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Value of Strong Ties to Disconnected Others: Examining Knowledge Creation in Biomedicine

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Knowledge creation requires the combination and exchange of diverse and overlapping knowledge inputs as individuals interact with exchange partners to create new knowledge. In this study, we examine knowledge creation among university research scientists as a function of their professional (ego) networks—those others with whom they collaborate for the purpose of creating new knowledge. We propose that knowledge creation relies, in part, on two attributes of a researcher's professional network structure—average tie strength and ego network density—and we provide insights into how these attributes jointly affect knowledge creation. Our study of over 7,300 scientific publications by 177 research scientists working with more than 14,000 others over an 11-year period provides evidence that the relationship between a research scientist's professional network and knowledge creation depends on both ego network density and average tie strength. Our evidence suggests that both attributes affect knowledge creation. Moreover, average tie strength interacts with density to affect knowledge creation such that researchers who maintain mostly strong ties with research collaborators who themselves comprise a sparse network have the highest levels of new knowledge creation.

Key words: knowledge creation; exchange networks
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1. Introduction

New knowledge creation is one of the most important success factors in organizations (Kogut and Zander 1996). Through a combination and exchange process, individuals create new knowledge as they obtain and develop knowledge inputs through interactions with others (Polanyi 1966, Schumpeter 1934). Among knowledge workers, i.e., those whose job focuses on creating new knowledge, professional (ego) networks are central to the knowledge creation process (Nahapiet and Ghoshal 1998). Professional networks embody a person's direct exchange partners as well as knowledge or other resources that may be acquired through those partners (Lin 2001). Theory suggests that knowledge creation and professional networks are inextricably linked because networks are central to the combination and exchange process (Bouty 2000, Tsai and Ghoshal 1998).

Recent studies provide evidence that differences in the structure of professional networks, i.e., average tie strength and network density, link to knowledge transfer between individuals and between organizational units (Burt 2004, Hansen 2002, Zhao et al. 2004). For example, strong ties typified by close and frequent interactions between a person and his or her exchange partners, promote the transfer of tacit knowledge, whereas weak ties are more efficient for the transfer of codified knowledge[1] (Hansen 1999, Polanyi 1966).

Regarding network density, sparse ego networks (when a person's direct exchange partners have few direct ties to each other) likely contain diverse knowledge resources, so sparse ego networks promote creativity (Burt 2001). Conversely, dense ego networks i.e., direct exchange partners with many direct ties to each other, contain much overlapping knowledge but less diverse knowledge. However, dense ego networks facilitate the development of group norms, expectations, and behaviors, decreasing the risk associated with exchanges (Coleman 1988) and increasing the efficiency of exchanges (Erickson 1998).

While some links between professional networks and knowledge are well established, much of this research focuses on knowledge transfer rather than knowledge creation (for a recent overview of the literature, see Argote et al. 2003). Knowledge transfer involves the movement of facts, relationships, and insights from one person or organization to another (Hargadon and Sutton 1997). Knowledge creation, on the other hand, involves the generation of facts, relationships, and insights that are new to the existing body of knowledge (Arrow 1962). Thus, new knowledge is not held by anyone prior to its creation and therefore is not subject to transfer. New knowledge is typically intangible when it is created, but it can be converted into new products, patents, publications, and other tangible forms (Nonaka and Takeuchi 1995). Studies that examine the relationship between professional networks and knowledge creation are few in number, and longitudinal empirical work is particularly lacking. Our study addresses these issues.

We study how network structural characteristics (ego network density and average tie strength) affect knowledge creation. Our study differs from previous research in three important ways. First, we examine knowledge creation rather than knowledge transfer. While the majority of studies examine knowledge transfer (Hansen 1999, Reagans and McEvily 2003), a few recent studies emphasized various phases of the creation process. Obstfeld (2005) for example, studied the individual's involvement in the creation process and the action problems associated with connecting and coordinating others. We emphasize the resources that individuals can access and develop because of the structure of their networks. As discussed below, our study focuses on the creation problem, and while related to the action problem, i.e., gaining acceptance of creative output, creation and action arise from distinctly different processes. Second, we develop theory to predict that average tie strength will interact with ego network density and affect knowledge creation beyond the main effects. Previous research considered only the main effects of average tie strength, e.g., McFadyen and Cannella (2004), or only the main effects of network density, e.g., Fleming et al. (2007).

Finally, while most prior research examines networks and knowledge with cross-sectional, single period data (see Nerkar and Paruchuri 2005, Fleming et al. 2007 for notable exceptions), our data and analyses are longitudinal. Because knowledge creation occurs over time, it is difficult to use cross-sectional data to predict knowledge creation, because applying a static model to a dynamic process may result in model misspecification (Greve and Goldeng 2004). Therefore, by using a longitudinal panel we are able to examine the effects of average tie strength and density on knowledge creation over time. In addition, our panel approach allows us to control for researcher heterogeneity (Baltagi 2001), separating the effects of factors specific to the researcher from those linked to the researcher's ego network.

Our study of over 7,300 knowledge creations (scientific publications) by 177 research scientists working with more than 14,000 others over an 11-year period provides evidence that the relationship between a research scientist's professional network and his or her knowledge creation depends on both density and average tie strength, and that the two factors have interactive effects on knowledge creation. We begin by integrating knowledge creation and social capital theory and then hypothesizing how density and average tie strength interact in the knowledge creation process. We then describe our methodology, test our hypothesis, and discuss the results. Conclusions and directions for future research end the paper.

