Network Structure and Knowledge Transfer: The Effects of Cohesion and Range

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This research considers how different features of informal networks affect knowledge transfer. As a complement to previous research that has emphasized the dyadic tie strength component of informal networks, we focus on how network structure influences the knowledge transfer process. We propose that social cohesion around a relationship affects the willingness and motivation of individuals to invest time, energy, and effort in sharing knowledge with others. We further argue that the network range, ties to different knowledge pools, increases a person's ability to convey complex ideas to heterogeneous audiences. We also examine explanations for knowledge transfer based on absorptive capacity, which emphasizes the role of common knowledge, and relational embeddedness, which stresses the importance of tie strength. We investigate the network effect on knowledge transfer using data from a contract R&D firm. The results indicate that both social cohesion and network range ease knowledge transfer, over and above the effect for the strength of the tie between two people. We discuss the implications of these findings for research on effective knowledge transfer, social capital, and information diffusion.●

The ability to transfer knowledge effectively among individuals is critical to a host of organizational processes and outcomes, including the transfer of best practices (Szulanski, 1996), new product development (Hansen, 1999), learning rates (Argote, Beckman, and Epple, 1990; Darr, Argote, and Epple, 1995), and organizational survival (Baum and Ingram, 1998). According to some scholars, the ability to transfer knowledge represents a distinct source of competitive advantage for organizations over other institutional arrangements such as markets (Arrow, 1974; Kogut and Zander, 1992). In this knowledge-based theory of the firm, organizations are viewed as social communities specializing in efficient knowledge creation and transfer (Kogut and Zander, 1996). Informal interpersonal networks are thought to play a critical role in the knowledge transfer process. Our understanding of how informal networks affect knowledge transfer, however, remains unclear because the effect of networks on knowledge transfer has yet to be examined directly. Instead, researchers have inferred the association between informal networks and knowledge transfer from one of two observed effects—the association between network structure and organizational performance (e.g., Ingram and Roberts, 2000; Reagans and Zuckerman, 2001; Tsai, 2001), whereby knowledge transfer is presumed to be the causal mechanism responsible for this relationship, or between the strength of ties between people and knowledge transfer, whereby tie strength is used as a surrogate for network structure (e.g., Uzzi, 1996, 1997, 1999; Hansen, 1999).

Several studies exemplify the approach of inferring knowledge transfer from the association between network structure and organizational performance. Ingram and Roberts (2000) described how dense friendship networks affected the performance of Sydney hotels. Hotel managers embedded in friendship networks (i.e., managers connected to each other through a dense web of third-party friendship ties) shared customers and best practices, which increased the profitabili-

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ty of their hotels. One explanation for the observed effect is that friendship networks promote knowledge transfer, allowing managers facing similar market conditions to learn from each other's experience. Reagans and Zuckerman (2001) also inferred knowledge transfer from the association between network structure and organizational performance. In their analysis of corporate research and development teams, Reagans and Zuckerman described how interactions among scientists with non-overlapping networks outside of their team improved productivity. Collaboration among scientists with different external contacts bridged gaps, or "structural holes," in the network outside the team. People on opposite ends of a structural hole have access to distinct knowledge and information. Bridging structural holes in the external network enabled the scientists to access and share with each other diverse knowledge, resulting in greater creativity and innovation, thereby improving the team's overall productivity. Tsai (2001) provided a third example of this approach, but with one variation. Instead of examining how the structure of social relations affected performance, Tsai considered how the position of business units in the knowledge network affected performance. Tsai found that the most innovative and profitable business units were central. In all three cases, knowledge transfer was assumed to be the causal mechanism linking network structure to performance. In each instance, however, the path from network structure to knowledge transfer was not examined. The network effect was inferred from the observed association between network structure and some form of organizational performance. For example, although Tsai examined how the structure of knowledge relationships affected business unit performance, he did not consider the impact of network structure on the ease of transferring knowledge.

Other researchers have inferred the network effect on knowledge transfer from the association between tie strength and knowledge transfer (Uzzi, 1996, 1997, 1999; Hansen, 1999). Hansen (1999) argued that strong ties promote the transfer of complex knowledge, while weak ties promote the transfer of simple knowledge. Although tie strength is central to this argument, network structure itself is also likely to affect knowledge transfer. Specifically, a strong tie could ease the transfer of complex knowledge because it is more likely than a weak tie to be embedded in a dense web of third-party relationships (Granovetter, 1973; Hansen, 1999). Because strong ties and social cohesion tend to co-occur, examining tie strength by itself creates the potential of observing effects on knowledge transfer that are actually due to cohesion. Under these circumstances, it is difficult to determine whether tie strength or cohesion is the driving force. Tie strength and network structure can be correlated but are conceptually distinct. For example, a strong tie can occur inside or outside a cohesive group (Lin, Ensel, and Vaughn, 1981; Burt, 1992). Only by investigating tie strength and cohesion simultaneously is it possible to disentangle their effects. Doing so also permits consideration of whether the effects of tie strength and cohesion on knowledge transfer are related to each other. In particular, it remains unclear if cohesion substitutes for or complements a strong tie in the transfer of complex knowledge.

In addition to the empirical problem of disentangling tie strength and cohesion, there is also a conceptual problem related to using tie strength as a surrogate for network structure. The research strategy has stymied theoretical developments in the area of networks and knowledge transfer (see Argote, McEvily, and Reagans, 2003, for a review). Research adopting tie strength as an indicator of network structure primarily focuses on how the social dynamics within two-way interactions (e.g., reciprocity, commitment) influence knowledge transfer. The social dynamics stemming from dyadic relationships, however, are not necessarily the same as those generated by a pattern of ties among a larger set of individuals. The problem applies equally well to research that indirectly infers network effects on knowledge transfer by examining the association between network structure and organizational performance. Since research examining the network effect on organizational performance does not explicitly model the association between network variables and knowledge transfer, it does not provide a theoretical explanation for how and why network structure might affect knowledge transfer. Consequently, research has yet to clearly articulate the causal mechanisms that can account for how and why different patterns of ties surrounding a knowledge transfer dyad might influence the flow of knowledge within that dyad. Therefore, a key theoretical question is, What are the network mechanisms that influence the transfer of knowledge?

To answer this question, we consider how two key properties of network structure, social cohesion and network range, affect the transfer process. Cohesion around a relationship can ease knowledge transfer by decreasing the competitive and motivational impediments that arise, specifically the fact that knowledge transfer is typically beneficial for the recipient but can be costly for the source. Dense third-party ties around the relationship may serve to overcome those impediments. Network range—relationships that span multiple knowledge pools—can also affect the transfer process. Networks that span multiple communities of practice can give people the ability to convey complex ideas to diverse audiences. Network cohesion and network range are likely to have distinct but complementary effects on knowledge transfer. Whereas cohesion stresses the value of overlapping ties among mutual third-parties, range points to the benefits associated with network connections that span important organizational boundaries.

EFFECTS OF NETWORK STRUCTURE ON KNOWELDGE TRANSFER

Knowledge transfer represents a cost to the source of knowledge, in terms of time and effort spent helping others to understand the source's knowledge. Presumably, the easier the transfer, the less time (Hansen, 1999) and effort required and the more likely that a transfer will occur and be successful. We focus on the ease of transfer from a source to a recipient, emphasizing the source's assessment of the ease of transfer for three reasons. First, knowledge transfer is a discretionary activity, and knowledge transfer, and therefore learning, follows the path of least resistance (Levinthal and March, 1993). Individuals are presented with numerous opportunities to share their knowledge with other members of the organization, although not all opportunities are acted upon. Understanding why individuals choose to transfer knowledge in some cases but not others is an important precursor to explaining successful knowledge transfer. Ease of transfer is a primary explanation for why individuals transfer knowledge to some individuals but not to others.

Second, previous research indicates that the recipients of knowledge may not always acknowledge when they have acquired new knowledge or accurately identify the source of knowledge (Argote and Ingram, 2000). For instance, recent research has shown that individuals who learn through observation can improve their performance on subsequent activities even though they are unable to articulate what they have learned (Nadler, Thompson, and Van Boven, 2003). Similarly, when knowledge is conveyed in a group setting, the source can be misattributed.

