cutoff point suggests that existing ties among a connector's alters were less than one third of all potential ties among them. Third, among the remaining inventors, we characterized as connectors those whose two-step reach in the network was higher than the mean. Therefore, among the inventors who spanned structural holes, we selected those whose ties allowed them to reach a larger share of the firm's internal collaborative network. The two step reach measure captures the percentage of the network's nodes that a node has access to through its direct and indirect ties. Hence, we combined density with reach in order

[1] We also experimented with a number of alternative empirical definitions for integrators. We used the number of direct ties that are both one and three standard deviations above the mean. Results remained robust. We strongly prefer these ego network-based metrics over alternative ones like bonanich or betweenness centrality because our theory is developed using the benefits of direct ties (and knowledge flows through these ties) without taking into account the structure of the overall network.

to identify inventors who span structural holes and at the same time have access to a broader share of the network.[2] An indicator variable with a value of one was assigned to inventors whose ego-networks passed all of the above mentioned cutoff points.

*Isolate***.** This is an indicator variable with a value one if the inventor has patents that are three standard deviations above the mean number of patents of all inventors with fewer than three collaborative ties during the same five-year window. We chose to accept this low level of connections for isolates to support our claim that they have an opportunity to somehow affect the knowledge directions of their organization. However, having two or fewer ties still makes these inventors relatively isolated from their firm's network. At the same time, isolates are the most productive inventors among those with a small number of collaborative ties. [3]

Using these indicator variables at the inventor level, we developed our independent variables at the firm level using counts of *integrators*, *connectors*, and *isolates*, that each firm possesses in each year from 1974 to 1998 (again counts from time window 74-78 go to 1978, counts from 75-79 go to 79, etc.).[4]

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[2] We also experimented with a number of alternative empirical definitions for connectors. We used initial cutoff points of more than two patents and only more than two ties. We also defined connectors using the broker and nbroker measures from UCINET. The broker measure captures the absolute number of pairs in an actor's network which remain unconnected. The nbroker measure is the broker metric normalized by the size of the network. Also, we used only density metrics to define connectors as knowledge brokers. We stayed with the combination of two metrics to better reflect the conceptual definitions of connectors.

[3] We also experimented with a number of alternative empirical definitions for isolates. First, allowing for no ties (complete isolation) resulted in very few inventors with more than two patents. Second, we altered the size cutoff point from three to five to the mean number of collaborative ties to relax the conditions of isolation. Results remained unchanged. We kept the strong cutoff point of three ties for the final measure to make a conservative test and stay closer to our claims of relative isolation of these inventors.

[4] When empirically defining our three individual roles, we follow two approaches: first, we allow individuals to be characterized as integrators, connectors, and isolates while they may at the same time be productivity stars. Second, we add the restriction of them not being productivity stars to capture the ones who play these roles without being necessarily very productive. We report results from the second approach to present a very conservative test of our hypotheses. In any case, not many individuals were at the same time productivity and relational stars. Evidence suggests that increased interaction for knowledge co-creation negatively affects individual productivity and that individual productive capacities are negatively associated with increased teamwork (McFadyen and Cannella, 2004; Jones, 2009).

Control Variables

We included a series of control variables to control for other factors that have shown to affect a firm's inventive output. First, in every model we included the *dependent variable (citations, claims, or counts) lagged* as a right hand side variable to make a very conservative test of our hypotheses, address any remaining endogeneity concerns, and possibly control for a specification bias. Further, we controlled for the number of *biotech patents and the ratio of biotech to all patents* to capture the performance and focus of firms in the emerging biotechnology paradigm which may also affect their overall inventive output. To identify biotech patents, we relied on the definition of a biotech patent provided by the Patent Technology Monitoring Division (PTMD) of the U.S. PTO. We also included the number of *all patents* (complete patent portfolio of each firm without sampling) assigned to each firm to rule out the effect of overall inventive performance or increased propensity to patent on the inventive output related to human therapeutics. In addition, we included the *number of total alliances and the number of exploration alliances (upstream knowledge-oriented alliances)* in our models to control for the effect of alliance activity on inventive output. We collected data on every firm's alliances portfolio from the BioScan directory and the ReCap database, data sources that are the arguably the most comprehensive of alliance activities. We also included the *number of biotech-related acquisitions* in our model to control for the effect of rapid talent infusion on inventive output. We relied on the SDC Platinum database for data on acquisitions. Finally, we used controls for merged entities (*merged*) as horizontal mergers are very common in the industry, for national origin (*US and EU*), and for the main industry of each firm's activities as there are many firms that are large diversified corporations with a presence in human therapeutics (*Pharma*).

We included in our models the number of star inventors (*stars*) that each firm possesses. We followed prior research and defined stars based on their above average productivity. At the inventor level, a star is an indicator variable with a value one if the inventor has patents that are three standard deviations above the mean number of patents of every other inventor in the same five-year time window. At the firm level, *stars* is a variable counting the number of star inventors for every five year window. Hence, we controlled for the impact of star inventors on their firm's inventive output. More importantly, we controlled for *network size* which is arguably one of the main drivers of the development of integrators, connectors, and isolates. The larger the network the more the opportunities for individuals to establish connections and become integrators or connectors and the greater the probability to find more isolates. Hence, by controlling for network size we were able to run very conservative tests for our hypotheses as we were able to show that integrators, connectors, and isolates all affect innovative output above and beyond any effect of the overall network size. By including network size which is the number of inventors in every five-year window, we also controlled for the size of each firm and we had a fine-grained measure of research investment in inventive activities.

Estimation

Our three dependent variables (patent citations, claims, counts) are all nonnegative overdispersed count variables. Therefore, we used the negative binomial estimation method which provides a better fit for the data than the restrictive Poisson. Both fixed- and random- effects specifications would allow us to control for any remaining unobserved heterogeneity (Greene, 2003). We run a Hausman test which suggested that there are no significant differences between the two estimation methods. Therefore, we chose to rely on a random-effects specification, which is preferable in our case because we want to include time invariant covariates as control variables

(Hsiao, 2003). However, as a robustness check, we also used the fixed-effects specification and our results remained the same. Overall, we included the dependent variable lagged as a control, and we constructed our independent variables using 5-year rolling windows. Therefore, along with the rich set of control variables we believe that we did our best to address any endogeneity concerns (Hamilton and Nickerson, 2003). For better interpretation of the results and in order to create our interaction terms for hypothesis four, we standardized all independent variables before entering them in the regressions (Cohen et al. 2003). To further alleviate simultaneity concerns and enhance any causality claims, we lagged the control variables related to innovative performance, alliances, and acquisitions by one year.

RESULTS

Table 1 depicts descriptive statistics and bivariate correlations for our variables. Correlations among our independent variables are well below the recommended ceiling of 0.70. To further evaluate the threat of collinearity, we estimated the variance inflation factors (VIFs) for each coefficient, with the maximum estimated VIF being 3.44, which is again well below the recommended threshold of 10 (Cohen et al. 2003). However, we observe that correlations among our types of relational stars, although below the recommended threshold, are still slightly elevated. This is the result of aggregation of roles at the firm level and does not reflect similarities at the individual level. To support this claim, we submit the correlation table at the individual level (Table 2), which shows that for our 550,000 individual observations, correlations among our independent variables are very close to zero showing that the three types of relational stars capture strongly different individual roles in a firm’s network. A second observation that is worth noting from the bivariate correlations is the role of network size as a significant driver of relational stars. Hence, we are confident that by including it as a control variable we are able to account for a strong firm-level driver of our independent variables and establish their importance above and beyond any effect coming from the size of network and the number of inventors in any firm's network.