2. Networks and Knowledge Creation

As noted earlier, the knowledge creation process is driven by individuals as they acquire and develop overlapping as well as diverse knowledge resources through interactions with others (Cohen and Levinthal 1990, Nonaka 1994, Simon 1985, Spender 1996). While a number of scholars have examined knowledge transfer (Cross and Sproull 2004; Hansen 1999, 2002; Levin and Cross 2004; Reagans and McEvily 2003; Tsai 2001), far fewer have explored knowledge creation. Importantly, knowledge transfer and knowledge creation are separate, yet difficult to disentangle, processes (Nonaka and Nishiguchi 2001). New knowledge is created through a process in which individuals seek to acquire and develop knowledge inputs through professional networks. Importantly to our study, the combine and exchange process requires some level of overlapping knowledge among exchange partners (Grant 1996). For scientific researchers, a fairly high level of overlapping knowledge is essential. For example, a person must have substantial basic knowledge—knowledge that overlaps that of exchange partners—to be an effective partner in a scientific experiment (Polanyi 1966).

By interacting with others, individuals gain tacit knowledge, combine and exchange diverse and overlapping knowledge inputs, and build a better understanding of how things work and how exchange partners think (Polanyi 1966). Interactions allow overlapping knowledge to converge, resulting in new justified beliefs. Much of the new knowledge they create is codified in tangible forms such as patents, publications, and new products.

Our study is based on the notion that two key characteristics of professional networks are central to knowledge creation for knowledge workers—average tie strength and network density. We describe the implications of these characteristics for the knowledge creation process below.

2.1. Average Tie Strength and Knowledge Creation

Average tie strength captures the frequency of interactions between a knowledge worker and his or her direct exchange partners. As such, it provides insight into the development of jointly held resources (Lin 2001). Because an individual's capacity to acquire and use knowledge is limited, interactions with others are essential to knowledge creation (Demsetz 1991). Further, research scientists must accumulate a large body of overlapping knowledge before they can recognize, acquire, understand, and reconcile diverse inputs in the creation process (Cohen and Levinthal 1990). Interactions facilitate the accumulation of overlapping knowledge and also strengthen direct ties (Bouty 2000, Lin 2001).

Research has established several benefits of strong ties relevant to knowledge creation. Individuals who have a history of interactions with one another are more helpful and accessible (Cross and Sproull 2004, Granovetter 1982, Krackhardt 1992), provide more assistance and support to one another (Seibert et al. 2001), and exhibit higher levels of trust (Levin and Cross 2004). Trusting relationships facilitate the sharing of exclusive knowledge, i.e., knowledge held only by members of the network (Szulanski 1996, Uzzi 1996, Allen and Henn 2007). Moreover, fine-grained, information that is more detailed, tacit, and holistic is efficiently transferred through strong ties, and this aids in generating solutions to problems (Uzzi 1997, Obstfeld 2005).

Weak ties are very important to knowledge transfer, although their role in knowledge creation is not as well established. A scientist will cautiously interact with other scientists, and if the initial interaction proves mutually beneficial, the scientist will be more likely to repeat the interaction (Bouty 2000). Weak ties indicate that the exchange partners have thus far had limited interactions. Hansen (1999) found that weak ties transfer codified knowledge efficiently and accelerate project completion when the needed knowledge is not complex. Further, weak ties are less costly to maintain. However, weak ties are not very effective for transferring tacit knowledge, which requires deeper interaction and a sizable base of overlapping knowledge (Polanyi 1966). This is particularly true for the scientific discovery process, which requires high levels of specialized and overlapping knowledge exchange (Zucker et al. 1995). Strong ties also help (up to a point) the absorption of knowledge developed outside the network (Bower and Hilgard 1981, Lindsay and Norman 1977).

2.2. Ego Network Density and Knowledge Creation

Network density provides insights about the resources a researcher might obtain through exchange partners (Bian 2003, Lin 2001) as well as potential constraints that the network might impose (Coleman 1988, Gargiulo and Benassi 1999, Portes and Sensenbrenner 1993). Dense ego networks are characterized by members with many connecting ties. In our context, a dense network is one in which many of a knowledge worker's direct exchange partners have direct ties to each other. Dense networks impact knowledge creation because they facilitate communication and cooperation among network members (Coleman 1988, Granovetter 1973). Further, productivity has been found to be higher in dense networks due to the increased capacity for communication (Reagans and Zuckerman 2001). Similarly, dense networks also tend to provide better access to overlapping knowledge (Boissevain 1974, Burt 2004, Granovetter 1973). Notably, overlapping knowledge allows for greater specialization (Demsetz 1991), a critical component of the creation process (Allen and Henn 2007), and overlapping knowledge promotes sharing and integration, consensus building, and problem solving (Grant 1996). All of these are important when the exchanged knowledge is tacit and complex (Polanyi 1966).

Of course, not all aspects of dense ego networks have positive impacts on knowledge creation. Two aspects may hamper new knowledge creation. First, the high level of connectivity facilitates the development of collectively held beliefs and norms (Haken 1978), and these can lead to the establishment and enforcement of sanctions. While sanctions make it less risky for individuals to exchange with each other, they may also dampen creativity among network members (Coleman 1988). Perhaps more important (and better understood) is the fact that dense networks are less likely to provide access to new or unique resources because the high level of connectivity among network members implies few links to others outside the network (Burt 2001). Further, knowledge creation may be restricted in ego networks containing too much overlapping knowledge (i.e., dense ego networks) because it limits the level of diverse inputs (Granovetter 1973, Ancona and Caldwell 1992).

