

Working Paper

The Impact of Discussion, Awareness, and Collaboration Network Position on Research Performance of Engineering School Faculty

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Abstract

We use a social network analysis to examine the role of various types of interactions among the faculty of an American engineering school, ranging from mere awareness to full coauthorship, on academic research productivity (measured by weighted publication rates) and impact (measured by weighted citation rates). Our results suggest that central positions in the discussion network have the most significant impact on individual work performance. However, we observe that increasing centrality exhibits diminishing returns, presumably because of the overhead associated with sustaining too many research interactions. Our results also suggest that interdisciplinary research discussions promote both research productivity and impact.

Keywords: collaboration, social networks, academic publishing, research performance

The Impact of Discussion, Awareness, and Collaboration Network Position on Research Performance of Engineering School Faculty

Organizations involved in knowledge-intensive work rely heavily on smart and creative people (Davenport, 2005; Goffee and Jones, 2007; Jacobson and Prusak, 2006). However, organizational success depends on more than the talent and effort of individuals. (Goffee and Jones, 2007)'s interviews with leading organizations (e.g., PricewaterhouseCoopers, Cisco Systems, the British Broadcasting Corporation) indicated that it is crucial to foster an environment within which smart people can fully utilize their potential. Since the most important resource in knowledge-intensive environments is intellectual capital, high performance environments are those that support knowledge sharing and collaboration (Cross and Cummings, 2004; Perry-Smith and Shalley, 2003; Uzzi and Dunlap, 2005).

To understand how collaboration influences performance, a number of researchers have used social network models (Borgatti and Cross, 2003; Borgatti and Foster, 2003; Hansen, 2002; Hansen et al., 2005; Fleming et al., 2006; Cummings, 2004; Reagans and McEvily, 2003; Tsai, 2001). In addition to providing a mechanism for quantifying collaboration and showing a correlation with performance, network models can help characterize different types of collaboration in order to determine which are most effective. For example, research has shown that positions of high brokerage (which measures the extent to which an individual's communication/collaboration spans different groups) are positively associated with work performance, presumably because a high brokerage position exposes the individual to different types of information (Burt, 1992, 2004; Brass et al., 2004; Tsai, 2001). Similarly, researchers have found that central (i.e., highly connected) positions promote good performance by enabling quick access to information from the rest of the network (Cross and Cummings, 2004; Perry-Smith and Shalley, 2003; Nahapiet and Ghosal, 1998).

In addition to network position, the nature of the ties within the network has been found to influence individual performance. For example, weak ties are sometimes more effective than strong ties (Granovetter, 1973; Perry-Smith, 2006) and new ties can sometimes promote more creativity than old ties (Uzzi and Spiro, 2005; Guimera et al., 2005). In particular, boundary spanning ties (which establish connections between departments/organizations/professions outside one's own) have been shown to benefit individual performance, presumably because integrating disparate types of knowledge promotes creativity (Cross and Cummings, 2004; Hargadon and Sutton, 1997; McEvily and Zaheer, 1999). Furthermore, the performance benefit of an interaction between two individuals likely depends on the nature of the relationship – a collaboration that consists of infrequent discussions may differ from one that involves joint publishing.

However, while favorable network positions provide access to information, the ability to transform this into better performance depends on whether an individual has the time to seek out and act on this information (McFadyen and Cannella, 2004). When an individual is highly central, he/she may have to devote considerable time to maintaining existing ties and hence have less time to exploit current connections and seek out new connections, which may hinder his/her performance (Perry-Smith and Shalley, 2003; Cummings and Kiesler, 2007). While the fact that people have limited capacity is well known, there has been little attention within the social network literature devoted to empirically investigating the role of capacity on individual performance. Moreover, while having boundary spanning ties may generally be valuable, it is not clear how valuable such network positions are in an environment, such as an academic research institution, that requires a high degree of specialized knowledge. Since time for collaboration is limited, it is important to understand the relative value of ties within one's own department/organization/discipline versus boundary spanning ties.

Modeling the influence of collaborative behavior on performance requires a precise definition

of performance, but in knowledge intensive environments this is a subtle issue. Managers typically use metrics based on immediate past performance, since these metrics are used in setting compensation. Hence, research that uses manager ratings considers only the very recent past (Cross and Cummings, 2004; Perry-Smith, 2006). Researchers have used metrics based on the intermediate past, such as counts of good ideas (Toubia, 2006), or the more distant past, such as citation counts of patents (Fleming and Marx, 2006; Miller et al., 2007). Since collaboration requires costly coordination between individuals, we might expect collaboration to have a only a long-term performance benefit. We measure performance along two dimensions, (i) publication rates, or *productivity*, and (ii) citation rates, or *impact*. Measuring these two facets of research performance allowed us to gain insight into what types of performance gains are associated with collaborative behavior.

In this paper, we investigate the impact of collaborative behavior on performance in a complex knowledge-intensive environment. We consider three different types of collaborative ties between the faculty members at an engineering school: (i) simply being aware of another faculty members research, (ii) engaging in detailed research discussions with another faculty member (iii) coauthoring a publication or grant proposal with another faculty member. Each network contains the same faculty members, is a subset of the previous one, and the types of ties are increasingly expensive to maintain. For each of the three social networks, we examine the relationship between performance, measured in terms of both productivity and long-term impact, and network position. We also investigate whether social ties that span departmental boundaries are associated with higher research performance. Finally, we look for evidence of diminishing returns in collaborative behavior both as social ties become more demanding, and as faculty become more central in the network. In addition to contributing to the literature on knowledge networks, our analysis of these questions offers insights relevant to the current trend of promoting interdisciplinary research within

educational institutions and funding agencies.

1 Theory and Predictions

1.1 Network Position and Work Performance

An advantageous position in an organizational network can provide information and resource benefits for the person who occupies the position. An example of a structurally advantageous position, which can have an important impact on an individual's work performance, is a position of high centrality (Scott, 2000). It is generally believed that a central position promotes an individual's capability to locate, absorb, disperse, and synthesize relevant information into useful resources and therefore eventually enhances individual performance (Bonacich and Lloyd, 2001; Borgatti, 2005; Cummings, 2004; Tsai, 2001; Nahapiet and Ghosal, 1998).

However, the term "central" may imply very different properties of an individual's position in a network depending on what metric is used to characterize centrality (Borgatti, 2005). For example, *flow betweenness centrality* of an individual measures a position's importance by considering the amount of information to which it has access. It is defined as the percentage of all information paths in the network to which that person has access (Wasserman and Faust, 1994)¹. As such, flow betweenness characterizes an individual's control over information flow. A position with a high betweenness score enables a person to both access a large quantity of information and quickly distribute information among peers. In contrast, *Eigenvector centrality* measures a position's importance as the extent to which it is connected to the most important positions in the network.