'Place Tables 1-2 about here'

Tables 3-4 depict the regression results for our two alternative measures of inventive quality: citations and claims. Table 5 reports the regression results for inventive quantity using our independent variables to predict simple patent counts. For every dependent variable we follow a similar approach. Model 1 includes only control variables. In Model 2, we add the direct effects of the three types of relational stars. In Model 3, we also include the two-way interactions among our independent variables and finally in Model 4, we add the three-way interaction among the relational stars. For every dependent variable, each subsequent model significantly improves the respective baseline model.

Hypothesis 1 predicts a positive effect of the number of integrators on inventive quality. From Model 2, integrators are positively and significantly associated with citations ($p<0.001$) and claims ($p<0.001$). This effect remains after inclusion of the various interactions thus providing support for our first hypothesis. Hypothesis 2 predicts a positive effect of the number of connectors on inventive quality. Similarly, connectors are positively and significantly associated with citations ($p<0.001$) and claims ($p<0.001$) and their effect remains after the addition of interactions in models 3 and 4, thus offering support for our second hypothesis. Finally, in hypothesis 3 we predict a positive effect of isolates on quality. Isolates are positively and significantly associated with both citations ($p<0.001$) and claims ($p<0.001$) and remain positive after inclusion of interactions, thus supporting our third hypothesis. As can be seen from Table 5, the three types of relational stars also have similar positive and significant effects on quantity of inventive output.

‘Place Tables 3-4 about here’

Although all three types of relational stars seem to have similarly positive effects on both inventive quality and quantity, we report here some interesting results from assessing the magnitudes of these positive effects. A standard deviation increase in the number of integrators results in a 9 percent increase in the number of citations, a 10 percent increase in claims, and an 8 percent increase in patent counts. A standard deviation increase in the number of connectors results in a 21 percent increase in citations, 24 percent increase in claims, and 15 percent increase in patent counts. Finally, a standard deviation increase in the number of isolates results in a 5 percent increase in citations, 9 percent increase in claims, and 6 percent increase in patent counts. The first important observation comes from identifying a pattern that seems robust for all three individual roles. Although all three have a positive effect on inventive quantity, their positive effect is much stronger when it comes to inventive quality. The second important observation comes from comparing the positive effects of the three roles. Connectors have the strongest effect on quality and quantity, followed by integrators and isolates. Therefore, we conclude that relational stars are more important for quality than they are for quantity and that individuals who span structural holes but at the same time reach out for a larger share of the network have the strongest effect on inventive quality.

Our results from the interactions among the three roles suggest a substitute relationship between relational stars. The coefficient of the interaction between integrators and connectors is negative and significant when predicting citations ($p<0.001$) and claims ($p<0.001$). The interaction between integrators and isolates is negative and significant for citations ($p<0.001$) but not significant for claims. Finally, the interaction between connectors and isolates is negative and significant for both citations ($p<0.001$) and claims ($p<0.001$). Interestingly, the coefficient of the triple interaction is positive and significant for both citations ($p<0.001$) and claims ($p<0.001$). These results are similar when predicting inventive quantity and simple patent counts.[5] We conclude that there seems to be a strong substitution between the positive effects on inventive quality coming from the three types of relational stars. Integrators, connectors, and isolates rely on various levels and composition of social capital to affect inventive quality for their organizations. However, the paths taken by the three roles seem to be just alternative paths to the same outcome: novel recombination of knowledge which may have its source in selecting the most promising recombinations among a large number of potential ones (integrators), in experimenting with novel recombinations between distant and unrelated clusters of knowledge (connectors), or in producing recombinations that remain unaffected by the organization's knowledge directions and therefore provide necessary diversity (isolates). These results are consistent with Burt's (1997) claim that positive effects of social capital are contingent on the number of individuals doing the same work. Based on this argument, we can also speculate that the interaction between integrators and isolates is not always significantly negative because these two roles are the farthest away from each other in their paths to knowledge recombination. From the results of triple interaction, we can conclude that the combined presence of three relational stars alleviates some of the negative effects from the two-way interactions.

'Place Figures 1-4 about here'

To provide a more intuitive and clear understanding of the interaction results, we display them graphically in Figures 1-4. In Figure 1, we plot the interaction between integrators and

[5] Our results for the direct and interaction effects remain robust (sign and significance) even when we include the squared terms for stars, integrators, connectors, and isolates thus controlling for any non-linear relationships between relational stars and inventive quality.

connectors and predict its effect on citations. We observe that clearly integrators have a much stronger positive effect on citations when the level of connectors is low. However, the two lines do not intersect. This is evidence of the very strong positive effect of connectors on citations (the lowest point of the pink line is still higher than the highest point of the blue line) and of the fact that the two roles compensate for each other but are not perfect substitutes. In Figure 2, we plot the interaction between integrators and isolates. We observe that the positive effect of integrators is slightly bigger when isolates are low than it is when isolates are high. This is further evidence of these two roles being very far from each other when it comes to their approach to knowledge recombination. Similarly, the two lines do not intersect showing that although compensating for each other, the two roles are not perfect substitutes. In Figure 3, we present the interaction between connectors and isolates. The positive effect of connectors is much stronger for low levels of isolates. Interestingly, the two lines intersect pointing to a clear substitution effect between connectors and isolates. A way to interpret this finding is to think that the positive effects of connectors and isolates both come from novelty and diversity of knowledge recombinations (albeit using different paths) and therefore are so close to each other that they substitute for each other's effect. Finally, in Figure 4 we plot the results of the triple interaction. We observe that the positive effect of integrators is the strongest when both connectors and isolates are low and decreases as the level of connectors and isolates increases. A very interesting finding is that the highest positive effect on citations comes when integrators and connectors are high but isolates are low. In fact, even the lowest point of that line is higher than any other line's highest point. This is further evidence of the substitution between connectors and isolates and provides important insights into the interactions among the three roles and the internal configuration that seems to be the most positively associated with inventive quality.

We also report some interesting results from our control variables. Dedicated pharmaceutical firms, European firms, and merged entities seem to perform worse in terms of inventive quality but generally not in terms of quantity. U.S. firms are better in inventive quality but not in inventive quantity. Alliances (total or only exploration) have no significant effects while acquisitions are negatively related with both inventive quality and quantity. Overall innovative performance is positively associated with citations and counts but negatively with claims. The performance and focus of firms in biotech has no consistent effect on inventive quality. When including our independent variables in Models 2, 3, and 4, we observe a negative effect of network size on inventive quality pointing to negative returns of scale on quality and some weak positive returns of size on inventive quantity. Productivity stars have a weak positive effect on inventive quality in Models 4 of citations and claims and a negative effect on inventive quantity in Model 2. Therefore, if productivity stars have a positive effect, it holds only for quality of inventive output. However, the results for stars should be interpreted with caution as we define them as star inventors and not as star scientists as prior literature does. In addition, the results for both network size and stars should be treated with caution because of elevated correlations between network size, stars, and our independent variables.

DISCUSSION

In this study, we extended current research on the role of individuals as origins of organizational innovative outcomes. In particular, we developed a theory on some of invention's structural individual microfoundations. We moved beyond existing research focus on individual productivity which may have obscured the importance of other critical individual skills for successful invention. Invention is increasingly a team-based endeavor (Wuchty, Jones, and Uzzi,

2007) and is often an outcome of knowledge recombination from existing knowledge stocks (Fleming, 2001). Therefore, there is a set of collaborative and social skills that individuals need to possess to facilitate invention process. To identify these individual roles more likely to drive quality of invention, we applied social network thinking to intraorganizational collaborative networks emerging through co-patenting individual efforts. Conceptualizing invention as a process of recombinant search, we argued for the critical role of three individual types: integrators, connectors, and isolates. Integrators are the individuals who have a very large network of collaborative ties. Sourcing knowledge from many alters, integrators have the capacity to explore for a great number of alternative knowledge combinations and select the most promising among them. Connectors are the individuals whose collaborative ties span structural holes in their organization's knowledge network and at the same time link not only unconnected but also distant clusters of knowledge. Their broad view of the knowledge network allows them to experiment with novel and diverse knowledge recombinations and therefore affect the quality of inventive output. Isolates are productive individuals who remain relatively unconnected from the collaborative network; they are independent producers of knowledge. Isolates are important because of the absence of collaborative ties. They can infuse the knowledge base with diversity as their knowledge remains unaffected by the organization's knowledge directions and therefore help avoid competence traps. Apparently, all three individual roles become important for the quality of inventive output not necessarily because they are extremely productive but mainly because their collaborative behavior facilitates effective recombinant search and high quality invention. We used the term 'relational stars' to emphasize the social nature of these critical individual capacities.