Conversely, sparse networks have a low degree of connectivity, i.e., few ties among members. In our context, sparse ego networks are those in which few of the knowledge worker's direct exchange partners have direct ties to each other. While not providing the deep social support of dense networks, sparse networks do provide more opportunities to secure new information and diverse perspectives (Burt 2001), thus aiding idea generation (Fleming et al. 2007). Previous research established the importance of diverse inputs in the knowledge creation process (Sutton and Hargadon 1996). Diverse inputs enable individuals to make novel associations and linkages (Amabile 1988, Cohen and Levinthal 1990, Simon 1985). Notably, many important discoveries have been made through the combination of diverse inputs (Hargadon and Sutton 2000, Hargadon 2003).

Finally, sparse networks permit effective transfer of codified knowledge, as this knowledge does not require trust, familiarity, or shared experience to facilitate the exchange (Hansen 1999). Collaborative interactions in a sparse network, however, do require greater effort and are more costly to develop and maintain, since the person must reach out beyond his or her own connected and familiar circle (Lin 2001) and be able to integrate diverse knowledge inputs (Williams and O'Reilly 1998). Additionally, the resources available through sparse networks are likely available to rivals as well and thus may lack exclusivity (Ahuja 2000).

2.3. Hypothesis Development

As described in the previous sections, a knowledge worker's professional network (i.e., ego network) is a key source for knowledge inputs as well as for the collaborative interactions required in the knowledge creation process. Prior research has found that average tie strength and network density impact knowledge transfer. In general, sparse networks most often been associated with creativity (Hargadon and Sutton 1997, Simon 1985), while average tie strength has been shown to have positive effects on knowledge transfer (Tsai and Ghoshal 1998, Hansen 1999) and knowledge creation (McFadyen and Cannella 2004).[2]

While earlier studies provided insights into the importance of average tie strength and network density, few studies have considered their interaction. Recently, Reagans and McEvily (2003) found that studying average tie strength alone may mask the effect of social cohesion.[3] For that reason, the authors studied average tie strength and social cohesion simultaneously in relation to knowledge transfer, finding that social cohesion increased knowledge transfer over and above the effects of average tie strength. We extend this earlier work by jointly analyzing average tie strength and ego network density in relation to knowledge creation. Below, we consider permutations of average tie strength (strong versus weak) and network ego density (dense versus sparse).

2.3.1. Weak Ties Coupled with a Sparse Ego Network. The knowledge worker with mostly weak ties to direct exchange partners will have few obligations to those partners, and will be able to locate and secure codified knowledge easily and efficiently. However, the weak ties will make the transfer of tacit knowledge—essential to the creation of new knowledge at the cutting edge—difficult. Further, if the degree of interconnectivity among the knowledge worker's partners is also low, he or she may seem to have the opportunity to couple independently developed knowledge and ideas with diverse perspectives derived from the sparse network. Yet, the independent ideas and diverse perspectives will often be inaccessible because the level of overlapping knowledge is low. In addition, the knowledge worker will lack the needed interactions with others to fully participate in the combine and exchange process. Therefore, we expect that the level of knowledge creation with this configuration (mostly weak ties and a sparse ego network) will be low.

2.3.2. Weak Ties Coupled with a Dense Ego Network. When a knowledge worker is weakly tied to exchange partners and his or her exchange partners are mostly tied to one another, the network of exchange partners has a high degree of knowledge overlap and reciprocal obligations and expectations. However, because the knowledge worker is not strongly tied to other members of the dense network, the individual is neither fully exposed to new knowledge nor participates in deep exchange relationships. Because the individual thus has neither broad access to diverse resources nor the ability to efficiently develop existing resources due to the lack of strong ties with others, knowledge creation will be limited.

2.3.3. Strong Ties Coupled with a Dense Ego Network. Mostly strong ties indicate that an individual interacts frequently with the same exchange partners. Frequent interactions have several effects on the knowledge creation process. First, they facilitate the combine and exchange process, leading to the generation of much overlapping knowledge. Second, if the strong ties are coupled with a dense ego network because of high connectivity among network members, exchange partners will have an even higher access to overlapping knowledge inputs and perspectives, yet will lack diverse inputs. To be sure, network members may develop an inward absorptive capacity, limiting their ability to recognize valuable knowledge outside the closed circle (Cohen and Levinthal 1990). This lack of awareness of external sources limits creative output (Allen and Henn 2007) because the creation process ignites when individuals combine diverse knowledge and perspectives (Hargadon 2002). Thus, while having a higher probability of creating new knowledge than mostly weak ties coupled with a sparse ego network, mostly strong ties coupled with a dense ego network will also provide limited knowledge creation opportunities.

2.3.4. Strong Ties Coupled with a Sparse Ego Network. A key advantage of a sparse network is access to diverse knowledge. However, problems with sparse networks include the uncertainty associated with the value and quality of the knowledge (Burt 2001), the risks associated with sharing knowledge when that knowledge may be appropriated by others (Szulanski 1996, Uzzi 1996, Allen and Henn 2007), and the fact that combining diverse inputs from a sparse network involves significant cost and effort (Williams and O'Reilly 1998). However, when the bridge between the source and the recipient is an exchange partner who is strong tied to both, most of these concerns are mitigated. Through frequent interactions, ties strengthen and exchange partners deepen their understanding of each other and their work, resulting in the accumulation of a large body of overlapping knowledge. The accumulated large body of knowledge increases the researcher's ability to recognize, acquire, and confidently and efficiently reconcile diverse resources in the creation process (Cohen and Levinthal 1990).

Therefore, theory leads us to propose that the optimal context for knowledge creation among research scientists will be the combination of strong direct ties and a sparse ego network. To clarify, this condition is met when knowledge workers have mostly strong ties to their direct exchange partners but the partners themselves have few direct ties to each other. We propose an interaction between average tie strength and ego network density on knowledge creation, implying a more positive relationship between sparse ego networks and knowledge creation as ties strengthen.