¹We chose *flow betweenness* over *node betweenness* (defined as the percentage of times a node occupies a position on a shortest path between any other two nodes (Wasserman and Faust, 1994)) because the former considers all information paths rather than only shortest paths and therefore avoids underestimating the possibility of a piece of information successfully traveling between two nodes.

Eigenvector centrality is defined as the weighted average of the importance of all the neighbors to which a position is directly connected (Bonacich, 1972).

Note that flow betweenness implicitly assumes that communications between any pair of people are equally important (e.g., a communication path between two managers is treated the same as that between two new hires) and concentrates only on the quantity of information paths. In many organizational settings, this violates our intuitive sense of the value of communication. Unlike flow betweenness, Eigenvector centrality takes into account both the number and the importance of the connections (e.g., a professor who collaborates with another professor who has many other collaborations will tend to have higher eigenvector centrality than if he were to collaborate with a less connected person).

Another difference between these two centrality measures is related to the number of direct neighbors. Like degree centrality, which is defined as a simple count of direct neighbors, eigenvector centrality also counts the number of connections, but unlike degree centrality, it weights connections by the centrality scores of the neighbors (Newman, 2007). Hence, both a large number of connections to people with low eigenvector centrality and a small number of connections to people with high eigenvector centrality can lead to a high eigenvector centrality score. This characteristic of eigenvector centrality is of particular importance when we consider the fact that each individual has limited capacity. For example, in a collaboration network in which links represent joint work, high eigenvector centrality indicates that either a person is collaborating with many people or he/she is collaborating with few people but each of them has many collaborators. In either case, high eigenvector centrality is apt to be correlate with high utilization of an individual capacity, since the individual is either busy working with many collaborators or working to sustain relationships with busy collaborators. Unlike eigenvector centrality, betweenness centrality has no clear association with the number of direct neighbors. For instance, an individual with few con-

nections but who serves as a mediator between two groups will have a higher betweenness score than an individual with many connections, provided that the less connected individual occupies a greater number of communication paths. Thus, while betweenness reflects an individual's control of information flow, it does not necessarily reveal the utilization level of his/her capacity.

Since there has been little research attention paid to the role of capacity on performance in knowledge-based organizations, incorporating eigenvector centrality into our analysis is of particular importance. With it, we can introduce the previously under-studied issue of individual capacity into social network analysis of organization performance.

1.2 Types of Social Networks

Our objective is to use network centrality concepts to understand the impact of collaboration on performance, but collaborative behavior can be characterized at different levels. Below, we discuss networks defined in terms of (a) direct collaborative interaction, (b) discussion between individuals, and (c) awareness of the expertise of other individuals. Each network contains the same faculty members and is a nested inside of the previous one (collaboration \subset discussion \subset awareness).

1.2.1 The Collaboration Network

We define the *collaboration network* by having nodes represent individuals and links indicate explicit collaboration on publication or grant proposals between pairs of individuals. In knowledge intensive environments, joint work enables collaborators to make use of each other's expertise in an efficient manner and therefore facilitates higher work performance without requiring individuals to digest and master new knowledge independently (Cross and Cummings, 2004). When an individual holds a relatively central position with access to a large amount of information, he/she can identify, locate and seek collaborators more efficiently and effectively, which may greatly improve

his/her work performance. At the same time, such a network position facilitates the spread of one's own work through these same channels, which attracts more attention and potential collaborators (Nahapiet and Ghosal, 1998).

However, we expect that the advantage of different knowledge stocks diminishes as one adds more collaborators (McFadyen and Cannella, 2004). As the number of collaborators increases, the chances that one of them will add to the heterogeneity of the knowledge resource for an individual diminishes. Furthermore, sustaining a collaboration requires significant coordination costs (Cummings and Kiesler, 2007). For these reasons, it is not clear whether or not individuals holding a central position in the collaboration network generally perform better than those with peripheral positions — we test this relationship in this paper.

1.2.2 The Discussion Network

We define the *discussion network* on the same set of nodes (i.e., people) as the collaboration network, but the links defined by the occurrence of detailed research discussions between pairs of individuals. We consider discussion links to be directed because the discussants may hold different opinions towards the discussion. For example, while one party may view a discussion as highly informative and relevant to his/her own work, the other party may not regard the discussion as a source of new research ideas. The benefits of discussions are multiple. Like collaboration, discussions help individuals tap into the expertise of others, learn new ways of thinking, and synthesize disparate knowledge into good ideas (Heinze and Bauer, 2007). Discussions help one improve his/her perspective and facilitate communication of his/her ideas to a more diverse audience (Cross and Cummings, 2004; Reagans and McEvily, 2003). The benefits of discussions increase as one has more control over information flows in the discussion network. This is because the more others depend on an individual for information, the more he/she can access useful information, frame and

solve new problems, and disperse his/her own ideas. Therefore, we conjecture the following:

Hypothesis 1. *Centrality in the discussion network has a positive impact on individual work performance.*

While establishing and maintaining a discussion tie does not detract as much from other work activities as does a full-fledged collaboration, it does require time and energy input. When an individual is in a relatively peripheral position, the benefit of moving toward the center of the discussion network (i.e., via increased access to information and ideas) is greater than the cost of maintaining more ties. However, moving to increasingly central positions in the discussion network (i.e., by having more discussions or having discussions with more central people) will eventually impose a cost in the form of time to maintain ties. Since a queuing-type description of congestion suggests that overhead cost will increase nonlinearly in the number of ties, we would expect it to eventually overwhelm the benefits. This implies that eigenvector centrality may exhibit a nonlinear effect on work performance (Perry-Smith and Shalley, 2003).

1.2.3 The Awareness Network

We define the *awareness network* on the same set of nodes (people) as the collaboration and discussion networks. Awareness links indicate detailed knowledge of one individual's expertise by another. The awareness network is similar to the concept of "close ties" in an organizational reference group, introduced in (Lawrence, 2006). Flow betweenness in a directed awareness network indicates the likelihood of an individual's information being distributed to his/her peers. People who occupy peripheral positions in the network are less known by their peers, as is their expertise. At first blush, it might seem that such relative anonymity would be associated with poor performance; after all stars get recognition. But in an innovative environment, such as an academic

research institution, there are reasons that this may not be the case.

First of all, recognition by peers may be a function of seniority, since people who have been in the system longer will have had time to make more people aware of their research. To ensure that this effect does not confound our interpretation of the influence of position in the awareness network, we control for both tenure (years at the institution) and rank (assistant, associate full).