Our results show that all three types of relational stars have strong positive effects on the inventive quality of their organizations. They are also positively associated with simple quantity of inventive output. Interestingly, they all appear to be much more impactful for inventive quality than quantity, suggesting that their collaborative behavior is even more important for generating inventions of higher quality rather than just more inventions. Comparing the magnitude of the positive effect on quality between the three types, we found that connectors have the largest positive impact on inventive quality, followed by integrators and isolates. Therefore, although all three are positive quality drivers, if one wants to prioritize one over others then connectors appear to be the most important individuals for invention. In addition, we found robust negative interaction effects between the individual roles. These results suggest that the ways in which relational stars affect quality of invention may just be alternative paths to the same outcome: a novel recombination of knowledge which may have its source in a number of different collaborative behaviors. However, the plots of these interactions revealed that two of our three interactions were simple compensating effects and not perfect substitutions. Although the positive effect of integrators was even stronger when connectors were low, still having many integrators and many connectors was better than having few connectors. We found the same result for integrators and isolates. Only connectors and isolates exhibited clear substitution effects. The three way interaction results provided very important insights for the most effective internal configuration of roles. The presence of many integrators combined with many connectors and few isolates had the most positive effects on inventive quality.

Our arguments and findings have several significant theoretical implications. First, we make an important contribution to the emerging literature on individuals as the microfoundations of organizational capabilities (Felin and Foss, 2005). We were able to show that at least when it comes to invention, certain individuals exhibit patterns of collaborative behavior which make them really valuable as sources of organizational capabilities to generate high quality inventions. With our findings, we echo early research on the promise of the industrial research laboratory to bring together “intuitive minds”, “experimenters”, and “observers” to result in successful inventions (Beer, 1959: 71), roles which arguably correspond to isolates, connectors, and integrators, respectively. More importantly, these individuals affect inventive quality without being necessarily extremely productive; instead, it is their collaborative behavior which provides them with opportunities for novel invention. We were able to show that relational stars positively affect inventive outcomes. Relying on a large sample of incumbent firms in the biopharmaceutical industry, we also showed that relational stars can make incumbent firms the origins of innovation under conditions of technological change in the industry (Tushman and Anderson, 1986; Anderson and Tushman, 1990). This finding opens the door for many research questions. Productivity stars are arguably driven solely by individual intellect and are a resource of given supply. Therefore, firms can either identify them ex ante or just try to hire them away from competition. On the other hand, relational stars can be an organizational product as well. What can firms do to identify or internally develop them? Which are the origins of relational stars? These are individuals who had both the ability and opportunity to become relational stars. Therefore, future research can follow the ‘ability’ path and build on existing evidence that such stars are often more educated, professional, read the literature more, and make greater use of individuals that are outside the organization (Allen and Cohen, 1969). Communication stars are generally technically competent (Tushman and Scanlan, 1981), are perceived by others as a source of work-related expertise (Kilduff, Tsai, and Hanke, 2006), become relational stars because of their prior performance (Lee, 2010) and of strong technical contributions (Fleming and Waguespack, 2007). Alternatively, future research can follow the ‘opportunity’ path and identify contexts which create opportunities for internal development of relational stars by training (Hatch and Dyer, 2004), incentives (Kaplan and Henderson, 2005), alliances or acquisitions (Paruchuri, Nerkar, and Hambrick, 2006; Paruchuri, 2010), human resource practices (Adler, Goldoftas, and Levine, 1999), or corporate culture logics (Felin, Zenger, and Tomsik, 2009).

Second, our study has important implications for research on intrafirm knowledge networks. Prior research has been able to document that position of individuals in these networks matters for their own individual outcomes and that the structure of the network affects network outcomes. Here, we showed how micro-level network phenomena can translate into macro-level network outcomes and how the presence of individual nodes in a network (relational stars) affects network level outcomes (inventive quality of the organization). Two recent reviews in the topic suggested that such efforts are necessary (Brass et al. 2004; Ibarra, Kilduff, and Tsai, 2005). To do that, we theoretically and empirically defined our relational stars as outliers in some meaningful network metrics not relatively to their peers in the same network but relatively to all individuals in every competing organization's network. Therefore, we were able to capture the best individuals from every category and suggest that firms with some of the best in their network will have an inventive quality advantage. For example, when it came to defining integrators we looked at the number of collaborative ties that every individual from every firm had during a certain five year time window. We argued that individuals at the top of that distribution were positioned to have the greatest opportunity to identify promising knowledge combinations. By definition, every additional tie resulted in an exponential increase in the number of alternative combinations. To be sure, our approach assumes that we can compare relational stars that had the position because of their own ability and relational stars who became that because of firm-specific structures or incentives. Combined with the issues outlined in the previous paragraph, future research should attempt to understand whether the two types of relational stars have similar positive effects.

Third, our study has significant implications for research in social capital. Our overarching idea was that knowledge co-creation and collaboration behavior, which is a strong form of social capital, results in the creation of human capital (Coleman, 1988). We were able to show that individuals with the right type and amount of collaborative ties had a superior capacity for knowledge recombination that resulted in quality of inventive output. To do that, we relied on a context where the network is not characterized by competitive relationships; rather, it is a structure that mostly resembles a creative collective (Hargadon and Bechky, 2006). In such a cooperative context, centrality seems to uncover the tertius iungens orientation (Obstfeld, 2005) in our integrators and they become sources of high quality invention. In addition, we extend current understanding on the positive role of knowledge brokers as experts fostering system-level innovation (Lingo and O'Mahony, 2010) by defining connectors as individuals who are knowledge brokers but at the same time link distant clusters of knowledge and access a wide range of the network. Connectors have the capacity to not only be more creative themselves (Fleming, Mingo, and Chen, 2007) but also uncover promising links by bridging knowledge silos. Our findings on isolates highlight the fact that even a lack of social capital can be very important in cooperative contexts like collaboration networks. We emphasized the need for diversity which can be provided by the often neglected role of productive isolates. Finally, our findings on interaction among the three types of relational stars provide additional evidence to support a contingent view of social capital (Burt, 1997), where its importance depends on the number of other individuals with similar levels of social capital. We submit here an additional limitation of our study: we relied on co-patenting to build internal knowledge networks and assume the creation of social capital from these ties. Although there is research supporting our claim that co-patenting involves significant knowledge flows (Singh, 2005), we were only able to observe co-patenting and assume knowledge flows. Hence, future research can exploit other sources of individual collaboration to extract information about individual social capital.

We conclude with our study's implications for managerial practice. Received wisdom suggests that individual productivity is the most important skill for innovation and therefore managerial incentive structures are often built to maximize effort and productivity. Our study suggests that the sole focus on productivity, effort, and star knowledge workers may be misleading. First, innovation is a deeply social process of knowledge recombination and collaborative skills are required for effective execution. Second, star workers are in limited supply and therefore come with important caveats: they may appropriate all of the value they create, leave the organization and transfer their knowledge to competitors (Almeida and Kogut, 1999), and they are pretty visible to the market and therefore more likely to be hired away (Gardner, 2005). In addition, except for their ex ante identification, there is no other straightforward way for managers to internally build them. On the other hand, relational stars are free from those weaknesses. First, they are not in limited supply: relational stars can be identified ex ante or developed internally through encouragement of collaboration. Individuals whose performance depends on interactions with others cannot transfer easily their performance to other organizations (Groysberg, Lee, and Nanda, 2008) and are therefore also less likely to leave. Individual collaboration generates spillovers (Oettl, 2009) and therefore firms can internalize these externalities and avoid full value appropriation by the individuals involved. In addition, they are less visible to the market because of their embedded nature in the organization's knowledge networks that it becomes less likely for them to become the target of competition. More importantly, managers can design practices, incentives, structures, or reward schemes to internally develop relational stars. Managers can do that by incentivizing the right type of collaboration among employees and develop internally the skills of their intellectual capital resources which may remain untapped.