A third reason for focusing on the source's assessment of the ease of transfer is that it permits us to consider a broader set of knowledge transfer relationships than other conventionally used measures. Specifically, performance-based outcomes that infer knowledge transfer do not capture those transfers that did *not* occur because the source viewed them to be too onerous or costly. Focusing on ease of transfer provides an opportunity to evaluate the full range of transfer opportunities, thereby providing an important complement to performance-based measures.

Knowledge can be transferred from the source to the recipient through a variety of mechanisms, and there are a number of explanations for how that transfer occurs (Argote et al., 2000). One class of explanations is grounded in cognitive and social psychology. Associative learning and absorptive capacity are frequently cited explanations for effective knowledge transfer (Cohen and Levinthal, 1990; Simon, 1991). A second class of explanations emphasizes the embedded nature of knowledge transfer, with its primary focus on tie strength (Uzzi, 1997; Hansen, 1999).

Absorptive Capacity and Associative Learning

One of the most important ways that people learn new ideas is by associating those ideas with what they already know. As a result, people find it easier to absorb new ideas in areas in which they have some expertise and find it more difficult to absorb new ideas outside of their immediate area of expertise. An implication is that it is easier for knowledge to transfer from the source to a recipient when the source and the recipient have knowledge in common. Consequently, knowledge is more likely to be transferred between people with similar training and background characteristics.

The origins of common knowledge and experience can vary. The knowledge that two individuals have in common could be a function of formal training inside or outside of an organization. Two electrical engineers have a substantial amount of knowledge in common because mathematics and physics are part of the engineering curriculum, but the source of common knowledge could be more informal. For example, two engineers who enter an organization in the same cohort group are more likely to share similar experiences, and therefore have more knowledge in common, than individuals who enter at different points in time. In a more abstract sense, two individuals who occupy the same position in an informal communication network, individuals who are structurally equivalent, have knowledge in common. The individuals are similarly positioned in the flow of knowledge and information and, due to factors associated with social influence and contagion, they will come to share common knowledge and information (Burt, 1987; Strang and Tuma, 1993; Rogers, 1995).

Consistent with arguments based on absorptive capacity and associative learning, we expect that common knowledge will ease the transfer of knowledge. Specifically, when a source and recipient share common knowledge, transfer is easier:

Hypothesis 1 (H1): Common knowledge will be positively related to the ease of knowledge transfer.

Strong Interpersonal Connections

The strength of an interpersonal connection can also affect how easily knowledge is transferred (Szulanski, 1996; Uzzi, 1997; Hansen, 1999). Individuals who communicate with each other frequently or who have a strong emotional attachment are more likely to share knowledge than those who communicate infrequently or who are not emotionally attached. More frequent communication can lead to more effective communication through, for example, the development of relationship-specific heuristics (Uzzi, 1997). The level of emotional attachment or commitment to the relationship is also important because it affects the motivation to provide assistance or support. In general, "strong ties have greater motivation to be of assistance and are typically more easily available [than weak ties]" (Granovetter, 1982: 113). The motivation may stem from social considerations, such as the desire to reciprocate (Granovetter, 1973), or it may be rooted in psychological considerations, such as the desire to maintain balanced relationships (Heider, 1958). The more emotionally involved two individuals are with each other, the more time and effort they are willing to put forth on behalf of each other, including effort in the form of transferring knowledge. Strong interpersonal attachments also facilitate the formation of trust, which may further ease the transfer of knowledge. Trust gives parties the confidence that the knowledge shared will not be appropriated or misused (Krackhardt, 1990; McEvily, Perrone, and Zaheer, 2003). Therefore, a strong interpersonal connection is expected to have a positive effect on the ease of knowledge transfer. More formally, we hypothesize:

Hypothesis 2a (H2a): Tie strength will be positively associated with the ease of knowledge transfer.

The effect of tie strength on knowledge transfer is also believed to vary with the type of knowledge being transferred. One critical dimension of knowledge that has been shown to influence the relative ease of transfer is its tacitness (von Hippel, 1994; Zander and Kogut, 1995; Szulanski, 1996). Tacitness is the degree to which knowledge is difficult to codify (e.g., in writing) or articulate. Because tacit knowledge is difficult to convey, its transfer requires greater effort. In some cases, tacit knowledge can only be transferred through up-close observation, demonstration, or hands-on experience (Hamel, 1991). The transfer of tacit knowledge should be easier between strong ties because the motivation to assist a contact is greater than in weak ties. Moreover, the relationship-specific heuristics and specialized language that develop between strong ties are conducive to conveying complex chunks of knowledge (Uzzi, 1999). While previous work has examined the relationship between tie strength, tacitness, and performance (Hansen, 1999), the relationships among tie strength, tacitness, and ease of transfer has yet to be investigated. Presumably, the ease of transfer is a key mechanism underlying the performance effect. Knowledge transfer takes time, and it takes even more time when that transfer is difficult (Hansen, 1999). Consequently, we offer the following hypothesis:

Hypothesis 2b (H2b): The positive association between tie strength and knowledge transfer will increase with the tacitness (decrease with the codifiability) of the knowledge being transferred.

Network Structure

Network structure can affect knowledge transfer independent of the effects of common knowledge and tie strength. Network-based models of social capital emphasize the importance of cohesion and range. Cohesion refers to the extent to which a relationship is surrounded by strong third-party connections. Range refers to the extent to which network connections span institutional, organizational, or social boundaries. Although both network patterns have been linked to the flow of information, they are often viewed as being in opposition. The benefits of cohesion are believed to come at the expense of the benefits provided by range and vice versa. Recent work indicates that the two network forms are not inherently at odds, however (Reagans and Zuckerman, 2001; Burt, 2002; Garguilo and Rus, 2002), but that an optimal network combines elements of cohesion and range. For example, the most productive teams are internally cohesive but have external networks full of structural holes (Reagans, Zuckerman, and McEvily, 2003). We extend this line of research by focusing on the complementary effects of cohesion and range on knowledge transfer.

Social cohesion. Social cohesion should have a positive effect on knowledge transfer, primarily through influencing the willingness of individuals to devote time and effort to assisting others. Like tie strength, cohesion affects the motivation of an individual to transfer knowledge to a coworker or colleague, although the source of that motivation differs. Whereas the knowledge sender's relationship with the recipient is the source of motivation with tie strength, strong ties to mutual third parties are the source of motivation in a dense social network. For both tie strength and cohesion, the willingness to assist others is relevant because knowledge transfer is typically beneficial to the recipient (and the broader organization) but can be costly for the source. At a minimum, the source has to devote time and effort to communicating what he or she knows. The source's willingness to transfer knowledge despite these costs represents cooperative behavior, and cooperation is more likely when strong third-party ties surround a relationship (Granovetter, 1985; Coleman, 1988). Reputation and cooperative norms are two general explanations given for why strong third-party connections promote cooperation.

In terms of reputation, people are more likely to cooperate with a colleague when strong third-party ties surround their relationship because they know that if they do not cooperate, news of their uncooperative behavior will spread to other network members quickly and limit their ability to interact with them in the future. When third parties are connected, it is easier for them to share information about uncooperative behavior than when they are disconnected. In addition, cohesion permits third parties to coordinate their actions in response to uncooperative behavior, resulting in more efficient and effective sanctioning (Coleman, 1990).

Networks characterized by strong third-party ties also promote the formation of cooperative norms (Granovetter, 1992). Individual behavior is guided by norms defining what is considered to be appropriate and inappropriate behavior (Portes and Sensenbrenner, 1993). From this perspective, people cooperate with others because cooperation represents a shared value in the network. Cohesion affects the way that people are socialized into a social circle and the internalization of group norms, including cooperation. Cooperative norms provide senders of knowledge with some assurance that if they share knowledge with somebody today, someone else will be willing to do the same for them in the future. Cooperative norms increase the knowledge senders' confidence that someone will be willing to assist them when they find themselves in a similar position, even if it is not in their short-term interests to do so (Uzzi, 1997).