In summary, pairing mostly strong ties with a sparse ego network should increase the level of new knowledge creation because sparse networks offer access to diverse resources, which are lacking in strong ties. Further, strong ties facilitate access to tacit knowledge and promote the exchange process, leading to the development of overlapping knowledge and the ability to reconcile diverse inputs; sparse ego networks provide the needed diverse inputs and perspectives. Taken together, knowledge workers with mostly strong ties to their direct exchange partners, coupled with exchange partners who tend not to be directly connected to each other, should lead to the highest levels of knowledge creation.

Hypothesis. *An interaction exists between a knowledge worker's network density and average tie strength, such that having mostly strong ties will increase knowledge creation more in a sparse ego network than in a dense ego network.*

3. Data and Methods

3.1. Sample

We obtained the vitas of university biomedical research scientists from the Community of Science expertise database and tracked their scientific publications and coauthors over an 11-year period (1989–1999). Using scientific publications to capture professional networks through coauthorship has become fairly widespread in the literature (see, for example, Cockburn and Henderson 1998, Newman 2001, Stephan 1996, Zucker et al. 1998).

We accessed the Science Citation Index, PubMed, the National Library of Medicine search service, and the Institute for Scientific Information's (ISI) search services to obtain and verify information about publications listed in the Community of Science profiles. We chose to examine the networks of scientists associated with two of the top National Institutes of Health-funded biomedical research universities in order to control for unobserved heterogeneities such as funding and access to resources. Through this process, we identified 177 scientists who were active researchers in one of 15 different departments, roughly corresponding to research areas, from university 1 (molecular virology and microbiology; pharmacology; cell biology; urology; and immunology) and university 2 (oncology; neuroscience; biological chemistry; gynecology and obstetrics; cardiovascular medicine; urology; gastroentology; molecular biology; cell biology; and pharmacology).

Our unit of analysis is the scientist-year. For each year analyzed, we used information from the previous year (the lagged value of new knowledge created and control variables) as well as the previous three years combined (the network structure measures) to predict the amount of knowledge created in the focal year. While our sample starts in 1989, the first three years of data are used only for measurement of independent and control variables, so our first prediction about the amount of knowledge created is for 1992.

Precedent for using a three-year moving window comes from several sources. First, Nerkar and Paruchuri (2005) used three-year windows to capture the relationships among R&D researchers at DuPont, noting that productivity is highest for groups that were together for about three years. Long (1978, p. 893) and Fleming et al. (2007) also used a three-year moving window to assess scientist and inventor productivity, and Katz (1982, p. 91) reported that R&D group productivity peaked when group tenure (the average time the group had been together) was about three years. As a check on this decision, we conducted post hoc sensitivity analyses by examining two- and four-year windows (see below). Consistent with previous research (Fleming et al. 2007, Katz 1982, Long 1978, Nerkar and Paruchuri 2005), our three-year windows provided the best fit.

3.2. Variables

3.2.1. Dependent Variable: Knowledge Creation. As mentioned earlier, we relied on a scientist's publication record in a given year to assess the level of knowledge created. In order to objectively assess the level of knowledge, Stephan and Levin (1991) recommend weighting each publication by the ISI impact factor for the journal in which it was published. Weighting a publication by impact factor allows us to evaluate the relative importance of the knowledge provided to the scientific community. The measure also eliminates any advantage of larger journals over smaller, frequently issued journals over less frequently issued, and older journals over newer. We constructed our measure of the level of knowledge created by summing the impact factors for all journal articles published by each scientist each year.

3.2.2. Independent Variables.

3.2.2.1. Average tie strength. Average tie strength derives from the amount of time spent and the emotional closeness of a relationship (Granovetter 1973, Marsden and Campbell 1984). We captured average tie strength through the frequency of interaction, indicated by the number of publications with a given coauthor during the previous three years. We then averaged this number across all of the researcher's coauthors.

One of the weaknesses associated with measuring average tie strength through observed interactions is that it ignores unobserved interactions (Marsden and Campbell 1984) as well as interactions that do not yield a publication. While we recognize that our approach has shortcomings, we believe our average tie strength measure is appropriate for several reasons. First, relying on scientific publications is a rigorous, unobtrusive, and objective way to capture professional networks (Cockburn and Henderson 1998; Newman 2001, 2004; Stephan 1996; Zucker et al. 1998). Second, since we focus only on those interactions associated with coauthoring publications (rather than all interactions), our models represent a conservative test of the proposed hypothesis. Finally, by using the fixed effects model, we control for any unobserved heterogeneity in coauthor choice based on individual scientist characteristics.

We calculated average tie strength as the mean number of publications per coauthor that a given scientist achieved during the previous three years. Specifically, we totaled the number of coauthors that a scientist published with during the previous three years (double counting those coauthors with whom the author published two papers, triple counting those with whom the author had published three papers, etc.) and divided by the number of unique coauthors. The measure reflects that working with the same coauthor on a given number of projects results in a higher frequency of interaction than working with different coauthors on the same number of projects. This two-step approach was based on definitions posed by Granovetter (1973) and has been previously used in empirical research (Hansen 1999, McFadyen and Cannella 2004, Uzzi 1996). Also, McFadyen and Cannella (2004) demonstrated that the effects of average tie strength are likely to be curvilinear, as the maintenance cost of maintaining large numbers of strong ties can outweigh the associated benefits. To control for this effect, we included average tie strength squared in our analyses.