REFERENCES

Abell P, T. Felin , and N. Foss. 2008.Building micro-foundations for the routines, capabilities, and performance links. Managerial and Decision Economics, 29: 489-502.

Adler, P. S., B. Goldoftas, and D.I. Levine. 1999. Flexibility versus efficiency? A case study of model changeovers in the Toyota production system. Organization Science, 10: 43-68.

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

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. Administrative Science Quarterly, 45: 425-455.

Allen T.J., and S.I. Cohen. 1969. Information flow in research and development laboratories. Administrative Science Quarterly, 14: 12-19.

Almeida, P., and B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. Management Science, 45: 905-917.

Amabile, T. M., R. Conti, H. Coon, J. Lazenby, and M. Herron. 1996. Assessing the work environment for creativity. Academy of Management Journal, 39: 1154-1184.

Anderson, P., and M.L. Tushman. 1990. Technological discontinuities and dominant designs: a cyclical model of technological change. Administrative Science Quarterly, 35: 604-633.

Argyres, N., and B.S. Silverman. 2004. R&D, organization structure, and the development of corporate technological knowledge. Strategic Management Journal, 25: 929-958.

Beer, J. J. 1959. The emergence of the German Dye Industry. Urbana, IL: University of Illinois Press.

Borgatti, S. P., and R. Cross. 2003. A relational view of information seeking and learning in social networks. Management Science, 49: 432-445.

Borgatti, S. P., and P.C. Foster. 2003. The network paradigm in organizational research: A review and typology. Journal of Management, 29: 991-1013.

Brass, D.J. 1984. Being in the right place: A structural analysis of individual influence in an organization. Administrative Science Quarterly, 29: 518-539.

Brass, D. J., J. Galaskiewicz, H.R. Greve, and W. Tsai. 2004. Taking stock of networks and organizations: A multilevel perspective. Academy of Management Journal, 47: 795-817.

Brown, S. L., and K.M. Eisenhardt. 1997. The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. Administrative Science Quarterly, 42: 1-34.

Burt R.S. 1997. The contingent value of social capital. Administrative Science Quarterly, 42: 339-365.

Burt R.S. 2000. The network structure of social capital." In R.I. Sutton and B.M. Staw (eds.), Research in Organizational Behavior, 22: 345-423. New York: Elsevier/JAI.

Burt R.S. 2004. Structural holes and good ideas. American Journal of Sociology, 110:349-399.

Cohen P., J. Cohen, S.G. West, and L.S. Aiken. 2003. Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences, 3rd ed. Erlbaum, Hillsdale, NJ.

Cohen W.M., R.R. Nelson, and J.P. Walsh. 2000. Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). NBER Working Paper No.w7552.

Coleman, J.S. 1988. Social capital in the creation of human capital. American Journal of Sociology, 94: S95-S120.

Conner K.R., and C.K. Prahalad. 1996. A resource-based theory of the firm: knowledge versus opportunism. Organization Science, 7: 477-501.

Cowan, R., and N. Jonard. 2003. The dynamics of collective invention. Journal of Economic Behavior & Organization, 52: 513-532.

Cross, R. and J.M. Cummings. 2004. Tie and network correlates of individual performance in knowledge-intensive work. Academy of Management Journal, 47: 928-937.

Dahlin, K., M. Taylor, and M. Fichman. 2004. Today's Edisons or weekend hobbyists: technical merit and success of inventions by independent inventors. Research Policy, 33: 1167-1183.

Felin, T., and N.J. Foss. 2005. Strategic organization: a field in search of micro-foundations. Strategic Organization, 3: 441-455.

Felin, T., and W.S. Hesterly. 2007. The knowledge based view, nested heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge. Academy of Management Review, 32: 195-218.

Felin, T., T.R. Zenger, and J.Tomsik. 2009. The knowledge economy: emerging organizational forms, missing microfoundations, and key considerations for managing human capital. Human Resource Management, 48: 555-570.

Felin, T. and T.R. Zenger. 2009. Entrepreneurs as theorists: on the origins of collective beliefs and novel strategies. Strategic Entrepreneurship Journal, 3: 127-146.

Fleming, L. 2001. Recombinant uncertainty in technological search." Management Science, 47: 117-132.

Fleming, L. 2002. Finding the organizational sources of technological breakthroughs: the story of Hewlett-Packard's thermal ink-jet. Industrial and Corporate Change, 11: 1059-1084.

Fleming, L., S. Mingo, and D. Chen. 2007. Collaborative brokerage, generative creativity, and creative success. Administrative Science Quarterly, 52: 443-475.

Fleming, L. and D.M. Waguespack. 2007. Brokerage, boundary spanning, and leadership in open innovation communities. Organization Science, 18: 165-180.

Galunic, C., and K.M. Eisenhardt. 2001. Architectural innovation and modular corporate forms.Academy of Management Journal, 44: 1229-1249.

Galunic, C., and S. Rodan. 1998. Resource recombinations in the firm: knowledge structures and the potential for Schumpeterian innovation. Strategic Management Journal, 19: 1193-1201.

Gardner, T.M. 2005. Interfirm competition for human resources: Evidence from the software industry. Academy of Management Journal, 48: 237-256.

Gargiulo, M. and M. Benassi. 2000. Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. Organization Science, 11: 183-196.

Gargiulo, M., G. Ertug, and C. Galunic. 2009. The two faces of control: network closure and individual performance among knowledge workers. Administrative Science Quarterly, 54: 299-333.

Gavetti, G., and D. Levinthal. 2000. Looking forward and looking backward: Cognitive and experiential search. Administrative Science Quarterly, 45: 113-137.

Gibbons R. 1999. Taking Coase seriously. Administrative Science Quarterly, 44: 145-157.

Grant, R.M. 1996. Toward a knowledge-based theory of the firm. Strategic Management Journal, 17: 109-122.

Greene, W.H. 2003. Econometric Analysis, 5th ed. Prentice Hall, Upper Saddle River, NJ.

Groysberg, B., L-E. Lee, and A. Nanda. 2008. Can they take it with them? The portability of star knowledge workers' performance. Management Science, 54: 1213-1230.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg. 2001. The NBER patent citation data file: lessons, insights and methodological tools. NBER Working Paper No. 8498.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg. 2005. Market value and patent citations. RAND Journal of Economics, 36: 16-38.

Hamilton, B.J., and J.A. Nickerson. 2003. Correcting for endogeneity in strategic management research. Strategic Organization, 1: 51-78.

Hansen, M.T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. Administrative Science Quarterly, 44: 82-111.

Hargadon, A.B., and B.A. Bechky. 2006. When collections of individuals become creative collectives: A field study of problem solving at work. Organization Science, 17: 484-500.

Hargadon,A.B., and A. Fanelli. Action and possibility: Reconciling dual perspectives of knowledge in organizations. Organization Science, 13: 290-302.

Hatch, N. W., and J.H. Dyer. 2004. Human capital and learning as a source of sustainable competitive advantage. Strategic Management Journal, 25: 1155-1178.

Henderson, R., and I. Cockburn. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. Strategic Management Journal, 15: 63-84.