Cooperative norms are important because they limit a potential side effect of successful knowledge transfer, namely, competition. Intense competition between different units inside an organization restricts the transfer of knowledge between them (Messick and Mackie, 1989; Szulanski, 1996; Argote, 1999). Competition can have the same effect on knowledge transfer between individuals. Successful knowledge transfer can increase the level of competition between the source and the recipient. When an individual shares what he or she knows with a colleague, the two individuals become more redundant inside the organization. The two individuals now have more knowledge in common and therefore represent substitutable points of exchange in the knowledge network. The potential for increased competition is one reason why people avoid sharing what they know. The cooperative norms promoted by cohesion, however, can act to mitigate potential conflict and promote knowledge transfer

(Ingram and Roberts, 2000). By limiting competition, social cohesion promotes knowledge transfer.

Based on the arguments above, we predict that social cohesion will have a positive effect on knowledge transfer. Specifically, when a relationship is surrounded by strong third-party connections, two individuals are more willing to share knowledge with each other, ultimately easing the transfer of knowledge:

Hypothesis 3 (H3): Social cohesion will be positively associated with the ease of knowledge transfer.

Network range. Network range is the prevalence of ties that cross institutional, organizational, or social boundaries (Burt, 1992: 148–149). The transfer of knowledge across boundaries, within or outside the organization, has been shown to improve performance. Inside the firm, for example, knowledge transfer between different shifts in a manufacturing facility has been shown to drive down production costs (Epple, Argote, and Davedas, 1991). Transfer across shifts allows different workers to benefit from each other's experience. The boundary can also be outside the firm, i.e., in the market surrounding the focal organization. For example, biotechnology firms that patent across distinct technological niches have more favorable market outcomes (Stuart and Podolny, 1996). It is clear that the transfer of knowledge across a boundary, inside or outside of an organization, can be beneficial for the recipient, but such transfers can also be problematic. To the extent that knowledge is being transferred across organizational boundaries that demarcate distinct bodies of knowledge, it is unlikely that individuals on either side of the boundary will have much knowledge in common. From an absorptive capacity standpoint, this lack of common knowledge is likely to frustrate attempts to transfer knowledge across the boundary. Because a strong tie between the individuals can help facilitate transfer, individual effort and motivation are important factors, but individual ability, in terms of framing and translating knowledge, also plays a role.

To transfer knowledge successfully across a boundary, the source has to frame what he or she knows in a language that the recipient can understand. When the source does not or cannot frame knowledge in a language that the recipient can understand, comprehending that knowledge can be difficult and therefore costly for the recipient (Borgatti and Cross, 2003). Knowledge transfer across organizational boundaries can be characterized by false starts, different interpretations of the same idea, and disruptions (Zellmer-Bruhn, 2003). Despite these difficulties, the source is likely to find it easier to transfer knowledge if he or she has experience considering multiple perspectives and different ways of framing what he or she knows.

Some network patterns may prepare an individual for this iterative process better than do others. Network range is likely to promote knowledge transfer by affecting people's ability to convey complex ideas across distinct bodies of knowledge. People connected to multiple bodies of knowledge are exposed to more worldviews. Considering an issue from the perspective of different contacts is part of their normal network activity. Moreover, they are more likely to recognize the need for discussion. And they are more likely to frame their communication in a language that a contact can understand (Padgett and Ansell, 1993). An individual who lives in a homogenous network is surrounded by contacts that view issues in similar ways. There is no need to consider multiple perspectives because most network members see the world in the same way. Framing is of little value because most network members share a common language. These factors facilitate communication and knowledge transfer inside the group. At the same time, it is difficult for these people to communicate what they know to outsiders (Burt, 2002). In contrast, people with networks characterized by range should find it easier to transfer knowledge because the behaviors that ease knowledge transfer are part of their everyday network activity. Individuals accustomed to interacting with contacts from diverse communities of practice are presented with a greater opportunity to learn how to convey complex ideas than are individuals limited to interactions within a single body of knowledge:

Hypothesis 4 (H4): Network range will be positively associated with the ease of knowledge transfer.

METHODS

The research setting for this study was a contract R&D firm located in a medium-size city in the American Midwest. The firm provides technical consulting in the area of materials science and includes such services as assisting clients with designing products and selecting materials, developing and improving manufacturing processes, performing scientific analyses, and assessing product performance and quality. The firm distinguishes itself from other technical consultants by offering support services for the entire life cycle of customers' products and by providing interdisciplinary scientific consulting. To deliver integrated solutions to its clients, the firm organizes temporary project teams composed of members drawn from the relevant areas of expertise (e.g., analytic services, applied science, engineering, materials, etc.). Given the need to provide integrated solutions that draw on expertise from different areas of expertise, project success depends critically on individuals' ability to transfer knowledge effectively. Consistent with the short-term, integrative nature of the work, the firm has a very flat organizational structure with no formal hierarchy. The majority of employees are scientists and engineers, holding master's degrees and doctorates. At the time of the study, the firm employed 113 people and had been operating for 15 years.

To test our predictions, we gathered data from multiple sources. We collected data on knowledge codifiability, area of expertise (to measure expertise overlap), tie strength, network structure, and ease of knowledge transfer using a survey instrument that we administered onsite at the firm over the course of two days. The survey had a very high response rate of 92 percent (104/113), and 84 percent of the respondents completed the entire survey. Independent of the survey, we gathered data from two additional sources. We collected data to measure expertise overlap from an executive in charge of knowledge management. We also obtained demographic data from the human resources department.

Even though we collected data from multiple sources, there is the potential that some independent variables are subject to single-source bias (Podsakoff and Organ, 1986; Aviolo, Yammarino, and Bass, 1991; Doty and Glick, 1998). Single-source bias occurs when some, or in extreme cases all, of the observed association between variables is due to artifactual covariance, such as a social desirability bias (Podsakoff and Organ, 1986). The knowledge codifiability, tie strength, and knowledge transfer variables are suspect because these data came from the same survey. The same is not true, however, for the key network variables used to test hypotheses 3 and 4. Our indicators of cohesion and range were constructed from interaction data provided by multiple respondents. Our indicator of network range also incorporates data about a person's area of expertise, collected from the executive in charge of knowledge management. The use of multiple individual responses and multiple data sources in constructing the network variables means that response bias does not affect the test of the network hypotheses (i.e., H3 and H4). To the extent that single-source bias does affect our results, it should create a more demanding test of the network hypotheses by inflating the significance of the other independent variables (i.e., knowledge codifiability and tie strength, H1–H2b).

Variables

Ease of knowledge transfer. The dependent variable in this study is the ease of knowledge transfer from a source to a recipient. Because knowledge transfer represents a cost to the source of knowledge, in terms of time and effort spent helping others to understand the source's knowledge, the source of knowledge is typically in the best position to evaluate these costs. A priori, recipients have little basis for assessing the ease of transfer since they do not yet possess the knowledge in question. Ease of knowledge transfer was measured with the items listed in table 1. Each item was measured with a 7-point Likert scale, ranging from strongly disagree to strongly agree. The items define a single knowledge transfer variable. Cronbach's alpha among the items is .87, and the first principle component from a factor analysis of the items explains 69.9 percent of the variance. Our indicator of *ease of transfer* is the mean of the items shown in table 1.