Second, the degree of self-promotion by faculty members varies widely among individuals. Some researchers are natural presenters and are thereby able to attract attention to their work, while other researchers are more reserved and hence prefer to let their publications speak for themselves. Since an academic institution has many controls to ensure that faculty are productive as researchers, we cannot take for granted that the people who promote more actually publish more (or receive more citations).

Finally, the basic question of whether high flow betweenness is correlated positively or negatively with performance depends on the properties of flow betweenness. In general, the way a person can have a high flow betweenness score in the awareness network is to have a variety of people from various disciplines know about his/her work. Someone who is only well-known by colleagues in his/her department is unlikely to have a high betweenness score, since he/she will not lie on a high percentage of paths between individuals in the full system. But being known by many individuals from different disciplines suggests that the person is working in an area that is widely known. (For example, in contemporary engineering schools, working on topics related to nanotechnology or biotechnology is likely to make one visible to a broad cross section of the faculty.) If this is the case, then high flow betweenness centrality in the awareness network may signal that the person is working in a relatively mature area, where publications and citations are harder to get. In contrast, people with low flow betweenness centrality scores may be working in newer, less well-known areas, that are more likely to yield novel results amenable to quick publications and

high citation rates. In any case, we would expect that network position in the awareness network would have much less impact on performance, as it has been demonstrated that being aware of other's research by means of conferences and reading are not sufficient to accelerate the creation of new knowledge (Cockburn and Henderson, 1998).

In a directed awareness network, eigenvector centrality is a weighted average of one's out-going degree, where the weights are the centrality scores of one's direct neighbors. Low eigenvector centrality implies an individual knows little about others' expertise. This lack of information tends to prevent the individual from locating resources and seeking out advice, help, and collaboration as necessary (Perry-Smith and Shalley, 2003; Cummings and Kiesler, 2007). As an individual increases his/her knowledge of others' expertise, he/she improves his/her ability to take advantage of the resources within the network and hence should result in better work performance. However, increasing one's awareness of other's expertise is not costless. Gaining knowledge about others requires time and effort, which are therefore unavailable for other productive activities. Since benefits from awareness are limited, one might expect that the cost of information gathering may eventually cancel or outweigh the benefits. Hence, we posit the following:

Hypothesis 2. *Centrality in the awareness network has a positive impact on individual work performance.*

1.3 Interdisciplinary Ties and Work performance

In addition to differing by the nature of the social relationship between two people, ties can also differ qualitatively if they represent a collaboration between two individuals with disparate knowledge stocks (McEvily and Zaheer, 1999; McFadyen and Cannella, 2004). We refer to such ties as *inter-disciplinary*. For example, a collaboration between a statistician and a biochemist in a clini-

cal trials project represents an interdisciplinary tie. Such ties increase the chance of an individual being exposed to alternative ways of thinking and therefore may help in synthesizing disparate knowledge into good ideas (Burt, 1992, 2004; Heinze and Bauer, 2007). Moreover, exploration beyond one's field may lead to results with a broader impact than idea exploitation within one's own field. For example, (Heinze and Bauer, 2007) found that prominent scientists outperform their peers with equivalent capabilities because they communicate with people who are otherwise disconnected and working in a broader range of disciplines.

However, since an individual's research discipline is subjective, we cannot measure interdisciplinary ties with precision. Therefore, we focus on an individual's department, which can be objectively determined, as a characterization of his/her research discipline. Consequently, we use inter-departmental ties, which are defined as collaborations that span departmental boundaries, as a proxy for interdisciplinary ties, and focus our analysis on these.

Translating these insights into an understanding of individual performance in a highly creative and knowledge-intensive work environment, we conjecture that having more inter-departmental ties increases the chance of producing high-impact work. More specifically, working on joint projects and discussing work-related issues with people outside one's own discipline will help an individual draw insights from disparate knowledge pools and therefore promotes more original research. Therefore, we state the following conjecture:

Hypothesis 3. *Inter-departmental ties have a positive impact on individual work performance.*

1.4 Diminishing Returns of Collaborative Interactions

The benefits of a central position and collaborations are limited because joint work requires engagement (Cummings and Kiesler, 2007). With limited time and energy (i.e., capacity), each individual

can only sustain a limited number of productive collaborations. Consequently, establishing more collaborations after one has reached his/her capacity results in less engagement in other collaborations and less time for translating ideas and information into useful outputs. Furthermore, since it may take more effort to sustain collaborative relationship with busy (central) individuals (e.g., because they are difficult to see, slow to respond to inquiries, etc.); the knowledge benefits of such collaborations may not improve performance.

In addition to time constraints, a second factor that may mitigate the benefits of direct collaboration is the fact that as one moves to a position of higher eigenvector centrality, it becomes increasingly likely that one's information sources overlap, which implies that the marginal benefit of information seeking decreases as centrality increases. (McFadyen and Cannella, 2004) show that these considerations lead to diminishing returns in knowledge creation in three ways: (i) diminishing returns for the number of relations that an actor maintains and the creation of new knowledge, (ii) diminishing return for the strength of relations that an actor maintains and the creation of new knowledge, and (iii) the marginal impact on knowledge creation is greater for strong relationships than it is for the number of relationships. Thus, we conjecture the following:

Hypothesis 4. *In the discussion network, there are diminishing and eventually negative returns between centrality and performance.*

2 Data and Methods

We tested the above hypotheses using the McCormick School of Engineering at Northwestern University as our environment. The McCormick school consists of nine departments: Biomedical Engineering (BME), Chemical and Biological Engineering (CBE), Civil and Environmental Engineering (CE), Electrical and Computer Engineering (ECE), Computer Science (CS), Engineer-

ing Science and Applied Mathematics (ESAM), Industrial Engineering and Management Sciences (IEMS), Material Science and Engineering (MSE), and Mechanical Engineering (ME). During the time interval of our study (1988-2006), all of the departments except for CS were located in the same building. This unique feature of the school simplifies the analysis by reducing possible bias due to differences in geographic distance.