Hsiao, C. 2003. Analysis of Panel Data, 2nd ed. Cambridge University Press, Cambridge, UK.

Ibarra, H. 1993. Network centrality, power, and innovation involvement: Determinants of administrative roles. Academy of Management Journal, 36: 471:501.

Ibarra, H., M. Kilduff, and W.Tsai. 2005. Zooming in and out: Connecting individuals and collectivities at the frontiers of organizational network research. Organization Science, 16: 359-371.

Inkpen, A., and E. Tsang. 2005. Social capital, networks and knowledge transfer. Academy of Management Review, 30: 146-165.

Jones, B. F. 2009. The Burden of knowledge and the "death of the renaissance man": Is innovation getting harder? Review of Economic Studies, 76: 283-317.

Kang, S., S.S. Morris, and S.A. Snell. 2007. Relational archetypes, organizational learning, and value creation: Extending the human resource architecture. Academy of Management Review, 32: 236-256

Kaplan, S., and R. Henderson. 2005. Inertia and incentives: Bridging organizational economics and organizational theory. Organization Science, 16: 509-521.

Katila, R., and G. Ahuja. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal, 45: 1183-1194.

Kilduff, M., and D.J. Brass. 2010. Organizational social network research: Core ideas and key debates. Academy of Management Annals, 4: 317-357.

Kilduff, M, W. Tsai, and R. Hanke. 2006. A paradigm too far? A dynamic stability reconsideration of the social network research program. Academy of Management Review, 31: 1031-1048.

Kleinbaum, A.M., and M.L. Tushman. 2007. Building bridges: the social structure of interdependent innovation. Strategic Entrepreneurship Journal, 1: 103-122.

Kogut, B., and U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization Science, 3: 383-397.

Lacetera, N., I.M. Cockburn, and R. Henderson. 2004. Do firms change capabilities by hiring new people? A study of the adoption of science-based drug discovery. In Baum J.A.C., & A. M. McGahan (Eds.), Business Strategy over the Industry Lifecycle: Advances in Strategic Management Vol.21. Boston, MA: Elsevier.

Langlois, R.N., and N. Foss. 1999. Capabilities and governance: the rebirth of production in the theory of economic organization. KYKLOS, 52: 201-218.

Lavie, D. 2006. Capability reconfiguration: An analysis of incumbent responses to technological change. Academy of Management Review, 31:153-174.

Lazer, D., and A. Friedman. 2007. The network structure of exploration and exploitation. Administrative Science Quarterly, 52: 667-694.

Lee, J. 2010. Heterogeneity, brokerage and innovative performance: endogenous formation of collaborative inventor networks. Organization Science: forthcoming.

Levitt, B., and J.G. March. 1988. Organizational learning. Annual Review of Sociology, 14: 319-338.

Lingo, E.L., and S. O'Mahony. 2010. Nexus work: Brokerage on creative projects. Administrative Science Quarterly, 55:47-81.

McFadyen, M. A., and A.A. Canella. 2004. Social capital and knowledge creation: Diminishing returns to the number and strength of exchange relationships. Academy of Management Journal, 47: 735-746.

Mehra, A., M. Kilduff, and D.J. Brass. 2001. The social networks of self-monitors: Implications for workplace performance. Administrative Science Quarterly, 46: 121-146.

Morrison, E.W. 2002. Newcomers's relationships: The role of social network ties during socialization. Academy of Management Journal, 45: 1149-1160.

Murray, F. and S. O'Mahony. 2007. Exploring the foundations of cumulative innovation: Implications for organization science. Organization Science, 18: 1006-1021.

Nelson, R.R., and S. Winter. 1982. An Evolutionary Theory of Economic Change. Harvard University Press: Cambridge, MA.

Nahapiet, J., and S. Ghoshal. 1998. Social capital, intellectual capital, and the organizational advantage. Academy of Management Review, 23: 242-266.

Nerkar, A., S. Paruchuri. 2005. Evolution of R&D capabilities: The role of knowledge networks within a firm. Management Science, 51: 771-785.

Nonaka, I. 1994. A dynamic theory of organizational knowledge creation. Organization Science, 5: 14-37.

Obstfeld, D. 2005. Social networks, the tertius iungens orientation, and involvement in innovation. Administrative Science Quarterly, 50: 100-130.

Oettl, A. 2009. Productivity and helpfulness: Implications of a new taxonomy for star scientists. Georgia Institute of Technology Working Paper.

O'Reilly, C., and M.L. Tushman. 2007. Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. Harvard Business School Working Paper 07-088.

Paruchuri, S. 2010. Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. Organization Science, 21: 63-80.

Paruchuri, S., A. Nerkar, and D.C. Hambrick. 2006. Acquisition integration and productivity losses in the technical core: Disruption of inventors in acquired companies. Organization Science, 17: 545-562.

Perry-Smith, J. E., and C.E. Shalley. 2003. The social side of creativity: a static and dynamic social network perspective. Academy of Management Review, 28: 89-106.

Podolny, J.M. 2001. Networks as the pipes and prisms of the market. American Journal of Sociology 107: 33-60.

Reagans, R., and B. McEvily. 2003. Network structure and knowledge transfer: The effects of cohesion and range. Administrative Science Quarterly, 48: 240-267.

Reagans, R., and E.W. Zuckerman. 2001. Networks, diversity, and productivity: The social capital of corporate R&D teams. Organization Science, 12: 502-517.

Reagans, R., E.W. Zuckerman, and B. McEvily. 2004. How to make the team: Social networks vs. demography as criteria for designing effective team. Administrative Science Quarterly, 49: 101-133.

Rothaermel, F. T., and A.M. Hess. 2007. Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. Organization Science, 18: 898-921.

Schumpeter, J.A. 1942. Capitalism, Socialism, and Democracy. New York: Harper and Brothers.

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. Management Science, 51: 756-770.

Singh, J. 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. Research Policy, 37: 77-96.

Singh, J. and L. Fleming. 2010. Lone inventors as sources of breakthrough: Myth or reality? Management Science, 56: 41-56.

Sorenson, O., J.W. Rivkin, and L. Fleming. 2006. Complexity, networks and knowledge flow. Research Policy, 35: 994-1017.

Teece, D., G. Pisano, and A. Shuen. 1997. Dynamic capabilities and strategic management. Strategic Management Journal, 18: 509-533.

Thomas-Hunt, M.C., T.Y. Ogden, and M.A. Neale. 2002. Who's really sharing? Effects of social and expert status on knowledge exchange within groups. Management Science, 49: 464-477.

Tichy, N. M., M.L. Tushman, and C. Fombrun. 1979. Social network analysis for organizations. Academy of Management Review, 4: 507-519.

Tsai, W. 2002. Social structure of "coopetition" within a multiunit organization: coordination, competition, and intraorganizational knowledge sharing. Organization Science, 13: 179-190.

Tsai, W., and S. Ghoshal. 1998. Social capital and value creation: The role of interfirm networks. Academy of Management Journal, 41: 464-476.

Tushman, M.L., and P. Anderson. 1986. Technological discontinuities and organizational environments. Administrative Science Quarterly, 31: 439-465.

Tushman, M.L., and E. Romanelli. 1983. Uncertainty, social location, and influence in decision making: A sociometric analysis. Management Science, 29: 12-23.

Tushman, M.L., and T.J. Scanlan. 1981. Boundary spanning individuals: Their role in information transfer and their antecedents. Academy of Management Journal, 24: 289-305.

Wuchty, S., B.F. Jones, and B. Uzzi. 2007. The increasing dominance of teams in production of knowledge. Science, 316: 1036-1039.

Xiao, Z., and A.S. Tsui. 2007. When brokers may not work: the cultural contingency of social capital in Chinese high-tech firms. Administrative Science Quarterly, 52:1-31.

Yayavaram, S., and G. Ahuja. 2008. Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. Administrative Science Quarterly, 53: 333-362.