3.2.2.2. Network density. Following Borgatti et al. (1999), we calculated a density score for each scientist's professional (ego) network. Density captures the extent of overlapping ties among individuals within a network, and is one of the most common measures of network structure (Marsden 1990). We calculated an average density measure for eight, three-year windows from 1989 through 1998. The ego network density score is computed as follows:

$$\begin{aligned}&\textit{Ego Network Density}\\&\quad=\textit{Actual Ties}/\textit{Maximum Number of Pairs}\end{aligned}$$

Actual ties are defined as the number of a scientist's coauthors who have published at least one other paper with another of the scientist's coauthors during the previous three years, while pairs are defined as potential ties (Borgatti et al. 1999).

3.2.3. Control Variables. We included a *Lagged dependent variable* to control for the scientist's previous knowledge creation, unobserved heterogeneity, and other potentially important but omitted predictors of knowledge creation (Greene 2000, p. 720 and Katila and Ahuja 2002). We believe that the lagged dependent variable is especially important to include when examining knowledge creation as knowledge is created cumulatively over time. By having a measure that captures knowledge created in a previous period, we control for any cumulative effects and are able to better isolate the network effects.

We also included several variables to control for individual differences in human and knowledge capital. We included the scientist's *Time in profession* in the medical research industry to capture variance in human capital. Further, this variable allowed us to control for the increased opportunities for coauthorships for scientists with longer tenure in the profession. Because we focused on biomedical research, we included the *Number of last-authored papers* as a control. Interestingly, in the medical sciences, the last author generally funds the research and drives the theory being tested (Shapiro et al. 1994). Put differently, the last author tends to be the key contributor, similar to the first author in management research. We also included the number of *First-authored papers* during the past three years as a control for the focal scientist playing a critical operational role in the research project.[4] First authors tend to be the project managers who implement the research and take an important role in writing the paper or papers. However, they are often post-docs or junior scholars. We added the *Number of long-term coauthors* to control for collaboration relationships that lasted six years or more. We also controlled for the number of each scientist's coauthors who were considered by ISI to be among the most *Highly cited coauthors* in the field during the past three years.[5]

Finally, we controlled for the introduction of new partners into the person's ego network during the previous three years, because new exchange partners may be sources of diverse knowledge. This measure was *Percent new coauthors*.

3.3. Statistical Methods

Our sample contains time series cross-sectional panel data consisting of scientific publications for 177 scientists over 11 years. Because our dependent variable is a nonnegative count measure, we selected a time series cross-sectional fixed effects negative binomial model to address the suspected overdispersion of the dependent variable distribution (Greene 2000, p. 886). We selected the fixed effects model to control for unobserved, scientist-specific factors (location, personality, etc.) that might otherwise affect our empirical results (Baltagi 2001). We selected the negative binomial model because our dependent variable was a nonnegative count

Table 1 Descriptive Statistics

Number	Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	Knowledge creation (the DV)	19.92	37.63										
2	Lagged dependent variable	19.77	37.45	0.794									
3	Time in profession	15.52	8.41	−0.033	−0.020								
4	Number of first authored papers	2.18	2.50	0.152	0.196	0.046							
5	Number of last authored papers	3.67	6.33	0.587	0.635	0.239	0.290						
6	Number of long-term coauthors	0.01	0.10	−0.007	0.008	0.063	−0.021	0.034					
7	Highly cited coauthors	0.02	0.15	0.578	0.557	0.050	0.107	0.512	−0.012				
8	Percent new coauthors	0.27	0.25	0.074	0.157	−0.064	0.055	−0.008	−0.005	0.001			
9	Average tie strength	1.53	0.74	0.169	0.202	0.149	0.199	0.289	0.088	0.151	−0.005		
10	Average tie strength squared	2.89	3.06	−0.034	−0.035	0.002	−0.040	−0.032	0.016	0.009	−0.102	0.512	
11	Ego network density	83.45	21.18	0.074	0.111	0.194	0.125	0.185	0.042	0.028	0.174	0.414	−0.069

Notes. Correlations > |0.05| are significant at $p < 0.05$.
*The mean and standard deviation reported for these two variables is not standardized.

measure that left-censored at zero. Further, we chose the negative binomial model over a Poisson model after a test indicated significant overdispersion in our data (Cameron and Trivedi 1990).

4. Results

Table 1 shows the means, standard deviations, and correlations for the variables used in the models. To provide a sense of the empirical context, on average, the researchers had eight publications a year; the median was six. The dependent variable was skewed toward zero, but this skewness was handled effectively through our negative binomial approach, an approach designed to address censored dependent variables. Because the negative binomial methodology does not provide statistics to test for the presence of multicolinearity, we made several checks for it. First, we examined the correlation matrix for highly correlated variables. The only potentially problematic correlations were the lagged dependent variable, highly cited coauthors, and the average tie strength squared measure, but our results did not change when we omitted these variables. To further check for multicolinearity problems, we ran a number of negative binomial regressions, omitting each independent variable one at a time to see if the results for the remaining independent variables were importantly changed by the omission. We noted no changes in coefficient signs or significance levels. We also ran the analysis with one independent variable at a time, and the results were unchanged. Further, we ran the models with only the variables of interest (average tie strength, ego network density, and the interaction), and our results held. We also note that the maximum likelihood algorithm will not converge with excessive multicolinearity. These analyses, while not definitive, provide evidence to support the assertion that multicolinearity has not importantly affected our conclusions.