2.1 Network Data

Data for constructing the collaboration/discussion/awareness networks were collected through an online survey. Before we conducted the survey, we spent considerable time understanding the nature of faculty interactions and determining the appropriate personnel to be included in the survey. After consultation with the school administration, we decided to include all faculty members who are tenured or on the tenure track. This gave us a relatively stable set of personnel. Accompanied by an introductory email from the Dean, the survey was conducted via a simple “point and click” website during the summer of 2005. Each faculty member was assured that the data provided be kept anonymous and only used for research purposes. Two weeks later, a reminder was sent by the Dean to each faculty member who had not responded, which included a link to the survey site. A total of 137 out of 184 eligible faculty members completed the entire survey (representing a 74.5% response rate).²

In the survey, each faculty member was asked to indicate his/her relationship with all other faculty members in the survey set. We classified relationships into six categories, each of which was described in detail to avoid misinterpretation. A person was instructed to choose the category “have had successful collaboration with”, which was coded as a Type 5 interaction, if he/she had

²We compared rank, tenure, quality adjusted publication rate and quality adjusted citation rate of respondents and non-respondents and found no statistical difference between the two groups. Hence, we have no evidence that non-responses biased the results.

worked on a joint paper or proposal with the person listed in the survey. Responses in this category were used to construct the collaboration network. Since collaboration ties are symmetric by nature, we replaced asymmetric ties with symmetric ties if either of the two parties indicated that he/she had done joint work with the other. We did this because, after talking to some faculty members, we found that the most common reason for an asymmetry was that one party forgot about the collaboration due to time lapse or other reasons. Hence, we decided that transforming all ties into symmetric ones gave the most accurate characterization of collaborative relationships we could get from the data.

The Type 4 category was labeled “have had research discussion with.” A person was instructed to choose this category if he/she had not written a joint paper or proposal with an individual but had engaged in detailed research discussion with him/her. Considering the fact that whether a particular discussion is viewed as a detailed research discussion depends strongly on the level and content of discussion, it is not unreasonable for two people to hold different opinions about the same discussion. For example, it is possible that a person who shared his/her domain knowledge with another faculty member does not regard that exchange as a detailed research discussion, while the person who received the information may well think that it is. With this in mind, we allowed asymmetric discussion ties. Since writing a joint paper or proposal implies detailed discussions, we combined the responses to the first two categories, i.e., ties of Type 4 and 5, to create the research discussion network.

Two other possible response categories were “know research area and socially acquainted” (coded as Type 3) and “know research area but not social acquainted” (coded as Type 1). The description of these areas made it very clear that “knowing” someone’s research area indicates that one’s knowledge of the other’s research goes well beyond simply knowing which department that person is from or a short phrase description of the person’s research field. Since one cannot collaborate

or have detailed research discussions with someone without being aware of their research area, we combined these responses with those in the previous two categories (i.e., resulting in the set of ties of Type 1, 3, 4 or 5) to construct the awareness network.

If an individual did not choose one of the above categories, they could choose “socially acquainted with but do not know research area” (coded as Type 2) or be defaulted to “do not know” (coded as Type 0).

To be precise, we formally define each of the networks. The node set \mathcal{N} consists of all faculty that responded to the survey. An undirected edge in the collaboration network, C_{ij} , exists if either faculty N_i or faculty N_j responded in the affirmative to the “have had [a] successful collaboration with” question in the survey. The set \mathcal{C} consists of all of these undirected edges. A directed edge in the discussion network, D_{ij} , exists if N_i indicated that he or she “have had [a] research discussion with” N_j . The set \mathcal{D} consists of all of these directed edges. A directed edge in the awareness network, A_{ij} , exists if N_i indicated that he or she “know [the] research area” of N_j . The set \mathcal{A} consists of all of these directed edges. The three networks are then defined as $\mathcal{G}_{collaboration} = (\mathcal{N}, \mathcal{C})$, $\mathcal{G}_{discussion} = (\mathcal{N}, \mathcal{D})$, and $\mathcal{G}_{awareness} = (\mathcal{N}, \mathcal{A})$. We assume that two faculty members that have collaborated have also had research discussions, and two faculty that have had research discussions are aware of the other’s work, thus each edge set is a subset of the next, i.e. $\mathcal{C} \subset \mathcal{D} \subset \mathcal{A}$.

2.2 Performance Measures

One of the benefits of conducting research in an academic environment is that objective performance measures are available. Unlike manager’s ratings, which can be highly subjective, performance measures based on publication information are largely objective. Furthermore, using publication data allows us to measure individual performance in terms of both productivity (i.e.,

based on publications) and impact (i.e., based on citations). Because publications and citations are good indicators of research performance they are frequently used in the tenure and promotion process (Gordon and Purvis, 1991; Park and Gordon, 1996). Data on both of these measures were collected from the Institute for Scientific Information (ISI). For each faculty member included in the survey, we collected detailed information for each of his/her papers published between 1988 and 2006. This information included: number of authors, year of publication, journal of publication, number of citations, and citing journal of each citation.

Of course, there are possible biases and pitfalls of using publication data to assess performance, which have been extensively analyzed in the literature (Nicolaisen, 2007). One of the most prominent criticisms is that a paper should not be judged by the journal in which it is published. However, there is evidence that the journal in which a paper is published and the journals that cite it are indicators of paper quality (Stringer, 2008; Bollen et al., 2006). Certainly tenure and promotion committees believe this, since many schools have explicit lists that indicate the relative importance of various publications as research outlets. Hence, we also collected journal quality information to use as a weighting factor for publications and citations. In the literature, the most commonly used metric of journal quality is *impact factor* (Ballas and Theoharakis, 2003; Newman and Cooper, 1993), which is the normalized total number of citations a journal receives within certain period of time (generally two years). However, impact factor can be misleading. It counts only the number of citations and ignores the quality of the citing journals. As a result, journals cited by many low-quality journals are inappropriately ranked higher than journals with fewer citations from high-quality journals. To address the shortcomings of impact factor as a measure, some researchers have adopted a metric called *perceptual ranking* (Hull and Wright, 1990; Hull and Ross, 1991), which is calculated based on a subjective rating provided by a selected pool of experts. While this metric partially addresses the problem of not considering citing journal quality,

it also has flaws. Experts selected may not be representative and or their opinions may be biased by their own experiences or benefits. For example, perceptual ranking is known to suffer from “self-serving bias”, which refers to the fact that people tend to rate journals high if they publish in or serve as reviewer or editor for them (Hull and Ross, 1991).