Zenger, T.R., and W.S. Hesterly. 1997. The disaggregation of corporations: selective intervention, high-powered incentives, and molecular units. Organization Science, 8: 209-222.

Zollo, M. and S. Winter. 2002. Deliberate learning and the evolution of dynamic capabilities. Organization Science, 13: 339-351.

Zucker, L. G., and M.R. Darby. 1997. Present at the biotechnological revolution: transformation of technological identity for a large incumbent pharmaceutical firm. Research Policy, 26: 429-446.

Zucker, L. G., M.R. Darby, and J.S. Armstrong. 2002. Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. Management Science, 48: 138-153.

Zucker, L.G., M.R. Darby, and M. Brewer. 1998. Intellectual human capital and the birth of US biotechnology enterprises. The American Economic Review, 88: 290-306.

Table 1

Descriptive Statistics and Bivariate Correlation Matrix

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Patent citations	323.26	476.90																	
2	Patent claims	523.10	767.36	0.89																
3	Patent counts	46.73	67.70	0.88	0.94															
4	Firm merged	0.12	0.33	0.14	0.15	0.18														
5	European firm	0.30	0.46	0.06	0.13	0.18	0.08													
6	US firm	0.34	0.47	0.31	0.23	0.17	0.16	-0.47												
7	Pharma firm	0.46	0.50	-0.23	-0.24	-0.24	0.01	0.03	-0.06											
8	Biotech patents	18.30	26.66	0.58	0.63	0.68	0.36	0.13	0.18	0.04										
9	Biotech ratio	0.42	0.45	-0.15	-0.13	-0.13	0.16	0.07	-0.13	0.35	0.18									
10	All patents	67.90	96.84	0.80	0.85	0.88	0.10	0.13	0.22	-0.30	0.58	-0.24								
11	Alliances	1.64	3.47	0.14	0.16	0.20	0.27	0.02	0.13	0.06	0.42	0.16	0.14							
12	Exploration alliances	0.72	1.62	0.17	0.21	0.23	0.28	0.04	0.12	0.02	0.43	0.13	0.18	0.88						
13	Acquisitions	0.25	1.04	0.13	0.14	0.16	0.30	0.03	0.12	0.08	0.35	0.13	0.12	0.33	0.38					
14	Stars	4.26	11.01	0.51	0.57	0.72	0.22	0.18	0.03	-0.12	0.60	-0.04	0.62	0.26	0.26	0.18				
15	Network size	237.38	292.67	0.74	0.79	0.87	0.26	0.18	0.06	-0.28	0.61	-0.11	0.79	0.25	0.28	0.19	0.76			
16	Integrators	2.69	8.25	0.25	0.26	0.40	0.08	0.14	-0.13	-0.03	0.34	0.03	0.33	0.14	0.14	0.07	0.65	0.51		
17	Connectors	4.06	4.25	0.31	0.31	0.44	0.12	0.10	0.01	-0.08	0.41	0.00	0.38	0.19	0.17	0.08	0.63	0.49	0.51	
18	Isolates	2.97	3.80	0.65	0.69	0.66	0.13	0.07	0.30	-0.16	0.42	-0.10	0.58	0.12	0.14	0.13	0.33	0.56	0.01	0.07

Note: N = 2442 firm-year observations

Table 2

Descriptive Statistics - Correlation Matrix At the Individual Level

		Mean	S.D.	1	2	3
1	Star	0.019	0.136			
2	Integrator	0.012	0.108	-0.02		
3	Connector	0.010	0.099	-0.01	-0.01	
4	Isolate	0.009	0.092	0.03	-0.01	-0.01

Note: N = 550921 individual-level observations

Table 3

Results of Random-Effects Negative Binomial Regression Predicting Number of Citations

Variable	Model 1	Model 2	Model 3	Model 4
Constant	0.456•••	0.556•••	0.624•••	0.644•••
	(0.064)	(0.065)	(0.066)	(0.066)
Firm merged	-0.219•••	-0.191•••	-0.163•••	-0.165•••
	(0.051)	(0.051)	(0.052)	(0.051)
European firm	-0.146••	-0.163••	-0.130••	-0.117•
	(0.073)	(0.073)	(0.073)	(0.073)
US firm	0.274•••	0.274•••	0.271•••	0.268•••
	(0.074)	(0.074)	(0.074)	(0.074)
Pharma	-0.222•••	-0.232•••	-0.250•••	-0.261•••
	(0.062)	(0.062)	(0.062)	(0.061)
Citations lagged	6.7E-04•••	6.2E-04•••	6.1E-04•••	6.0E-04•••
	(4.6E-05)	(4.9E-05)	(5.0E-05)	(4.9E-05)
Alliances	3.7E-03	4.4E-03	5.0E-03	3.0E-03
	(7.4E-03)	(7.4E-03)	(7.5E-03)	(7.5E-03)
Acquisitions	-0.026••	-0.009	-0.014	-0.014
	(0.016)	(0.015)	(0.015)	(0.015)
Exploration alliances	-0.018	-0.015	-0.017	-0.017
	(0.017)	(0.017)	(0.017)	(0.017)
All patents	6.0E-04••	7.5E-04•••	1.0E-03•••	1.3E-03•••
	(3.0E-04)	(3.0E-04)	(3.0E-04)	(2.9E-04)
Biotech patents	-3.8E-04	-1.3E-03•••	-1.8E-03••	-1.4E-03••
	(7.9E-04)	(8.2E-04)	(8.5E-04)	(8.4E-04)
Biotech ratio	0.025	0.024	0.020	0.019
	(0.043)	(0.043)	(0.044)	(0.044)
Network size	1.1E-04	-1.4E-04	-3.1E-04•••	-4.1E-04•••
	(1.1E-04)	(1.2E-04)	(1.2E-04)	(1.2E-04)
Stars	0.008	-0.027	0.033	0.046•
	(0.024)	(0.024)	(0.029)	(0.027)
Integrators		0.059•••	0.092•••	0.091•••
		(0.019)	(0.019)	(0.019)
Connectors		0.105•••	0.179•••	0.198•••
		(0.017)	(0.020)	(0.020)
Isolates		0.084•••	0.072•••	0.056•••
		(0.015)	(0.017)	(0.017)
Integrators x Connectors			-0.039•••	-0.041•••
			(0.007)	(0.007)
Integrators x Isolates			-0.007	-0.018••
			(0.009)	(0.012)
Connectors x Isolates			-0.069•••	-0.120•••
			(0.015)	(0.018)
Triple Interaction				0.031•••
				(0.006)
No. of observations / groups	2414 / 106	2414 / 106	2414 / 106	2414 / 106
Log likelihood	-14377.75	-14349.79	-14705.61	-14628.84
Chi square	1044.97	1117.87	1167.81	1214.54
Δ chi square		72.90•••	122.84•••	169.57•••

Notes: ● $p < 0.1$; ●● $p < 0.05$; ●●● $p < 0.01$; standard errors in parentheses