Knowledge codifiability. Codifiability represents "the degree to which knowledge can be encoded" (Zander and Kogut, 1995: 79). Each respondent was asked to describe the codifiability of knowledge in his or her primary area of expertise. The variable *codifiability* was measured with five items adapted from an instrument developed and validated by Zander and Kogut (1995). Items were measured with a 7-point Likert scale, ranging from strongly disagree to strongly agree. The items are displayed in table 1 and define a single codifiability measure. Cronbach's alpha for the five items is .75, and the

Table 1

Measures*

Item	Mean	S.D.	Loading
Ease of knowledge transfer			
It would be easy for me to explain to this person a key idea, concept, or theory in my area of expertise.	4.1	.96	.79
This person's expertise makes it easy for me to explain a key idea, concept, or theory in my area of expertise.	3.8	1.1	.79
Anyone in my area of expertise can explain easily to this person a key idea, concept, or theory in our area.	3.7	1.2	.81
I can explain easily to anyone in this person's area of expertise a key idea, concept, or theory in my area.	3.8	.94	.69
It would be easy for me to explain to this person new developments in my area of expertise.	4.0	.98	.87
Knowledge codifiability			
A useful manual or document describing my area of expertise could be easily written.	4.7	1.9	.54
Extensive documentation describing critical parts of my area of expertise exists in our company.	3.0	1.7	.63
Standardized procedures for applying my expertise to address applied problems could be easily developed.	4.6	1.6	.64
Extensive documentation describing how to apply my expertise to address applied problems exists in *our company.*	2.7	1.5	.89
Extensive documentation describing how to apply my expertise to address applied problems exists in *our industry.*	4.0	1.8	.53
Tie strength			
How close are you with each person (especially close, close, less than close, distant)?	2.9	.87	—
On average, how often do you talk to each (any social or business discussion) (daily, weekly, monthly, less often)?	3.0	.97	—
Tie content			
Advice: These are people that you would go to for advice or help if you had a question or ran into a problem at work. (dummy variable)	.71	.45	—
Friendship: These are people with whom you like to spend your free time—people with whom you get together for informal social activities such as going out to lunch, dinner, drinks, films, visiting one another's homes, and so on. (dummy variable)	.39	.49	—

* Unless indicated otherwise, items were measured with a 7-point Likert scale, ranging from strongly disagree to strongly agree.

first principle component from a factor analysis of the items explains 43.4 percent of the variance. Our indicator of knowledge codifiability is the mean of the five items.

Common knowledge. Common knowledge is expected to have a positive effect on knowledge transfer, for the same reasons that it is easier for an individual to accumulate knowledge in areas in which he or she has made prior investments. Because the foundation for common knowledge can vary, we have multiple indicators of how much knowledge two people have in common. The first indicator is based on social similarity with respect to significant background characteristics (e.g., race, sex, level of education). Individuals who share important social characteristics are presumed to have common experiences, resulting in shared knowledge. Data from the human resource management department allowed us to measure how similar individuals were with respect to race, sex, education level, and tenure in the organization. The organization was relatively homogenous with respect to sex and race. Eighty-four percent of the individuals were male, and 92 percent were white. Most ties occurred between individuals of the same race (86 percent) or the same sex (78 percent). To examine how being of the same race or same sex affects knowledge transfer, we created two indicator variables. *Same race* equals one if the respondent and the contact share the same racial heritage. *Same sex* equals one if the respondent and the contact are the same sex.

The firm is more diverse with respect to organizational tenure and level of education. Tenure was measured as the length of time (in years and months) that the firm had employed an individual. The variable *tenure dissimilarity* was measured as the difference in tenure between a respondent and a contact, $ts_{ij} = |tenure_i - tenure_j|$. Level of education is an ordinal variable that takes on one of four values (1 = high school, 2 = bachelor's, 3 = master's, 4 = doctorate). The variable *education dissimilarity* was measured as the difference in educational level between a respondent and a contact, $es_{ij} = |education_i - education_j|$. Both variables measure the absence of social similarity and therefore the absence of common knowledge. Each can be expected to have a negative effect on knowledge transfer.

The degree of common knowledge could also be based on areas of expertise inside the organization. To collect data on areas of expertise, we asked each respondent to respond to the following question: "Imagine introducing yourself to an associate at [name of firm]. How would you quickly summarize your areas of expertise? Be complete, but concise. We want to know the areas of expertise that you would highlight to give other people a basic understanding of what you do." Each respondent was asked to indicate his or her primary and secondary areas of expertise. The executive in charge of knowledge management reviewed those responses and used them to define eleven areas of expertise in the firm. After defining those areas, the executive then assigned each person to those areas. Each respondent could be assigned to multiple areas of expertise. Sixty-one percent of the respondents were assigned to a single area, 29 percent were assigned to two areas of expertise, and 10 percent were assigned to three or more areas of expertise. The variable *expertise overlap* was constructed using the expertise data, with a_{ik} equal to one if person i is an expert in area k and a_{jk} equal to one if person j is an expert in area k. The product of the two variables equals one when the two individuals are experts in the same area. Summing the product across all areas of expertise and dividing by the number of areas, N_i, for the focal individual defines the level of expertise overlap.

$$eo_{ij} = \sum_{k=1}^{11} a_{ik}a_{jk}N_i$$

Expertise overlap ranges from 0 to 1, with higher values indicating more knowledge overlap.

Functional expertise is another form of common knowledge. Respondents work in different areas inside the firm. The functional areas are analytical services, applied science, business services, delivery, engineering, materials, and product-life prediction. Individuals who work in the same function can be expected to share some knowledge. To account for this effect, we constructed a dummy variable, *same functional area,* and set it equal to one if the focal contact worked in the same functional area as the respondent and zero otherwise.

Network Data

We collected network data using a combination of sociometric and egocentric techniques (Wasserman and Faust, 1994: 45–50). Sociometric techniques provide each respondent with a fixed contact roster and ask him or her to describe his or her relationship with every individual on the roster. A virtue of the sociometric approach is that it provides information on all interactions inside a network. The technique, however, can also introduce inaccuracies into network data. Defining an appropriate boundary around the network, the set of individuals who are interconnected, is critical (Laumann, Marsden, and Prensky, 1983). To the extent that the network boundary varies from one person to the next, asking each respondent to report on connections that lie outside his or her frame of reference can be problematic. Individuals provide more accurate network data on that part of the network with which they are most familiar (Kumbasar, Romney, and Batchelder, 1994). Their assessment of network connections involving distant individuals is less accurate (Krackhardt and Kilduff, 1999).

An alternative approach is to collect network data using egocentric techniques. Each individual responds to a series of questions that generate names, resulting in a roster of contacts (Fischer, 1982; Burt, 2002). Next, the respondent describes the relationship with each cited contact. In some applications of egocentric techniques, respondents are asked to describe the relationships among their contacts. In this study, however, since we surveyed contacts as well, we constructed information about ties among a respondent's contacts using the responses from contacts themselves. A virtue of the egocentric technique is that it asks an individual to report on that part of the network with which he or she is most familiar. Individual responses can be aggregated to describe the total network. A network can be constructed between different members of the firm based on their reported relationships with each other. A potential drawback of the technique is that it can miss important interactions that lie outside a respondent's frame of reference.

In the current study population, we used both techniques to gather network data. We implemented the sociometric technique as follows. First, we constructed a roster of potential knowledge-sharing contacts for each respondent. The firm provided a list of projects completed during the previous year and the number of hours that each individual worked on a project. We assumed that individuals who dedicated a large number of hours to the same projects in the previous year had more opportunities to share knowledge with each other. By focusing on contacts with whom individuals had more opportunities to interact, we were asking them to report on that part of the network with which they would be most familiar. Based on the project data, we constructed a roster of contacts for each respondent and drew a random sample of fifteen contacts from that roster. During the survey, each respondent was presented with his or her fixed roster and was asked to eliminate the names of individuals with whom he or she had not shared knowledge during the previous year. For instance, two individuals who worked on the same project at different points in time would not have the opportunity to share knowledge. The respondent was then asked to copy the remaining names to his or her contact list. Each respondent could copy up to ten names. On average, respondents eliminated six of the fifteen names on their roster.

Drawing a random sample of contacts from the fixed roster and limiting potential contacts to that roster can be problematic. The technique could result in important contacts being excluded from a respondent's network. To collect the names of important contacts missed by the sociometric technique, we also solicited egocentric data. Each respondent was asked to respond to the following name-generator questions: (1) "Think of the people who *acted as a critical source* of knowledge for your projects during the past year. These are people you contacted when you needed assistance with one of your projects." and (2) "Now think of the people for whom *you have been a critical source* of knowledge for their projects during the past year. These are the people who contacted you when they needed assistance with one of their projects." For each name generator, a respondent could nominate up to five contacts. In response to the two name-generator questions, respondents provided six new names, on average. In general, those contacts were evenly distributed across the two questions. Three sent knowledge to the respondent and three received knowledge from the respondent.