In our study, we employed a different alternative to impact factor, known as *Journal Pagerank* (Bollen et al., 2006). The idea of Journal Pagerank originated from “Google Pagerank”, which is used to rank websites based on two factors: how often a website is linked and the ranks of the sites that link to it. The same idea can be applied in calculating journal pagerank, thereby incorporating both the number and source of citations into the score. To calculate journal pagerank, all journals indexed by ISI as of 2006 were included in a citation network, in which journals are nodes and citation links are directed links. The formula for journal v_i 's pagerank score is given by:

$$PR_w(v_i) = \frac{\lambda}{N} + (1 - \lambda) \sum_j PR_w(v_j) \times w(v_j, v_i) \quad (1)$$

where N is the total number of journals in the network, PR is the pagerank score, $w(v_j, v_i)$ is the fraction of journal v_j 's pagerank it transfers to journal v_i , and λ is an arbitrarily chosen constant between 0 and 1 (We used 0.15)³. Note that pagerank is similar to eigenvector centrality in a network of journals with links defined by inter-journal citation rates. This metric indicates that when N and λ are fixed, having more citations and linking to journals with higher pagerank indices lead to a higher pagerank score for the journal. The benefits of using journal pagerank are: (1) it

³ $\frac{\lambda}{N}$ represents the minimal weight assigned to each journal. When $\lambda = 1$, the pagerank of each journal is equally assigned; when $\lambda = 0$, the pagerank of each journal is fully dependent on the pageranks of its neighbors; a λ value between 0 and 1 indicates that the pagerank is partially dependent on how well connected its neighbors are. For λ , we chose a relatively small number, i.e., $\lambda = 0.15$, in order to emphasize that a journal's pagerank is largely determined by which other journals cite it. However, since $\frac{\lambda}{N}$ is constant for any given N , varying the value of λ only affects the weight allocation and does not change the relative order of journal pageranks, i.e., relative importance of each journal. Consequently, analysis results based on journal pagerank will not be affected.

is a objective measure and so avoids the bias introduced by perceptual ranking, and (2) it takes into account both the frequency and quality of citations and is therefore a more convincing metric of journal quality than impact factor. In order to reflect the most up-to-date journal quality, we computed Journal Pagerank using journal information for a two-year time for all journals in the ISI index in 2006.

In our analysis, for each faculty member of the engineering school we used the following two performance measures:

Pagerank weighted research productivity ($Prod_{pr}$):

$$Prod_{pr} = \frac{\sum_{year} \sum_{paper} \frac{PublishingJournalPagerank}{NumberofAuthors}}{Number\ of\ Years\ since\ 1st\ publication} \quad (2)$$

Pagerank weighted research impact ($Impact_{pr}$):

$$Impact_{pr} = \frac{\sum_{year} \sum_{paper} \sum_{citation} \frac{CitingJournalPagerank}{NumberofAuthors}}{Number\ of\ Years\ since\ 1st\ publication} \quad (3)$$

The first measure tracks research productivity, while the second is a proxy for research impact.

2.3 Independent Variables

To provide insights into the factors that influence performance as measured by the above metrics, we considered the following as independent variables:

Number of Inter-Departmental Ties We use the number of ties one has outside one's own department to measure how likely a person is to be connected to people outside his/her own discipline. As noted earlier, since departments provide a rough classification of research areas, we used department as a proxy for discipline and consider inter-departmental ties to be interdisciplinary.

We considered three types of inter-departmental ties. *No. inter-departmental collaboration ties* is given by the number of people outside one’s own department with whom he/she has collaborated. This measure is computed from responses to the first survey question (i.e., Type 5 responses only). Similarly, *No. inter-departmental discussion ties* is the number of people outside one’s own department with whom he/she has had research discussions. This is computed using only responses to the second questions in the survey (i.e., Type 4). Finally, *No. inter-departmental awareness ties* is the number of people outside a faculty member’s own department about whom he/she has detailed knowledge of their research areas. This is calculated from responses to the first and third.

Eigenvector Centrality We computed eigenvector centrality (Eigen-cent) (Bonacich and Lloyd, 2001) for the collaboration, discussion, and awareness networks respectively. In addition to using this directly as an independent variable, we also included the second-order term for eigenvector centrality as an independent variable. This was calculated as:

$$\text{eigenvector Centrality}^2 = (\text{eigenvector centrality} - \text{mean}(\text{eigenvector centrality}))^2. \quad (4)$$

where the “mean(eigenvector centrality)” is calculated as the summation of the eigenvector centrality scores of all individuals divided by the total number of individuals.

By using the squared difference, instead of the simple square of the eigenvector centrality, we reduced the likelihood of multicollinearity problems. A negative coefficient in this second order term would indicate diminishing returns in the eigenvector centrality score. That is, when a person is on the periphery of the network, moving toward the center promotes his/her creative work, but when a person is already at a relatively central position, moving toward an even more central position jeopardizes his/her creativity (Perry-Smith and Shalley, 2003)

2.4 Control Variables

Since research productivity and impact are influenced by more than collaboration and communication behaviors, we included several control variables in our model.

Tenure Tenure counts the years of employment at the university.

Rank Rank of professors is represented by a pair of indicator variables, *asso* and *full*. The pair “*asso* = 0, *full* = 0” indicates an assistant professor, “*asso* = 1, *full* = 0” indicates an associate professor, and “*asso* = 0, *full* = 1” indicates a full professor.

Department It is used to control for departmental differences in, such as publication and citation rates across disciplines, departmental sizes, research capability and etc. Since individuals from the same department usually are more familiar with each other’s research, they tend to collaborate more frequently than people from different departments. As a result, we see higher tendency of clustering within departments. This clustering leads to a serious violation of the basic assumptions of ordinary least square regression models, which assumes homogeneous variance across all individuals. To address this issue, we will use a mixed model approach. The effect of department will be reflected by the coefficient of the model intercept.

Size of network This control measures how well an individual is connected to his/her adjacent neighbors. Since awareness network is the largest network with both collaboration and discussion networks nested in it, this variable is calculated as the number of awareness ties.

Number of years since degree This variable counts the number of years since the faculty member obtained his or her PhD.

Ratio of single / co-authored publications This ratio is calculated as the number of single-authored paper divided by the number co-authored publications. It controls for people’s different tendency in leveraging multi-author collaborations. A value more than 1 indicates an individual publishes mostly single-authored paper and a value less than 1 suggests that an individual has better leverage over other knowledge capital.

3 Analysis and Results

Table 1 shows the Pearson’s correlations among all variables. This indicates that number of inter-departmental discussion ties and Eigenvector centrality have significant correlation with the two dependent variables. While some correlations exist among the other network related variables, they are sufficiently small to allow joint inclusion of variables without serious multicollinearity problems.

insert Table 1 about here

We used a multilevel random intercept and random slope model to analyze the data Bryk and Raudenbush (1992). The regression at the individual level is formulated as:

$$Y_{ij} = \beta_{0j} + \sum_{k=1}^p \beta_{kj} x_{kij} + \sum_{k=p+1}^{p+1+q} \beta_i x_{kij} + \varepsilon_{ij}$$

where Y_{ij} is the response for i th individual of j th department. β_{0j} is the *random intercept* and $\beta_{1j}, \dots, \beta_{pj}$ are the *random slopes*, both of which vary over departments. $\beta_{p+1}, \dots, \beta_{p+q}$ are coefficients for control variables and network measures (including both the number of inter-departmental ties and network centrality measures). They are fixed effects and do not vary over departments. ε_{ij} is the individual-level error term. It follows a normal distribution with mean 0 and variance σ^2 .