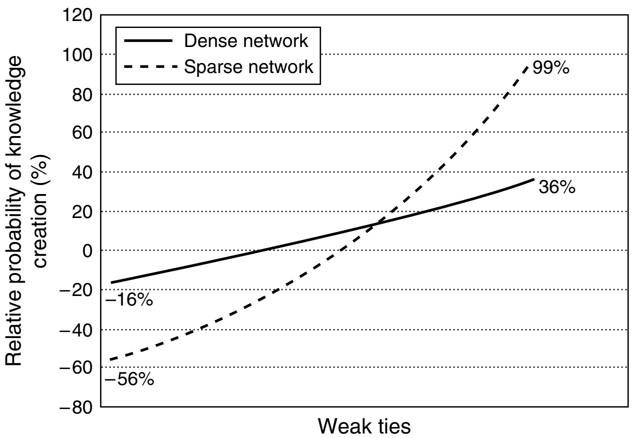
The results of the negative binomial regression models are reported in Table 2, with standardized beta coefficients reported. Model 1 includes only control variables. Model 2 includes the variables of interest (average tie strength and ego network density). Model 3 provides the full model with interaction between average tie strength and ego network density. We used a Wald χ^2 post-estimation test to test for model improvement, and in every case the model improved significantly. In Model 2,

Table 2 Fixed-Effects Negative Binomial Regressions Dependent Variable: Amount of Knowledge Created

	Model 1	Model 2	Model 3
Constant	−1.086***	−0.855***	−0.879***
	(0.099)	(0.104)	(0.106)
Lagged dependent variable	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Time in profession	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)
Number of first authored papers	−0.002	−0.002**	−0.003**
	(0.001)	(0.001)	(0.001)
Number of last authored papers	−0.002	−0.001	−0.001
	(0.002)	(0.002)	(0.002)
Number of long-term coauthors	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Highly cited coauthors	0.009***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)
Percent new coauthors	0.003***	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
Average tie strength		0.008***	0.013**
		(0.001)	(0.003)
Average tie strength squared		−0.016***	−0.014***
		(0.002)	(0.000)
Ego network density		0.001*	0.002
		(0.026)	(0.026)
Density ∗ Average tie strength			−0.007**
			(0.004)
N	1,416	1,416	1,416
Log likelihood	−4,812.47	−4,786.07	−4,785.16
Chi-squared	389.042	415.945	416.109
Wald chi-squared test		26.903***	27.067***

Notes. Standardized beta coefficients and transformed standard errors reported.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 1 Moderating Effect of Average Tie Strength on the Relationship Between Network Density and Knowledge Creation



Notes. This graph illustrates the relative level of knowledge creation. The variables network density and average tie strength are illustrated from to +1 to −1 standard deviation from the sample mean values. The relative level of knowledge creation refers to the increase or decrease in levels of knowledge produced relative to observations at sample mean values of network density and tie strength.

we add the average tie strength and density measures, and Model 3 includes both main effects and the interaction. Results displayed in Model 2 indicate that both average tie strength and density are positively related to knowledge creation ($b = 0.008$, $p < 0.001$ and $b = 0.001$, $p < 0.05$ respectively).

We hypothesized that average tie strength would interact with ego network density to affect knowledge creation. As indicated in Model 3 of Table 2, our analysis provides support for the hypothesized interaction effect, with the interaction coefficient negative and significant ($b = -0.007$; $p < 0.01$). The interaction effect is graphed in Figure 1. Because the modeling technique is negative binomial, the graph represents exponentiated values, and therefore the changes are not linear. In Figure 1, we considered ties strong if they were one standard deviation above the mean of zero and weak if they were one standard deviation below the mean; likewise, ego networks were considered dense if they were one standard deviation above the mean for ego network density and sparse if they were one standard deviation below the mean. The axis for level of knowledge creation is scaled in percentage terms, where 10% means the given configuration of average tie strength and ego network density increases the level of knowledge creation (relative to the mean) by 10%.

Figure 1 graphically illustrates that as ego networks become more sparse, the strength of a scientist's ties becomes increasingly important for knowledge creation. First, it is easy to observe the positive main effect for average tie strength because given a density level (either dense or sparse), increasing average tie strength increases the level of knowledge created. However, while average tie strength increases the level of knowledge creation for both dense and sparse ego networks, its effect on sparse networks substantially exceeds its effects on dense networks. Moving from weak to strong direct ties, the level of knowledge creation increased from 16% below the mean to 36% above the mean if the researcher's ego network was dense. In contrast, moving from weak to strong ties increased the level of knowledge creation from 56% below the mean to 99% above the mean if the network was sparse. To test for significance, we used a linear combination point estimate test to compute a p-value for the significance of these point estimates, and found both significant ($p < 0.001$ and $p < 0.05$, respectively).

The lowest levels of knowledge creation occur when average tie strength is weak and networks are sparse. This aligns with our theory that a researcher in this context has few trusted partners with whom to collaborate (weak ties) and lacks the overlapping knowledge of a dense ego network. The implication is that although the sparse ego network includes diversity, the lack of strong ties suggests few interactions, limiting effective exchange of potentially available diverse inputs. Further, as predicted, both average tie strength conditions (strong and weak) of dense networks are midlevel in knowledge creation relative to the average tie strength conditions of sparse networks. Finally, when ties are strong and the network is sparse, the level of knowledge creation is 99% higher compared to average tie strength and ego network density at sample averages, suggesting that the benefits provided by strong ties and sparse ego networks enhance one another to dramatically enhance the level of knowledge creation.

To check the robustness of our results to windows of different lengths, we conducted the same analyses, using window lengths of two and four years.[6] We found similar results with the four-year windows as we have reported with the three-year windows, yet the three-year windows provided better fit. For the two-year windows, all variables of interest (average tie strength, ego network density, and their interaction) were of the same sign, but only average tie strength was significant. The evidence we report here is consistent with previous research that used three-year windows to examine scientist productivity over time (Nerkar and Paruchuri 2005, Long 1978, Katz 1982, Fleming et al. 2007). Additionally, the mixed results for the two-year versus the three- and four-year windows underscore the commonly held but generally untested belief that ego networks change over time (Burt 2007).