Combined, the sociometric and egocentric techniques yielded an average of sixteen contacts in a respondent's network. Nine names came from the sociometric technique using a fixed roster, and six were generated by the egocentric technique using free recall. An additional contact was generated by both techniques (i.e., the name appeared on the original fixed roster and was also listed in response to egocentric name-generator questions). Sixteen is close to the maximum number of twenty contacts allowed during the survey, which might indicate that respondents have more contacts than we collected. If this were the case, however, we would have expected the egocentric name-generator questions to produce more unique names than they did. On average, respondents generated only six of a possible ten names from the egocentric free recall questions, suggesting that critical contacts were not omitted. Our sampling strategy provided the additional advantage of increasing the likelihood that the relationships surrounding each respondent would vary from strong to weak, an important consideration, since previous research suggests that the ease of knowledge transfer varies with tie strength. By using egocentric and sociometric data collection techniques, the network will contain a wider circle of colleagues around each respondent than a network based on either technique alone. While the egocentric technique is more likely to elicit the names of strong contacts, the sociometric technique is more likely to include weak ties. We used the network data to construct the tie strength and network structure variables.

Tie strength. After compiling a list of contacts, respondents were asked to describe their relationship with each contact. Respondents were asked to indicate the intensity of their connection in terms of emotional closeness and communication frequency (Granovetter, 1973; Fischer, 1982; Burt, 1984; Hansen, 1999). A tie exists from the respondent to the contact if the respondent reports a relationship. We did not require that the contact corroborate the tie. Results reported below are the same if we did, except that the network contains fewer weak ties, which, as noted above, are important for testing the conceptual framework. In addition to the strength of ties, respondents were asked to describe the content of their ties in terms of whether the cited contact was a source of advice and/or friendship. The items used to solicit this information about tie strength and content, along with their descriptive statistics, are provided in table 1 above.

We used the advice and friendship variables as controls. If the contact was cited as a source of advice, the *advice* dummy was set equal to one. If the contact was cited as a friend, the *friendship* dummy was set equal to one. We used the emotional closeness and communication frequency variables to compute tie strength. The two variables represent different dimensions of interaction intensity (Marsden and Campbell, 1984). Table 2 contains the joint distribution of emotional closeness and communication frequency. There was a single dimension of interaction intensity in the organization we studied. Individuals were emotionally close to contacts with whom they communicated more frequently. The intensity of a network connection, z_{ij}, was measured as the product of emotional closeness and communication frequency (Goodman, 1984; Burt, 1992). In addition to computing tie intensity as the product of emotional closeness and communication frequency, we also measured tie intensity as the average of these two variables. Results were substantively the same.

Consistent with prior research, tie intensity was transformed into tie strength using network proportions (Burt, 1992, 2002; Uzzi, 1996, 1999). The *tie strength* from respondent i to contact j is p_{ij},

Table 2

Joint Distribution of Tie-strength Variables

	Communication Frequency			
Emotional closeness	Less often	Monthly	Weekly	Daily
Distant	57	36	17	8
Less than close	56	117	139	51
Close	40	92	304	265
Especially close	4	12	91	307

$$p_{ij} = z_{ij} \Big/ \sum_{q=1}^{N} z_{iq,\ q = j}$$

where z_{ij} is the intensity of the relationship from respondent i to contact j. Network proportions define the strength of a tie within the context of the aggregate level of affect across a person's network.

Social cohesion. Following Burt (1992: 54–56), our indicator of social cohesion is indirect structural constraint c_{ij},

$$c_{ij} = \sum_{q=1}^{N} p_{iq}p_{qj},\ q \neq j$$

where p_{iq} is the strength of the network connection from person i to person q, and p_{qj} is the strength of the network connection from person q to person j. The variable is a triadic density measure. *Network density* indicates the presence of strong third-party connections around a relationship. Strong third-party ties connect person i to person j indirectly to the extent that person i has a strong network connection with contact q and contact q has a strong network connection with person j. To measure the overall strength of the third-party connections around the focal relationship, $p_{iq}p_{qj}$ was summed across all contacts q.

Network range. We considered the importance of network range at the level of expertise areas. Each expertise area is a distinct pool of knowledge. An individual who spreads his or her network connections across multiple pools bridges holes between people in the broader community of knowledge and, as a result, is exposed to more diverse knowledge. Network diversity is therefore high. Our indicator of network range is *network diversity*. The indicator has two distinct components. The first is a function of how an individual allocates his or her network connections across expertise areas. The second is a function of the strength of the connections within those areas. To calculate network diversity, each contact was assigned to one of six primary areas of expertise, as designated by the executive in charge of knowledge management. Network diversity (Burt, 1983) is defined as nd_i,

$$nd_i = 1 - \sum_{k=1}^{6} p_k p_{ik}^2$$

where p_{ik} is the strength of the network connection from person i to area k, and p_k describes the strength of the connections between individuals in area k; p_{ik} is defined as

$$p_{ik} = \sum_{j=1}^{Nk} z_{ij} \Big/ \sum_{q=1}^{N} z_{iq},\ q = j$$

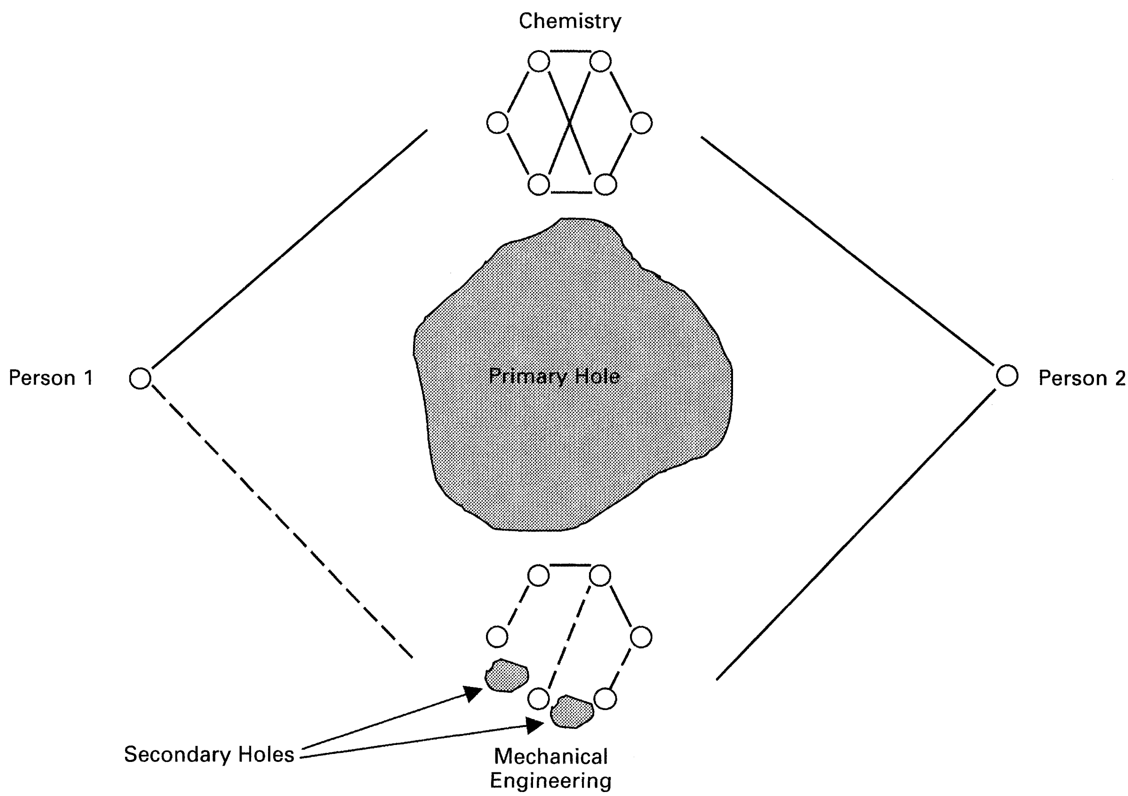
where N_k is the number of contacts that respondent i cited from area k, N is the number of contacts cited by respondent i, and z_{iq} is the intensity of the relationship that person i had with contact q. Tie strength within area k was measured as p_k,

$$p_k = \sum_{j=1}^{M_k} z_{ij} \Big/ \sum_{q=1}^{S_k} z_{iq}, \; q = j$$

where S_k is the number of contacts cited by respondents in area k, M_k is the number of respondents in area k, z_{iq} is the intensity of the relationship from an individual in area k to any contact, and z_{ij} is the intensity of the relationship from an individual in area k to a colleague in the same area. An individual is surrounded by a diverse network to the extent he or she spreads his or her network connections across multiple areas and the connections within contacted areas are weak.