Table 4

Results of Random-Effects Negative Binomial Regression Predicting Number of Claims				
Variable	Model 1	Model 2	Model 3	Model 4
Constant	0.287●●●	0.452●●●	0.498●●●	0.517●●●
	(0.064)	(0.066)	(0.067)	(0.067)
Firm merged	-0.370●●●	-0.317●●●	-0.296●●●	-0.294●●●
	(0.060)	(0.060)	(0.060)	(0.060)
European firm	-0.230●●	-0.257●●●	-0.238●●●	-0.236●●●
	(0.073)	(0.073)	(0.073)	(0.073)
US firm	0.144●●	0.109●	0.104●	0.099●
	(0.072)	(0.073)	(0.073)	(0.073)
Pharma	-0.155●●●	-0.170●●●	-0.179●●●	-0.183●●●
	(0.062)	(0.062)	(0.062)	(0.062)
Claims lagged	5.8E-04●●●	6.0E-04●●●	5.7E-04●●●	5.3E-04●●●
	(3.6E-05)	(3.5E-05)	(3.8E-05)	(3.8E-05)
Alliances	-6.9E-03	-6.8E-03	-6.9E-03	-1.1E-02
	(9.0E-03)	(9.1E-03)	(9.2E-03)	(9.2E-03)
Acquisitions	-0.080●●●	-0.036●●	-0.044●●	-0.045●●
	(0.021)	(0.019)	(0.020)	(0.020)
Exploration alliances	-0.009	-0.005	-0.004	-0.003
	(0.019)	(0.019)	(0.019)	(0.019)
All patents	-7.8E-04●●	-6.9E-04●●	-4.1E-04	-4.3E-05
	(4.0E-04)	(3.7E-04)	(3.9E-04)	(3.8E-04)
Biotech patents	7.6E-04	-7.9E-04	-1.1E-03	-7.6E-04
	(8.3E-04)	(8.5E-04)	(9.0E-03)	(9.0E-04)
Biotech ratio	0.038	0.036	0.030	0.033
	(0.047)	(0.048)	(0.049)	(0.049)
Network size	4.6E-05	-4.5E-04●●●	-5.0E-04●●●	-5.8E-04●●●
	(1.2E-04)	(1.4E-04)	(1.4E-04)	(1.4E-04)
Stars	0.011	0.008	0.029	0.044●
	(0.029)	(0.027)	(0.030)	(0.030)
Integrators		0.078●●●	0.103●●●	0.101●●●
		(0.021)	(0.021)	(0.021)
Connectors		0.144●●●	0.203●●●	0.215●●●
		(0.018)	(0.022)	(0.022)
Isolates		0.112●●●	0.100●●●	0.088●●●
		(0.017)	(0.018)	(0.019)
Integrators x Connectors			-0.028●●●	-0.030●●●
			(0.007)	(0.007)
Integrators x Isolates			0.002	-0.006
			(0.010)	(0.011)
Connectors x Isolates			-0.071●●●	-0.127●●●
			(0.017)	(0.023)
Triple Interaction				0.027●●●
				(0.007)
No. of observations / groups	2414 / 106	2414 / 106	2414 / 106	2414 / 106
Log likelihood	-15662.21	-15617.65	-15601.71	-15594.06
Chi square	1177.35	1294.44	1339.04	1371.50
Δ chi square		117.09●●●	161.69●●●	194.15●●●

Notes: ● $p < 0.1$; ●● $p < 0.05$; ●●● $p < 0.01$; standard errors in parentheses

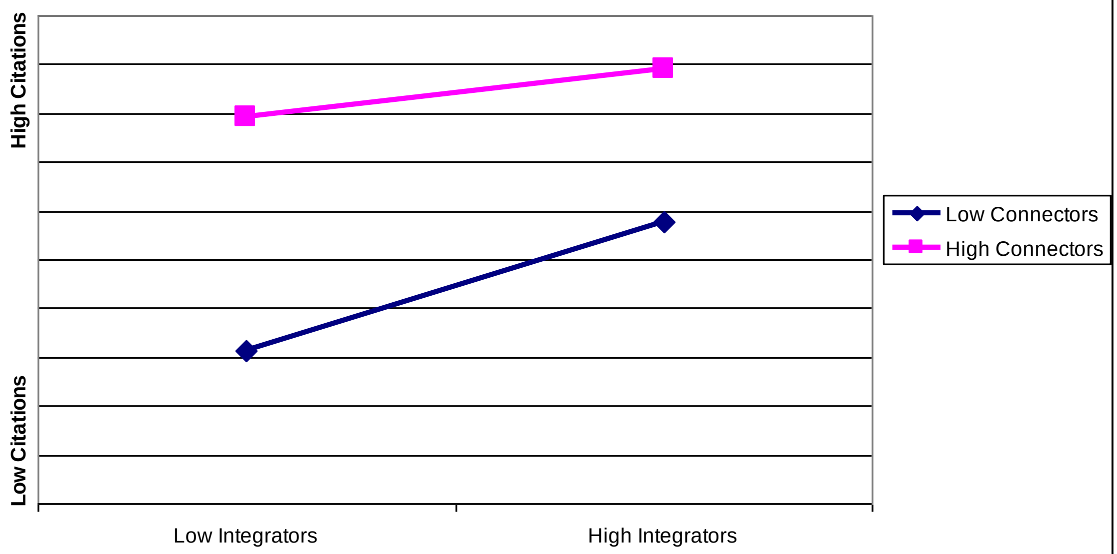
Table 5

Results of Random-Effects Negative Binomial Regression Predicting Number of Patents

Variable	Model 1	Model 2	Model 3	Model 4
Constant	1.347•••	1.441•••	1.517•••	1.536•••
	(0.077)	(0.077)	(0.078)	(0.078)
Firm merged	- 0.072••	- 0.051•	- 0.043	- 0.046
	(0.040)	(0.040)	(0.040)	(0.040)
European firm	- 0.494•••	- 0.500•••	- 0.467•••	- 0.452•••
	(0.093)	(0.093)	(0.092)	(0.092)
US firm	0.068	0.041	0.022	0.020
	(0.091)	(0.091)	(0.091)	(0.091)
Pharma	- 0.081	- 0.091	- 0.117•	- 0.136••
	(0.075)	(0.075)	(0.074)	(0.074)
Patents lagged	2.9E-03•••	2.8E-03•••	2.5E-03•••	2.2E-03•••
	(5.3E-04)	(5.2E-04)	(5.3E-04)	(5.2E-04)
Alliances	6.5E-03	7.4E-03•	7.6E-03•	5.6E-03
	(5.4E-03)	(5.3E-03)	(5.4E-03)	(5.4E-03)
Acquisitions	- 0.045•••	- 0.028•••	- 0.032•••	- 0.033•••
	(0.012)	(0.012)	(0.012)	(0.012)
Exploration alliances	- 0.018•	- 0.016•	- 0.016•	- 0.015
	(0.012)	(0.012)	(0.012)	(0.012)
All patents	1.3E-03•••	1.3E-03•••	1.4E-03•••	1.7E-03•••
	(3.0E-04)	(2.9E-04)	(3.0E-04)	(3.0E-04)
Biotech patents	- 1.1E-03••	- 1.5E-03•••	- 1.9E-03•••	- 1.5E-03••
	(6.6E-04)	(6.6E-04)	(6.8E-04)	(6.8E-04)
Biotech ratio	0.140•••	0.139•••	0.141•••	0.142•••
	(0.026)	(0.026)	(0.025)	(0.025)
Network size	3.5E-04•••	1.3E-04••	4.2E-05	- 6.2E-06
	(9.0E-05)	(9.5E-05)	(9.5E-05)	(9.6E-05)
Stars	- 0.026•	- 0.043•••	0.008	0.014
	(0.018)	(0.018)	(0.020)	(0.020)
Integrators		0.053•••	0.084•••	0.086•••
		(0.015)	(0.015)	(0.015)
Connectors		0.073•••	0.131•••	0.145•••
		(0.014)	(0.016)	(0.016)
Isolates		0.077•••	0.078•••	0.067•••
		(0.011)	(0.013)	(0.013)
Integrators x Connectors			- 0.031•••	- 0.035•••
			(0.005)	(0.005)
Integrators x Isolates			- 0.013••	- 0.019••
			(0.007)	(0.008)
Connectors x Isolates			- 0.045•••	- 0.086•••
			(0.011)	(0.015)
Triple Interaction				0.020•••
				(0.004)
No. of observations / groups	2414 / 106	2414 / 106	2414 / 106	2414 / 106
Log likelihood	-9490.39	-9458.37	-9431.04	-9421.45
Chi square	826.29	901.45	967.37	996.14
Δ chi square		75.16•••	141.08•••	169.85•••