5. Discussion

We sought to examine the interactive effect of two attributes of professional networks on knowledge creation. Our theory and evidence substantiates the growing number of voices in the literature asserting that knowledge creation relies heavily upon professional networks. Specifically, our results indicate that attributes of professional networks, as characterized by average tie strength and ego network density, are important antecedents to the creation of new knowledge among scientific researchers. While density provides insight into the types of resources (diverse and overlapping knowledge inputs) that might be accessed in order to develop the resources, individuals also rely on interactions with the same others—captured by the strength of direct ties. Further, the two attributes are interdependent. Therefore, it is important to examine ego network density and average tie strength not only concurrently but also interactively, because one affects the other's relationship to knowledge creation. Our findings inform both knowledge creation theory and network theory by empirically demonstrating not only the joint main effects of ego network density and average tie strength but also the interaction.

Our graph of the interaction between ego network density and average tie strength (Figure 1) suggests that a sparse network coupled with strong ties provides the best condition for knowledge creation. We interpret this as indicating that dense ego networks are less valuable than sparse for the researcher whose direct ties are strong. Dense networks provide overlapping knowledge, a critical enabling factor of knowledge creation as it facilitates consensus building and problem solving (Nonaka 1994). However, the researcher with strong direct ties may effectively develop overlapping knowledge through his or her direct ties. Strong direct ties, however, do not provide diverse resources, which are obtained most efficiently through a sparse network. The benefits of strong ties allow the researcher to take advantage of the diverse inputs provided by a sparse ego network. Thus, while strong ties do not provide diverse knowledge resources per se, they are efficient for capturing and utilizing the diverse knowledge made available through sparse ego networks.

This finding contributes to previous research that emphasized the importance of sparse networks and their associated diverse inputs to the knowledge creation process (see, for example, Hargadon and Sutton 1997). We extended this line of research and found that in order to fully utilize diverse knowledge, scientific researchers need strong ties. Specifically, the extent to which a sparse ego network is important to knowledge creation depends on the strength of the scientist's direct ties. In general, our theory and evidence points to the conclusion that strong ties coupled with a sparse ego network is the best configuration to have if the ultimate objective is knowledge creation.

Our analyses yielded evidence that some might find surprising. That is, we found a strong and positive main effect for ego network density. In other words, our results indicate that dense networks, when examined as a main effect, relate positively related to knowledge creation. This may seem to contradict the evidence from research on creativity and idea generation, which concluded that sparse networks are best (Burt 2004). Our evidence, however, points toward a somewhat different explanation. We studied knowledge creation among those on the cutting edge of knowledge in scientific fields. Scientific researchers need a great deal of overlapping knowledge, or "knowledge in common," with other researchers—e.g., knowledge about the current literature, scientific methodologies, statistical methodologies, and so forth. For other forms of creativity, especially settings in which much creativity research has been conducted, much less overlapping knowledge may be needed (see, for example, Woodman et al. 1993, MacCrimmon and Wagner 1994, Zhou and George 2001). Therefore, outside the scientific research setting, the positive main effect we report for network density may not hold. The extent to which overlapping knowledge is needed for more socially driven processes, like organizational innovation, is a topic that needs further research.

Importantly, however, theory predicts a positive main effect for network density. For example, dense networks encourage communication and may facilitate the comprehension and understanding necessary for scientific progress along a particular path (Lakatos 1970). This idea is consistent with Nonaka (1994), who contended that overlapping knowledge is essential at the development stage of knowledge creation as it bridges knowledge sets between exchange partners, forming a critical precondition for knowledge creation. Further, knowledge creation requires the integration of knowledge held by exchange partners, which is facilitated by dense networks (Provan and Sebastian 1998). Dense ego networks may also benefit the scientific researcher by reducing risk of exchange (e.g., idea pilfering). Furthermore, while the diversity provided by sparse ego networks is important, overlapping knowledge is also important in the pursuit of "normal science" (Kuhn 1962).

Further, Figure 1 vividly illustrates the importance of considering both the strength of direct ties and the overall density of the ego network when studying scientific knowledge creation. Our evidence suggests that dense networks link to more knowledge creation than sparse networks only when direct ties are weak. Further, Figure 1 shows that higher average tie strength increases knowledge creation when the researcher's ego network is dense, but its impact is relatively weak compared to the effect in sparse ego networks. Sparse networks progress from least productive, in terms of new knowledge, to most productive simply by changing the strength of the researcher's direct ties. The graph illustrates that while dense networks are important when ties are weak, they become less important when ties are strong. Interestingly, sparse networks provide the most value when ties are strong. Therefore, research on knowledge creation should consider both the main and the interactive effects of average tie strength and ego network density.

Although the insights gained from our study are important, the study also has several limitations. Our research examined the professional networks of biomedical research scientists, a setting characterized by relatively dense ego networks that naturally contain strong ties. While we believe that our findings are also generalizable to some other settings, there are also settings where the generalizability of our study is probably quite limited. Specifically, we believe that our findings may apply to other knowledge-intensive contexts, e.g., science and engineering settings. We focused on knowledge workers, and recommend caution when applying our insights outside similar contexts. Others have noted that the processes of idea generation and idea diffusion differ importantly, especially in very socialized settings such as organizational innovation (Obstfeld 2005). Our setting captured the day-to-day work of the researcher, as opposed to settings where knowledge creation is the exception rather than the routine.