Figure 1 helps illustrate how network diversity varies as a function of the two components described above. The two clusters in the figure are knowledge pools. For the purpose of illustration, the top cluster is chemistry and the bottom cluster is mechanical engineering. Solid lines indicate strong ties, and dashed lines represent weak ties. Connections are stronger among the chemists than among mechanical engineers. Chemistry and mechanical engineering represent two distinct areas of expertise, so there is a primary hole between them. Disconnects inside an area, secondary holes, indicate internal heterogeneity. The stronger ties among chemists indicate less internal heterogeneity than in mechanical engineering. Strong network connections, or the absence of secondary holes, inside an area indicate the *absence* of diverse knowledge (e.g., chemists have less diverse knowledge than engineers). Therefore, increasing p_k indicates the absence of diverse knowledge inside a knowledge pool.

Figure 1. Network range.



The second element of network diversity is how an individual's network connections are spread across areas. The two individuals in figure 1 are exposed to the same contacts, but Person 2 has the more diverse network. Person 1 has a stronger connection with chemistry than mechanical engineering. Person 2's network connections extend equally across both areas. Network diversity increases as an individual's network connections are distributed more evenly across multiple areas of expertise and ties among people in the same area of expertise are weak.

Although network diversity and network density are distinct, they are not mutually exclusive. Density around a relationship exists when two people are strongly connected by mutual third parties. But the network can still be diverse if it includes people from different areas of expertise (e.g., engineering, biology, mathematics, etc.). Accordingly, network density does not come at the expense of network diversity. In the current analysis, network density measures the presence of strong third-party ties around a connection, and range measures the distribution of connections across different areas of expertise.

Structural equivalence. Finally, as another indicator of common knowledge, we used the network data to define the extent to which two individuals occupy the same network position. Individuals who are involved in the same pattern of connections are equivalent and can be expected to have similar knowledge and information. We measured the degree of *nonequivalence* between the network pattern surrounding the respondent and the pattern surrounding the focal contact as

$$d_{ij}, d_{ij} = \sqrt{\sum_{q=1}^{104} (z_{iq} - z_{jq})^2 + (z_{qi} - z_{qj})^2}.$$

The measure is the Euclidean distance between two network patterns. The distance is high when two individuals interact with different colleagues in the organization.

Analysis

The dependent variable is the ease of transfer. A total of 104 individuals responded to our survey, but two did not complete the network survey. The remaining 102 individuals were involved in 1,626 relationships or an average of 15.94 contacts for each respondent. The 1,626 dyads are the observations. We excluded 296 observations because of missing data. The remaining 1,330 observations are not independent. There can be multiple observations for each respondent and multiple observations for each contact. This violates a key assumption in ordinary least squares regression. Error terms in the regression will be correlated across observations from the same source or object of a relationship, which is known as network autocorrelation. Without accounting for this non-independence, the standard errors of the estimates are reduced artificially. There are several solutions to the problem (Simpson, 2001). One solution is to introduce a fixed effect for each source or recipient of a relationship (Mizruchi and

Koenig, 1988; Mizruchi, 1989). Following this technique, we created a dummy variable for each person who received or sent a tie. Within a particular dyad, the dummy variables for the focal respondent and the focal contact were set equal to one, and all other dummy variables were set equal to zero. The fixed effects estimation also serves as a control for any unobserved heterogeneity among respondents (e.g., age, tenure, hierarchical position, etc.), including any tendency for respondents who rated themselves high on knowledge transfer ability to inflate their popularity (in the form of strong ties with contacts). Finally, the fixed effects also control for unobserved differences among contacts, including their ability to absorb knowledge and information.

We also controlled for other network and individual-level factors that were possible confounds. Since not all respondents reported the same number of contacts, we included *network size* as a control. We also controlled for individual differences in knowledge, using the variable *knowledge breadth,* which reflects a respondent's number of expertise areas.

RESULTS

Descriptive statistics are in table 3, and the results are displayed in table 4. Effects are introduced across columns. Estimates for control variables are included in model 1. The estimates for common knowledge, defined by background characteristics, expertise overlap, and nonequivalence are introduced in model 2. Race, sex, education, tenure, expertise overlap, and function-based similarity have no effect on

Table 3

Descriptive Statistics and Correlations*

Variable	Mean	S.D.	1	2	3	4	5	6	7
1. Ease of transfer	3.9	.82							
2. Network size†	2.8	.22	−.09						
3. Knowledge breadth†	.90	.27	.02	.16					
4. Knowledge codifiability	3.9	1.2	.10	−.02	−.06				
5. Same race	.88	.32	−.02	.09	−.12	−.09			
6. Same sex	.79	.41	.06	.05	.08	.02	.02		
7. Education dissimilarity	.84	.82	−.03	.05	−.03	−.15	−.07	−.17	
8. Tenure dissimilarity	2.1	1.24	−.01	−.03	−.006	−.10	.11	.05	.02
9. Expertise overlap†	.24	.29	.13	−.07	−.10	.04	−.07	.08	−.08
10. Nonequivalence†	1.6	.17	−.10	.24	.06	.05	.06	.02	.12
11. Same function	.40	.49	.11	−.14	−.12	.01	−.06	.03	−.10
12. Source of advice	.74	.44	.31	−.07	−.11	.005	.02	−.04	.09
13. Friendship	.40	.49	.22	−.06	.005	.05	.03	.06	−.14
14. Tie strength	.06	.05	.34	−.34	−.05	.01	−.01	−.01	−.10
15. Network density	.02	.02	.21	−.15	−.09	.02	.01	.05	−.09
16. Network diversity	.87	.10	−.02	.27	.21	.03	.17	−.01	−.07

Variable	8	9	10	11	12	13	14	15
9. Expertise overlap†	.04							
10. Nonequivalence†	.09	−.12						
11. Same function	.04	.20	−.24					
12. Source of advice	−.03	.02	.06	−.01				
13. Friendship	−.13	.10	−.17	.12	.05			
14. Tie strength	−.05	.15	−.31	.33	.20	.42		
15. Network density	.06	.15	−.15	.43	.09	.19	.38	
16. Network diversity	.003	−.29	.12	−.10	−.12	.003	−.07	−.11

* Correlations >=|.06| are significant at $p < .05$.
† Logged variable.