The random intercept β_{0j} and the random slopes $\beta_{1j}, \dots, \beta_{pj}$ are formulated as regressions at the department level:

$$\beta_{0j} = \gamma_{00} + U_{0j}$$

$$\beta_{kj} = \gamma_{k0} + U_{kj} \text{ for } k = 1, 2, \dots, p$$

where γ_{00} and γ_{k0} (for $k = 1, 2, \dots, p$) are fixed intercept. U_{0j} and U_{kj} (for $k = 1, 2, \dots, p$) follow a multivariate normal distribution with mean 0 and $\text{var}(U_{0j}) = \tau_0^2$, $\text{var}(U_{kj}) = \tau_k^2$ and $\text{cov}(U_{kj}, U_{k'j}) = \tau_{kk'}$.

The multilevel model is obtained by combining the individual- and department-level regressions:

$$Y_{ij} = \gamma_{00} + \sum_{k=1}^p \gamma_{k0} x_{kij} + \sum_{k=p+1}^{p+1+q} \beta_i x_{kij} + U_{0j} + \sum_{k=1}^p U_{kj} x_{kij} + \varepsilon_{ij}$$

Since $\text{var}(Y_{ij}) = \text{var}(\sum_{k=1}^p U_{kj} x_{kij} + \varepsilon_{ij})$ is dependent on x_{kij} , this model assumes heterogeneous variances.

To reflect the fact that individuals nested under the same department may be clustered and therefore the difference in their network measures may differ from that between individuals from diverse departments, we assume the error term of the regression to be dependent on eigenvector centrality measures in the three networks, i.e., x_{kij} ($k = 1, 2, 3$) are the eigenvector centrality measures in the collaboration, discussion, and awareness networks.

Table 2 summarizes the results of the mixed linear regression analysis on pagerank weighted performance measures.

Prior to testing the effect of the independent variables, we examined the impact of the control variables. Models *p1* and *c1* regress the control variables on both the research productivity and impact metrics. Note that these did not indicate a significant effect of *tenure*, *rank*, *number of years since degree*, or *ratio of single/co-authored publications*. However, the effect of *department*

is significant, indicating that there exist large differences in publication and citation rates across disciplines and that these differences have been largely captured by the department variable. Both models also indicate a slightly negative impact of tenure on work performance ($p < 0.1$ for both models).

insert Tables 2a and 2b about here

3.1 Network Position and Performance

To test the effect of eigenvector centrality on individual work performance, we examined the effect of holding a central position in the collaboration, discussion, and awareness networks step by step. Note that betweenness centrality was found to be uncorrelated with performance and hence was omitted from the regression analysis.⁴ However, models p4, c2, c3, and c4 show that eigenvector centrality in the three networks are positively associated with work performance ($p < 0.05$ for model p4 for research productivity, $p < 0.05$ for models c2 and c3, and $p < 0.01$ for model c4 for research impact), lending support for Hypothesis 1 and Hypothesis 2⁵.

However, when all three networks are considered jointly, models c6 and p6 show that the first-order effect of eigenvector centralities becomes insignificant, which indicates that the interaction among the three networks leads to a much more complex impact of network centrality. However, the positive effect of eigenvector centrality on impact in the discussion network is stable, even when all other variables are included in the regression.

⁴We conjecture that betweenness centrality does not have an impact on performance because it is the number and quality of individuals to whom one is connected (which is measured by eigenvector centrality) that influences performance. In contrast, betweenness centrality characterizes one's position on paths between individuals in the organization, which might impact their role as a communicator, but does not strongly influence research output.

⁵The size of the network effect is not as big as the effect of department membership. We conjecture that this difference has to do with differing publication practice by field, and that "equally qualified" faculty in different departments can have vastly varying publication rates. For example, an outstanding professor in Industrial Engineering may produce two to three papers per year, whereas an outstanding professor in Biomedical Engineering may produce more than ten papers per year.

insert Figure 1 about here

The result is present in models c3, c5, c6, p3, and p6. The results showed that the second order term of eigenvector centrality in the discussion network is negative and significant (i.e., $p < 0.05$ for research productivity and $p < 0.01$ research impact). This is consistent with our conjecture that moderate centrality in the discussion network leads to the highest performance because both highly central and highly peripheral positions hinder good performance, the former due to the negative influence of high overhead associated with centrality and the latter due to lack of access to vital information. This result provides support for Hypothesis 4. We did not observe a similar effect of eigenvector centrality in either the collaboration network or the awareness network, where centrality showed no significant correlation with performance.

3.2 Inter-Departmental Ties and Performance

Recall that Hypotheses 3 conjectures that inter-departmental ties promote individual work performance. Models c6 and p6 reveal that the *No. inter-departmental discussion ties* have a positive correlation with both individual research productivity and impact (i.e., $p < 0.001$ for both research productivity and research impact). *No. inter-departmental awareness ties* is also positively associated with both individual research productivity and impact (i.e., $p < 0.05$ for both research productivity and research impact). But the coefficients of *No. inter-departmental discussion ties* is roughly three times that of *No. inter-departmental awareness ties* suggests that effect of inter-departmental awareness is much smaller than inter-departmental discussion. This result supports Hypothesis 3 that inter-departmental discussion improves work performance. Models c6 and p6 also showed that *No. inter-departmental collaboration ties* significantly improves research productivity but not research impact.

Interestingly, we did not find a significant impact of inter-departmental ties in either the collaboration or the awareness network. These results imply that inter-departmental interactions are primarily valuable at the discussion level. Being aware of other people's expertise is not valuable unless it is translated into action in the form of detailed discussions. However, once the detailed discussions are held, it is not essential that one actually write papers with someone from another department. Evidently, simply holding inter-departmental conversations is the crucial step.

4 Conclusion

This research study extends our understanding of the impact of network positions and inter-departmental ties on individual work performance in a knowledge intensive environment. Specifically, we studied the impact of network positions and ties in collaboration, discussion, and awareness networks in a research-oriented engineering school. Our results suggest that central positions and inter-departmental collaborations in the discussion network have the most significant impact on the research performance of individual faculty members.

A distinguishing feature of this study is the use of multiple types of networks. Previous research has explored the impact of network position on work performance primarily relying on coauthorship information and publication data, which represent a quite formal collaboration between two actors. In this study, we have examined three survey-based social networks of increasing "formality" and characterized work performance of actors embedded in these networks. Our results suggest that informal ties may be more beneficial than formal ties. That is, being aware of research outside of one's home department and having more inter-departmental research discussions increases one's chance of producing high impact work.