Our study is also limited because we examined only two attributes of researchers' networks—density and average tie strength. Previous research found that both network density and average tie strength impact knowledge transfer and that the benefits of average tie strength associate with relational characteristics such as trust. For example, Levin and Cross (2004) found that strong ties tend to be trusting ties. In this context, our results might suggest that trust benefits are best derived from dyadic ties and not from dense ego networks, whereas access to diverse knowledge is best derived from sparse ego networks and not from weak ties (Burt 1992, 2001 and Uzzi 1997). This is, however, speculative on our part, since we did not measure trust, tacit knowledge, or knowledge diversity directly. In other words, while our results imply that relational characteristics such as trust may derive best from strong ties, more research is needed to explicitly examine the impacts of both average tie strength and ego network density in association with knowledge creation.

Finally, our use of coauthored publications to track network membership was based on a growing body of published work (see, for example, Cockburn and Henderson 1998; Newman 2001, 2004; Stephan 1996; Stephan and Levin 1991; Zucker et al. 1998, 1995). However, some close ties probably existed for our research scientists, but were not captured by our methodology because we were unable to directly observe the interactions. Scientists may mentor one another, yet this collaborative action might never result in a published paper. Importantly, however, scientific norms suggest that individuals will read one another's work, present ideas and papers to one another, provide feedback to one another, and even jointly serve on committees. Further, individuals more than likely interact informally through written and oral correspondence. Coauthorship networks, however, capture only successful interpersonal exchange relationships that have led to knowledge creation, i.e., research publications, and not interactions that did not lead to publication or interactions prior to publication. Despite these shortcomings, coauthorship networks are important objective indicators of affiliation networks that reflect genuine professional interaction between scientists (Newman 2004). Studies that more directly observe the interactions among network members are needed.

On a related point, like Obstfeld (2005), our study takes the position that knowledge workers tend to fill the role of *tertius iungens* (one who joins) rather than *tertius gaudens* (one who enjoys). In our context, it is not in our researchers' broad interests to keep their network partners apart, but rather to bring them together. In the more frequent conceptualization of tertius gaudens (see, for example, Burt 1992), the linking agent has incentives to keep his or her network partners separated, in order to retain the gains from serving as intermediary. While we did not capture the extent to which our researchers aligned with each role (gaudens versus iungens), our underlying assumption is that knowledge workers tend toward iungens and benefit from the mutual gains that their joining role yield.

Our study examined semi-static networks, using a moving three-year window. This permitted us to capture some network changes while controlling for those factors linked to scientific researchers that did not change during our observation period. This approach allowed us to separate the effects of networks from those of other researcher-specific (but constant) characteristics. Further, there are good reasons to expect that knowledge worker networks are dynamic, as indicated by our robustness check. For example, Granovetter (1973) proposed that strong ties will, over time, lead to increased ego network density, as a person's exchange partners will naturally get to know one another. Granovetter's (1973) logic provides a framework for examining how, over time, strong direct ties lead to dense ego networks. Moreover, in a knowledge creation setting the network of a knowledge worker with strong ties and a sparse ego network will likely become more dense over time, negatively affecting the researcher's ability to create new knowledge. As the knowledge resources required by a given knowledge worker change over time, his or her professional network will probably change as well, as he or she seeks new exchange partners with diverse knowledge and adds them to the network. Our study's scope prevented direct consideration of these network dynamics, but we encourage future researchers to develop and test these ideas empirically. Of course, the rate at which knowledge workers' direct ties come to know each other relates directly to the extent to which the knowledge workers perceive their roles in terms of *tertius gaudens* versus *tertius iungens*.

Our study also has implications for managers of knowledge workers. Those who manage research scientists, both in universities and in industry, should understand the key roles of professional interpersonal networks in the knowledge creation process. While our study focused on university researchers, we see no obvious reason why our conclusions would not apply to researchers in industry (see, for example, McFadyen and Cannella 2005). Certain network compositions are more conducive to the creation of new knowledge than others, and time spent with others is probably well spent as long as the associations are productive (yielding publications, patents, etc.). Managers of those whose job it is to create new knowledge must recognize the tensions inherent in the knowledge creation process. Knowledge creation requires interpersonal exchanges, and many of those exchanges are likely to be with others outside the organization and involve potentially proprietary information (McFadyen and Cannella 2005). While retaining control of proprietary knowledge or information is important, too much emphasis on intellectual property protection may hamper knowledge workers as they strive to build effective networks.

Overall, our study provides new insights into the relationship between knowledge creation and professional networks and contributes to the ongoing dialogue about the strength of ties and network density. Our findings bolster the notion that it is important to disentangle the structural attributes of interpersonal networks. Our results indicate that density and average tie strength are not clear substitutes, at least for knowledge workers seeking to create new knowledge. Increased average tie strength increases knowledge output for both dense and sparse ego networks. However, the impact in sparse networks is much more pronounced.

Endnotes

[1]Some authors (e.g., Hansen 1999, Zander and Kogut 1995) perceive tacit and codified knowledge on a continuum. Codifiable knowledge can be written down, is easily transferable, and may be acquired or transferred with or without inter-personal contact. Tacit knowledge, in contrast, is difficult to transfer without experience, and overlapping experience with partners facilitates the transfer.

[2]In addition to the positive main effect for tie strength, McFadyen and Cannella (2004) also showed that the effect was curvilinear as at high levels of tie strength the relationship with knowledge creation decreased.

[3]Social cohesion measures network density (Reagans and McEvily 2003).

[4]We also ran this variable as a cumulative number of first authored papers, and there was no significant change to the models.

[5]As with first authored papers, we ran the analyses with the cumulative number of highly cited coauthors, and the models did not change significantly.

[6]These analyses are available from the first author upon request.

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