Table 4

Effects of Network Structure on Ease of Knowledge Transfer*

	Model								
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Intercept	4.5•••	6.4•••	4.5•••	3.1•••	2.9•••	2.2•••	1.8•••	.90	1.7•••
	(.43)	(.53)	(.52)	(.54)	(.55)	(.57)	(.60)	(1.1)	(.63)
Network size†	–.55•••	–.56•••	–.36•••	–.11	–.12	–.02	–.10	–.07	–.09
	(.14)	(.14)	(.13)	(.13)	(.13)	(.13)	(.14)	(.14)	(.14)
Knowledge breadth†	.08	.10	.20•	.18•	.18•	.22••	.18•	.19•	.17
	(.12)	(.12)	(.11)	(.11)	(.11)	(.11)	(.11)	(.11)	(.11)
Knowledge codifiability	.11•••	.10•••	.10•••	.10•••	.14•••	.12•••	.12•••	.33	.09••
	(.03)	(.03)	(.03)	(.02)	(.03)	(.03)	(.03)	(.21)	(.02)
Same race		.02	–.09	–.10	–.11	–.13	–.14	–.13	–.14
		(.13)	(.13)	(.12)	(.12)	(.12)	(.12)	(.12)	(.12)
Same sex		.02	.02	.05	.05	.05	.05	.05	.05
		(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)
Education dissimilarity		–.01	–.005	–.003	–.009	–.01	–.009	–.01	–.005
		(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
Tenure dissimilarity		–.03	–.007	–.002	–.002	–.008	–.01	–.01	–.01
		(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Expertise overlap†		.13	.16••	.13•	.14•	.14•	.14•	.14•	.13•
		(.09)	(.08)	(.08)	(.08)	(.08)	(.08)	(.08)	(.07)
Nonequivalence†		–1.4•••	–.70•••	–.15	–.12	.27	.29	.26	.31
		(.23)	(.23)	(.23)	(.24)	(.25)	(.25)	(.25)	(.25)
Same functional area		.06	.11••	.06	.05	.01	.02	.01	.02
		(.06)	(.05)	(.05)	(.05)	(.05)	(.05)	(.05)	(.05)
Source of advice			.62•••	.55•••	.55•••	.54•••	.54•••	.54•••	.54•••
			(.05)	(.05)	(.05)	(.05)	(.05)	(.05)	(.05)
Friendship			.31•••	.20•••	.20•••	.20•••	.21•••	.21•••	.20•••
			(.05)	(.05)	(.05)	(.05)	(.05)	(.05)	(.05)
Tie strength				3.6•••	5.7•••	5.3•••	5.0•••	5.1•••	3.8•••
				(.51)	(1.3)	(1.3)	(1.3)	(1.5)	(.57)
Tie strength x					–.54•	–.50	–.45	–.48	—
Knowledge codifiability					(.31)	(.31)	(.31)	(.35)	—
Network density						6.3•••	6.5•••	7.0•	6.8•••
						(1.5)	(1.5)	(4.2)	(1.5)
Network density x							—	–.16	—
Knowledge codifiability							—	(1.0)	—
Network diversity							.74••	1.8•	1.4••
							(.37)	(1.1)	(.66)
Network diversity x								–.25	—
Knowledge codifiability								(.25)	—
Model fit									
Number of observations	1,330	1,330	1,330	1,330	1,330	1,330	1,330	1,330	1,330
R-squared	.208	.251	.355	.380	.381	.390	.392	.393	.393
Adj. R-squared	.144	.186	.298	.324	.325	.335	.337	.336	.338
Model improvement F-test	10.27•••	10.01•••	98.48•••	48.48•••	2.99•••	18.8•••	3.89•••	1.05	—

• $p < .10$; •• $p < .05$; ••• $p < .01$.

* Standard errors are in parentheses.

† Logged variable.

ease of transfer. In model 3, in which friendship and advice are introduced, nonequivalence and expertise overlap have an effect. Nonequivalence and expertise overlap are indicators of common knowledge, one in the informal network and the other in terms of formal training. Both variables affect the ease of transfer. The results provide support for hypothesis 1. That evidence, however, weakens once a control for tie strength is introduced in model 4. The effect for tie strength is positive and significant. Tie strength does ease knowledge transfer, providing support for hypothesis 2a. The effect for tie strength is above and beyond the effect for the content of the tie. For example, the model includes a control for friendship. There is a tendency in the social sciences to associate friendship with a strong network connection. This is not always the case. Some respondents reserve the word friend for especially close contacts or contacts that they communicate with frequently. For others, a friend need not be an especially close contact or even someone they meet with daily (Laumann, 1966; Burt, 1990). While conceptually distinct, tie strength and friendship are correlated in most situations. In the current organization, the correlation between the two is .42. The positive effect for tie strength, however, does not depend on having friendship in the model. When we remove friendship from the equation in model 4, the estimate for tie strength is larger and more significant. This indicates why friendship is an important control variable. Not all strong ties reach friends. To use friendship as the indicator of a strong tie would have underestimated the impact that tie strength had on knowledge transfer.

Hypothesis 2b is tested in model 5, which contains an interaction between tie strength and knowledge codifiability, to estimate contingent tie strength. The estimate indicates that the effect of tie strength on knowledge transfer is even stronger when the knowledge being transferred is tacit, or, as shown in table 4, the effect is less positive when the knowledge is codified. The estimate provides support for hypothesis 2b, but the effect is weak.

Network density and network diversity are introduced in models 6 and 7. The estimates indicate that both social cohesion (as indicated by network density) and range (as indicated by network diversity) ease knowledge transfer. The positive effects for network density and diversity are above and beyond the positive effect for a strong interpersonal connection. The estimates in models 6 and 7 provide support for hypotheses 3 and 4. Informal network patterns influence the knowledge transfer process. Both network density and range improve knowledge transfer from a source to a recipient. Moreover, when network density is introduced into the equation, the contingent effect of tie strength on ease of transfer weakens further. This is due in part to the fact that tie strength and network density are correlated ($r = .38$), suggesting that strong ties are frequently surrounded by strong third-party connections (Granovetter, 1973).

We were also interested in whether the effects for network density and network diversity varied with knowledge codifiability. The theoretical arguments for the contingent network effects parallel those for the contingent effects of strong ties. Specifically, given the added difficulty of transferring tacit knowledge, the motivation stemming from network density and the ability derived from network diversity could take on even greater importance. Two interactions for the contingent effects of network structure are added in model 8. Those coefficients are not significant. The positive effects for network density and network diversity do not vary with the kind of knowledge being transferred. Finally, the estimates in model 9 are based on the logs of the tie strength and network variables. The estimates indicate the nonlinear association between these variables and ease of transfer. The effects indicate that the positive effect for each network feature increases the ease of knowledge transfer, but the positive effect increases at a decreasing rate. The positive effect provided by a strong connection, for example, increases up to a point, but after that point, the positive effect flattens out. The estimates indicate that a person would not need to have maximum tie strength, network density, or network diversity to gain from the benefits these different network features provide.

DISCUSSION

At the beginning of this paper, we raised a question about the contribution of network structure to the knowledge transfer process. Previous research had suggested that network structure was an integral part of the transfer process, but the "network effect," while widely recognized, had not been examined directly. We focused on two distinct features of network structure, cohesion and range. The evidence indicated that both network features facilitated knowledge transfer. The findings are important because they clarify and extend past research.

The findings clarify and extend the role of strong ties in the transfer process. Strong connections have occupied a privileged position in the knowledge transfer process, in part because such connections are assumed to occur within a dense web of affiliations. We found that strong ties and social cohesion were correlated but that it was a mistake to equate their effects. Each feature made a distinct contribution to the knowledge transfer process. The benefits provided by a strong tie did not require social cohesion. The evidence also provided an important boundary condition for strong connections. Previous research had assumed that strong ties were even more valuable for the transfer of knowledge that was tacit or difficult to codify. Hansen (1999), in his analysis of team performance, found that team performance increased as a function of the strength of connections from the team to the broader organization and also as a function of the kind of knowledge being transferred by the team. And team performance was even higher when strong ties were used to transfer tacit knowledge. Based on these findings, Hansen concluded that a strong tie facilitated the transfer of tacit knowledge more than it facilitated the transfer of codified knowledge. He concluded that strong ties should be used for the transfer of tacit knowledge and weak ties for the transfer of codified knowledge (Hansen, 2002). We tested this idea in our analysis. We found some support for the initial conclusion, that strong ties facilitated the transfer of tacit knowledge more than they facilitated the transfer of codified knowledge. But the evidence was weak. Moreover, the effect disappeared altogether once controls for cohesion and range were introduced into the model. The contingent effect of tie strength was actually tapping into the effect for network structure, providing further support for the need to distinguish tie strength from network structure in empirical analysis.