This research also contributes to the literature by empirically examining the influence of indi-

vidual capacity on the benefits of network ties. Specifically, we found that performance in terms of both productivity and impact increases as individuals move from peripheral positions to positions of increasing centrality. However, this advantage diminishes, and may even become negative as individuals become increasingly central. We interpret this as a consequence of the overhead associated with maintaining so many relationships, which hinders the ability of an individual researcher to translate the insights from them into tangible outputs.

Much remains to be done to understand the influence of collaborative and interdisciplinary activities on individual performance in knowledge-intensive work systems. One direction that this research could be extended is a longitudinal study of how network positions evolve over time. For instance, it may be the case that peripheral positions in the awareness network are initially indicators of strong performance, but that individuals become more central as they succeed. Beyond this, extending the analysis to include multiple institutions would provide a more rigorous test of the robustness of our results. Finally, expanding the analysis to other knowledge-intensive work environments would allow us to examine the extent to which these insights for academic research are transferable.

Our findings should be of interest to those who are promoting interdisciplinary research within educational institutions and funding agencies, as well as managers in knowledge-intensive work environments. Our results indicate that a high percentage of boundary-spanning ties significantly correlates with research impact. Thus, boundary-spanning teams produce better work. Also, the presence of negative returns with increasing centrality suggests that there is actually a penalty for having too central of a position in one's social network. Once collaboration become too time-consuming, one does not have time to perform well. Finally, a central position in the discussion network shows significant and positive correlation with performance, whereas a central position in the collaboration does not. This suggests that, by engaging in detailed discussion with colleagues

from a different discipline, one may reap the cognitive benefits of a new source of knowledge without incurring as much of the associated coordination cost.

APPENDIX

McCormick Collaboration Network Survey

In the questionnaire that follows department names are listed by schools. Faculty names are listed alphabetically in each department. For each name please choose one answer that best describes your relationship with that person. There are six categories to choose from, which are defined below:

Have had successful collaboration with: choose this option if you have ever (i) written a joint paper (or book) with this person and the paper (or book) has turned into a publication or (ii) written a funded grant proposal and you had research discussion with this person. You should not select this choice if you had written a grant proposal but have never had research discussion with this person.

Have had research discussion with: choose this option if you have (i) had a substantive discussion about research with this person via face-to-face conversation, email correspondence, or through other means, or (ii) had collaborated on a grant proposal but the project was not funded. You should not select this choice if you had a talk with this person and exchanged only basic information about the area and sub-areas you work in.

Know research area and socially acquainted: choose this option if you both know the research area of the person and are socially acquainted with him/her. "Knowing" the research area of the person requires more detailed information than what department the person works in (e.g., that he/she works on the application of chaos theory to turbulent mixing processes). "Socially acquainted" means that you know the person on a first name basis (e.g., through joint committee work, teaching collaborations or social interactions).

Don't know research area but socially acquainted: choose this option if you know this

person on a first name basis but do not know his/her research area in any detail (e.g., you have worked with him/her on a committee or teaching effort but have never studied his/her research).

Know research area but not socially acquainted: choose this option if you know the research area of the person (in detail) but are not socially acquainted with him/her (e.g., you may have seen a presentation, read a paper or heard about him/her from someone else, but you have never had an extended conversation with him/her).

Neither know research area nor socially acquainted: choose this option if you neither know this person on a first name basis nor have detailed information about his/her research.

- Please check the one choice that best describes your relation with each and every McCormick faculty member.
- The expected time to fill out the survey is approximately 20 minutes.
- If you have any questions, please contact xxx, xxx@northwestern.edu,

| Faculty Name | Have had successful collaboration with | Have had research discussion with | Know research area and socially acquainted | Don't know research but socially acquainted | Know research area but not socially acquainted | Neither know research area nor socially acquainted |
|--------------|--|-----------------------------------|--|---|--|--|
| Professor 1 | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Professor 2 | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| Professor 3 | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Please click on the submit button below to submit your survey. Thanks you for your participation.

Notes: At the top of each new page add “You’ve completed xx% of the survey. The rest of the survey will take about xx more minutes to finish”.

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Table 1: Correlation Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|--|-------|------|-------|------|-------|------|-------|------|
| 1 $\ln(\text{Prod}_{pr})$ | | | | | | | | |
| 2 $\ln(\text{Impact}_{pr})$ | 0.87 | | | | | | | |
| 3 Tenure | -0.03 | 0.13 | | | | | | |
| 4 Asso | 0.10 | 0.27 | 0.51 | | | | | |
| 5 Full | 0.11 | 0.24 | 0.60 | 0.63 | | | | |
| 6 Year Since PhD | 0.04 | 0.21 | 0.86 | 0.63 | 0.69 | | | |
| 7 Ratio of Single-Author Paper | 0.02 | 0.06 | -0.03 | 0.06 | -0.09 | 0.00 | | |
| 8 Size of Network | 0.19 | 0.23 | 0.16 | 0.23 | 0.28 | 0.15 | 0.09 | |
| 9 No. Inter-Departmental Collaboration Ties | 0.25 | 0.27 | 0.11 | 0.22 | 0.29 | 0.16 | -0.03 | 0.51 |
| 10 No. Inter-Departmental Discussion Ties | 0.41 | 0.41 | 0.06 | 0.16 | 0.20 | 0.19 | 0.05 | 0.42 |
| 11 No. Inter-Departmental Awareness Ties | 0.08 | 0.13 | 0.17 | 0.20 | 0.24 | 0.13 | 0.09 | 0.92 |
| 12 Eigen-cent Collaboration Network | 0.41 | 0.44 | 0.13 | 0.21 | 0.35 | 0.19 | -0.05 | 0.44 |
| 13 Eigen-cent Collaboration Network ² | 0.23 | 0.23 | 0.12 | 0.14 | 0.21 | 0.20 | -0.03 | 0.21 |
| 14 Eigen-cent Discussion Network | 0.51 | 0.55 | 0.14 | 0.27 | 0.33 | 0.25 | 0.03 | 0.46 |
| 15 Eigen-cent Discussion Network ² | 0.29 | 0.26 | 0.08 | 0.11 | 0.23 | 0.23 | -0.05 | 0.26 |
| 16 Eigen-cent Awareness Network | 0.29 | 0.35 | 0.20 | 0.27 | 0.31 | 0.20 | 0.11 | 0.97 |
| 17 Eigen-cent Awareness Network ² | -0.02 | 0.01 | 0.11 | 0.14 | 0.21 | 0.16 | 0.09 | 0.59 |