Notes: ● $p < 0.1$; ●● $p < 0.05$; ●●● $p < 0.01$; standard errors in parentheses

Figure 1. Interaction between integrators and connectors



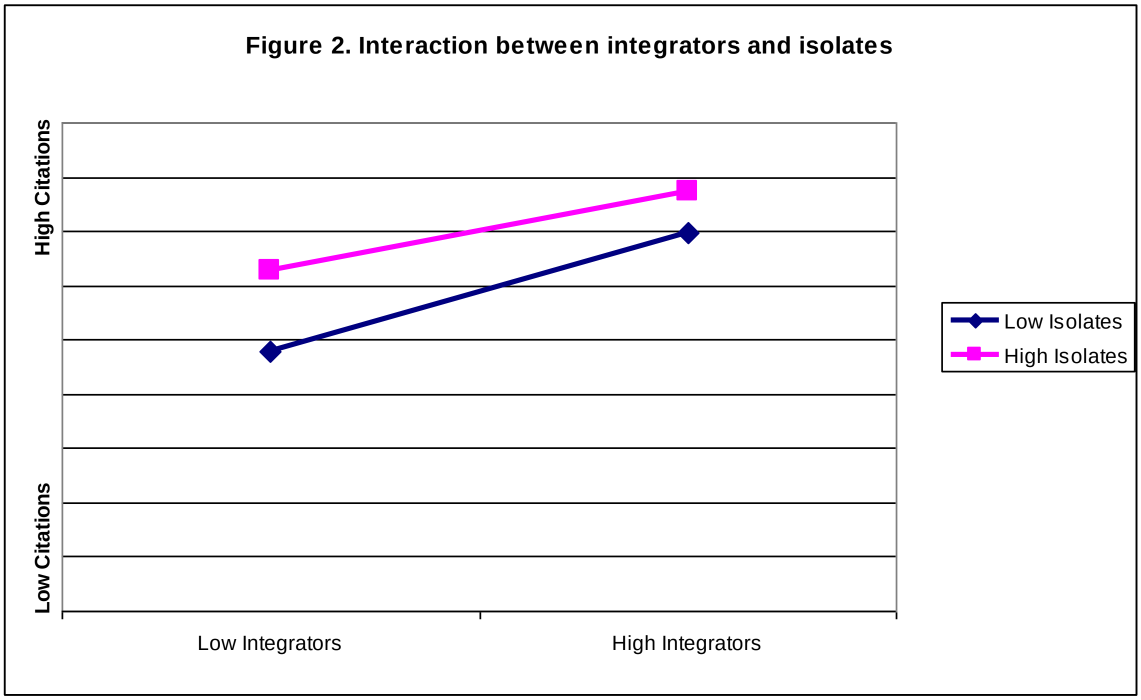
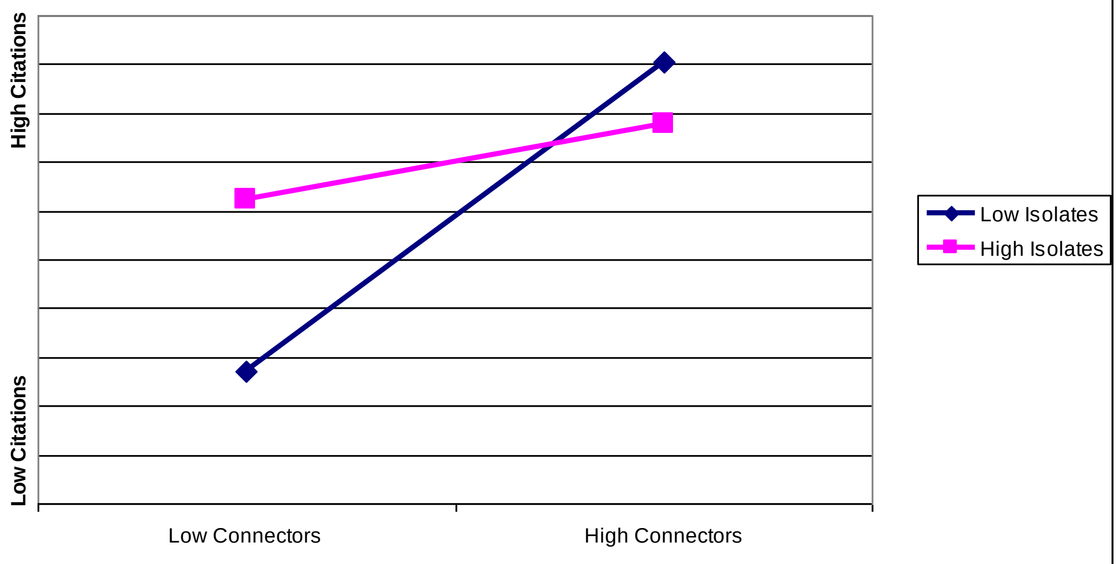


Figure 2. Interaction between integrators and isolates
High Citations
Low Citations
Low Integrators
High Integrators
Low Isolates
High Isolates

Figure 3. Interaction between connectors and isolates



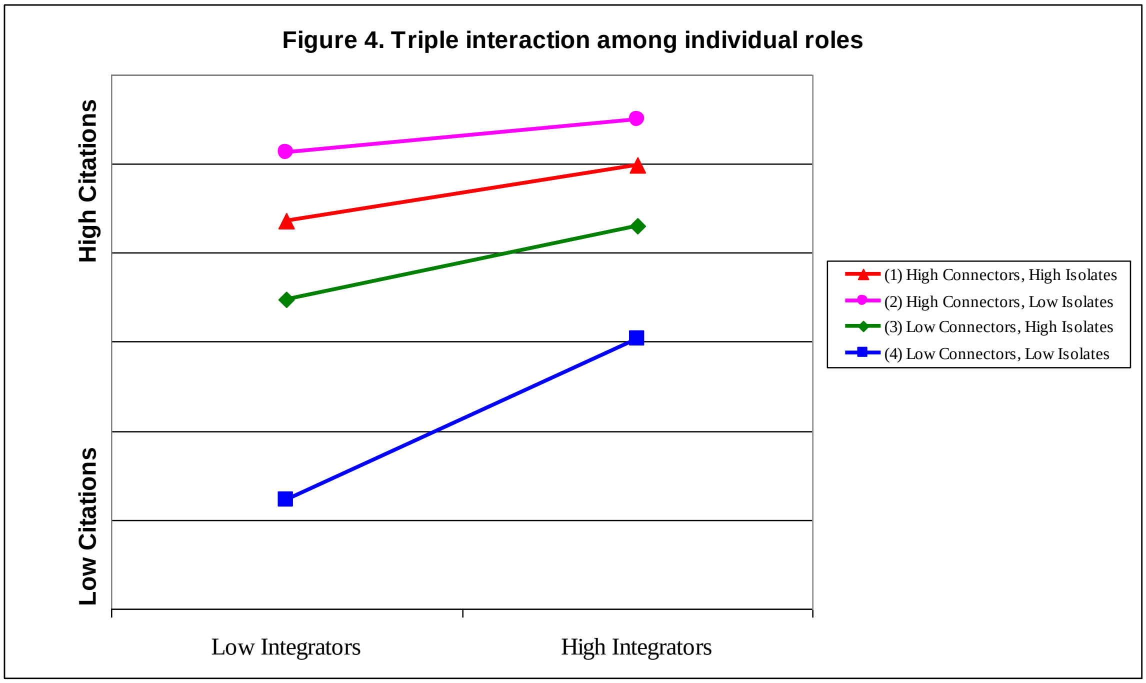


Figure 4. Triple interaction among individual roles
High Citations
Low Citations
Low Integrators
High Integrators
(1) High Connectors, High Isolates
(2) High Connectors, Low Isolates
(3) Low Connectors, High Isolates
(4) Low Connectors, Low Isolates