Although we did not find a contingent effect of tie strength on knowledge transfer, it does not mean that Hansen was incorrect when he asserted that it is best to match the type of tie to the type of knowledge being transferred. Our results showed that it is easier to transfer all kinds of knowledge in a strong tie and more difficult to transfer all kinds of knowledge in a weak tie. Our results also showed that tacit knowledge was more difficult to transfer than codified knowledge. Combined, the two results indicate that it is more efficient to use strong ties to transfer tacit knowledge and weak ties to transfer codified knowledge. Given that strong ties require a greater investment of time, it is inefficient to use strong ties to transfer codified knowledge. Time spent using a strong tie to transfer codified knowledge could be spent transferring tacit knowledge. The greater efficiency here is based on matching type of tie to type of knowledge. That matching does not require an interaction between tie strength and type of knowledge. A significant interaction between tie strength and type of knowledge would have implied that individuals exerted significantly more effort during the transfer of tacit knowledge than they exerted during the transfer of codified knowledge.

The estimates of the nonlinear effects in model 9 provided further support for the matching hypothesis. Those estimates were based on the logs of tie strength, network density, and network diversity. The model provided the best fit to the data. Given the nonlinear effect that tie strength had on knowledge transfer, it makes sense for an individual to allocate just enough network time and effort to facilitate transfer and then to allocate the rest of his or her time and effort to other knowledge transfer relationships. After some point, the marginal returns to additional time and effort begin to decline. The individual would be better off allocating the additional time and effort to a different knowledge transfer relationship, where the time and effort would have more of an impact.

At the same time, to say that it is more efficient to use weak ties to transfer codified knowledge, as in the matching hypothesis, is not to say that network range plays a limited role during knowledge transfer, as Hansen concluded. The estimates in table 4 indicated that range eased transfer. Therefore, by equating weak ties with network range (or boundary spanning ties), previous research has neglected the important role that range plays in the transfer process. Our findings, therefore, clarify existing research by identifying how strong ties contribute to knowledge transfer but also when they do not. We extend previous work by identifying the important role that network range plays during the transfer process as well, an effect that has been ignored in past work.

Our work also has important implications for the study of network structure in general. Previous research has focused on the benefits of knowledge transfer across a structural hole (e.g., Stuart and Podolny, 1996) but has not addressed the problematic nature of such transfers. Presumably, people at opposite ends of a structural hole do not have much knowledge in common, which can impede knowledge transfer. The baseline effects in table 4 illustrated this point. A structural hole existed between two individuals when those individuals were not connected through strong third-party ties (the strength of third-party ties is zero) and nonequivalence was at its maximum value. The estimates indicated that it was difficult to transfer knowledge under this condition. A strong tie across a structural hole eased transfer. An individual surrounded by a diverse network could transfer knowledge across a structural hole, even when the connection was weak. This suggests that the behaviors required to maintain a diverse network assist an individual during the transfer of knowledge. Transferring knowledge and maintaining a diverse network are related activities. Experience at one task helps in performing a related activity.

In addition to advancing our understanding of how knowledge is transferred across a structural hole, this research advances our understanding of how range and cohesion influence important organizational outcomes. The positive effect that cohesion and range had on knowledge transfer demonstrated the compatibility of network-based models of social capital typically viewed in opposition, namely, the cohesion hypothesis proposed by Coleman (1988) and the structural holes argument presented by Burt (1992). The benefits of network cohesion need not come at the expense of network range. On the contrary, the results reported here are consistent with an emerging line of work emphasizing that the optimal network structure combines elements of cohesion and range (Burt, 2000; Reagans and Zuckerman, 2001; Reagans, Zuckerman, and McEvily, 2003).

Moreover, the results advance our understanding of information diffusion in general. In the diffusion literature, knowledge is typically undifferentiated. Our results demonstrate that it is important to distinguish between the types of knowledge being diffused. In particular, we found that it was more difficult to transfer tacit knowledge than codified knowledge, suggesting that tacit knowledge requires more motivation, effort, and ability to transfer than codified knowledge. To the extent that informal networks affect individual motivation, effort, and ability, our findings suggest that an individual is more likely to exert greater effort to transfer knowledge to a close personal contact, and an individual who is surrounded by a diverse network is better able to transfer knowledge. Strong interpersonal connections within a dense network cluster ensure that knowledge will diffuse quickly within that cluster. A bridging tie between clusters enables diffusion across clusters. When knowledge is simple, the presence of a bridge is both a necessary and sufficient condition for knowledge to diffuse across it. Transferring simple knowledge does not require much effort, so a large number of individuals are willing to do it. Transferring simple knowledge also does not require much ability, so a large number of individuals are able to complete the transfer.

In contrast, tacit knowledge is more difficult to transfer. Tacit knowledge transfers across organizational boundaries more slowly than codified knowledge (Zander and Kogut, 1995). Gaps in social structure, therefore, represent critical bottlenecks to the knowledge transfer process. Limits on the number of strong-tie bridges and network range mean that tacit knowledge is more likely to remain embedded in local communities of practice. Unlike codified knowledge, tacit knowledge does not diffuse across a network. The process is more active. Tacit knowledge is more likely to transfer across a structural hole when the individual who bridges the structural hole either has a strong tie across the hole or has a diverse network. The knowledge diffuses across the structural hole either because the individual exerts more effort or because the amount of diversity in his or her network makes the transfer easier to complete.

Knowledge codifiability highlights an important difference between network-based models of diffusion and active knowledge transfer. Transferring tacit knowledge is more sensitive to having the right person with the right connection at the right place, ultimately limiting the number of people who can contribute to the process. When knowledge is difficult to codify, not many are willing and even fewer are able to transfer it. By considering the tacitness of knowledge, we can gain important insights into the diffusion processes. Understanding how other properties of knowledge affect network-based models of diffusion is an important area for future research. For instance, recent research indicates that knowledge can be characterized according to whether it is public versus private and that the learning and transfer processes associated with each type of knowledge differs (Uzzi and Lancaster, 2003).

While this research advanced our understanding of networks and knowledge transfer, it was not without its limitations. Although we provided a more direct assessment of network structure than previous work, we did not provide the same precision with regard to individual behaviors. For example, we observed an association between network diversity and ease of transfer and attributed that effect to taking multiple perspectives and more effective framing during knowledge transfer. Alternatively, it is possible that individuals who bridged holes and who found it easier to transfer knowledge simply had greater absorptive capacity. Individuals with more absorptive capacity could have maintained more diverse networks and found it easier to transfer what they knew. This alternative explanation cannot be ruled out completely, but our models included fixed effects for individuals and a control for their knowledge breadth. These controls should have accounted for a significant amount of the individual differences in terms of absorptive capacity. Given these controls, we emphasized the behaviors induced by network structure. Maintaining a diverse network requires taking multiple perspectives and crafting communication, behaviors that are learned in maintaining a diverse network. An additional benefit is that those same behaviors ease knowledge transfer. Future research should continue to probe how knowledge transfer is affected by behaviors induced by network structure and consider how these effects interact with other factors influencing the knowledge transfer process.

The findings also provide some insight into how informal networks can be managed to affect knowledge transfer. In the current study population, projects and assignments were driven in part by factors external to the organization. Customers' demands and preferences affected the composition of projects and assignments. Some projects drew on individuals from one area of expertise, and other projects required that individuals from multiple areas work together. Usually, managers evaluated projects in terms of the products they produced and how long it took for them to be produced. The network effects on knowledge transfer indicate that projects should also be evaluated in terms of the network patterns they generate. For example, projects and assignments that limit network range can trap an organization into existing routines and practices. When projects bring individuals from the same area of expertise into contact, those individuals do not gain experience transferring what they know to people outside their area of expertise. Because it is easier for people to transfer knowledge to contacts inside their area of expertise, however, this network configuration can be effective in the short term. Projects are completed in a timely manner.

Projects and assignments that promote network diversity can be less efficient in the short term than those that limit range. Individuals from different areas of expertise find it more difficult to share knowledge and information with each other and, as a result, their work will suffer. The long-term implication of these interactions, if they are maintained, however, is that these individuals will be able to transfer knowledge inside and outside their immediate area of expertise. Projects and assignments that promote network diversity are potentially more valuable in the long term because diverse projects can produce individuals who integrate the knowledge network. Projects and assignments that produce network diversity might seem inefficient today, but those projects can add social capital that could be infinitely more valuable to the organization tomorrow.

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