| | | | | | | | | |
|--|------|------|-------|------|------|------|------|------|
| 10 No. Inter-Departmental Discussion Ties | 0.44 | | | | | | | |
| 11 No. Inter-Departmental Awareness Ties | 0.28 | 0.11 | | | | | | |
| 12 Eigen-cent Collaboration Network | 0.80 | 0.51 | 0.17 | | | | | |
| 13 Eigen-cent Collaboration Network ² | 0.51 | 0.46 | 0.00 | 0.64 | | | | |
| 14 Eigen-cent Discussion Network | 0.62 | 0.81 | 0.16 | 0.82 | 0.54 | | | |
| 15 Eigen-cent Discussion Network ² | 0.38 | 0.79 | -0.02 | 0.55 | 0.68 | 0.75 | | |
| 16 Eigen-cent Awareness Network | 0.54 | 0.49 | 0.86 | 0.52 | 0.25 | 0.59 | 0.31 | |
| 17 Eigen-cent Awareness Network ² | 0.16 | 0.12 | 0.70 | 0.03 | 0.14 | 0.05 | 0.18 | 0.50 |

$p < 0.01$ for all correlations ≥ 0.23 and $p < 0.05$ for all correlations ≥ 0.18

Table 2a: HLM Results on Research Productivity

| | Model p1 | Model p2 | Model p3 | Model p4 | Model p5 | Model p6 |
|--|--------------------|--------------------|----------|-------------------|---------------------|----------|
| Intercept | 0.94** | 0.85* | 0.95* | 1.37** | 1.02 | 1.61 |
| Human and knowledge capital control variables | | | | | | |
| tenure | -0.02 [†] | -0.02 [†] | -0.02 | -0.01 | -0.02* | -0.02 |
| Asso | 0.11 | 0.11 | 0.04 | 0.13 | -0.04 | 0.03 |
| Full | 0.08 | 0.01 | 0.09 | 0.04 | 0.14 | 0.05 |
| Year Since PhD | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 |
| Ratio of Single-Authored Paper | 0.04 | 0.05 | 0.02 | 0.02 | 0.01 | -0.01 |
| Network control variables | | | | | | |
| Size of Network | 0.00 | 0.00 | 0.00 | -0.08** | 0.00 | -0.1** |
| Predictor Variables | | | | | | |
| No. Inter-Departmental Collaboration Ties | | 0.01 | 0.01 | 0.06 [†] | 0.02 | 0.09* |
| No. Inter-Departmental Discussion Ties | | | 0.06** | 0.06* | 0.07** | 0.15*** |
| No. Inter-Departmental Awareness Ties | | | | 0.05 [†] | | 0.06* |
| Eigen-cent Collaboration Network | | 2.92 | | | -0.74 | -0.03 |
| Eigen-cent Collaboration Network ² | | -10.16 | | | -0.22 | 3.65 |
| Eigen-cent Discussion Network | | | 2.43 | | 1.23 | -0.99 |
| Eigen-cent Discussion Network ² | | | -43.45* | | -48.11 [†] | -57.95* |
| Eigen-cent Awareness Network | | | | 25.11* | | 22.98 |
| Eigen-cent Awareness Network ² | | | | -24.67 | | -27.75 |
| N | 136 | 136 | 136 | 136 | 136 | 136 |
| -2 Log-Likelihood | 342 | 333 | 321 | 327 | 342 | 326 |

[†] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$.

Table 2b: HLM Results on Research Impact

| | Model c1 | Model c2 | Model c3 | Model c4 | Model c5 | Model c6 |
|--|--------------------|-------------------|-------------------|------------------|-----------|--------------------|
| Intercept | 1.54* | 1.32* | 1.35* | 2.34** | 1.45 | 2.75 |
| Human and knowledge capital control variables | | | | | | |
| tenure | -0.04 [†] | -0.03 | -0.03 | -0.02 | -0.04* | -0.02 |
| Asso | 0.61 | 0.67 [†] | 0.38 | 0.57 | 0.32 | 0.48 |
| Full | 0.21 | -0.01 | 0.19 | 0.10 | 0.22 | 0.04 |
| Year Since PhD | 0.03 | 0.03 | 0.03 | 0.01 | 0.03 | 0.02 |
| Ratio of Single-Authored Paper | 0.17 | 0.19 | 0.10 | 0.15 | 0.10 | 0.07 |
| Network control variables | | | | | | |
| Size of Network | 0.00 | 0.00 | -0.01 | -0.20*** | -0.01 | -0.22*** |
| Predictor Variables | | | | | | |
| No. Inter-Departmental Collaboration Ties | | -0.08 | -0.03 | 0.1 [†] | -0.06 | 0.09 |
| No. Inter-Departmental Discussion Ties | | | 0.07 [†] | 0.11* | 0.11* | 0.27*** |
| No. Inter-Departmental Awareness Ties | | | | 0.09* | | 0.13* |
| Eigen-cent Collaboration Network | | 11.45* | | | 2.99 | 5.94 |
| Eigen-cent Collaboration Network ² | | -2.76 | | | 21.67 | 21.32 |
| Eigen-cent Discussion Network | | | 14.38* | | 7.84 | 0.78 |
| Eigen-cent Discussion Network ² | | | -109.39** | | -138.29** | -158.68** |
| Eigen-cent Awareness Network | | | | | | 51.14 [†] |
| Eigen-cent Awareness Network ² | | | | | | 11.73 |
| N | 136 | 136 | 136 | 136 | 136 | 136 |
| -2 Log-Likelihood | 499 | 484 | 472 | 472 | 494 | 470 |

[†] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$.

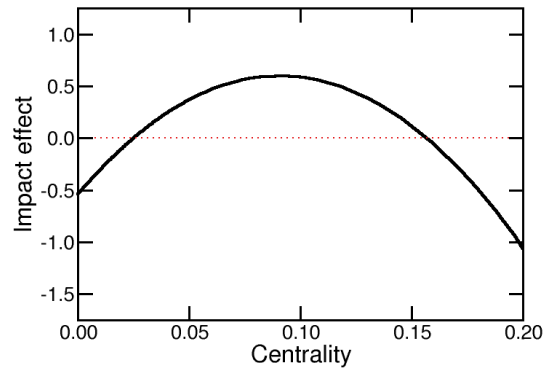


Figure 1: **Diminishing and negative returns in the effect of eigenvector centrality on performance.** This inverted-U relationship is only present in the discussion network. Collaboration in joint work is beneficial because diverse knowledge stocks can be combined in innovative ways, yet this benefit is tempered by the inevitable saturation of capacity once one becomes too involved in time-consuming collaborations.