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KNOWLEDGE SHARING IN ORGANIZATIONS: MULTIPLE NETWORKS, MULTIPLE PHASES

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Different subsets of social networks may explain knowledge sharing outcomes in different ways. One subset may counteract another subset, and one subset may explain one outcome but not another. We found support for these arguments in an analysis of a sample of 121 new-product development teams. Within-team and interunit networks had different effects on the outcomes of three knowledge-sharing phases: deciding whether to seek knowledge across subunits, search costs, and costs of transfers. These results suggest that research on knowledge sharing can be advanced by studying how multiple networks affect various phases of knowledge sharing.

What determines the occurrence and effectiveness of knowledge sharing in an organization? Scholars have examined this question from different viewpoints, focusing on the problem of transferring tacit and complex knowledge across organization subunits (e.g., Zander & Kogut, 1995), the nature of informal relationships between two parties to a transfer (e.g., Gupta & Govindarajan, 2000; Reagans & McEvily, 2003; Tsai, 2002), and the problem of searching for knowledge (e.g., Ancona & Caldwell, 1992). This growing body of literature has shed much light on the various problems underlying knowledge sharing in organizations. Yet, because the overarching process of knowledge sharing has been shown to consist of multiple phases—each with their own associated challenges—existing research on this question is quite disparate and has not shed much light on whether variables that explain one phase of knowledge sharing also explain other phases (Eisenhardt & Santos, 2002).

In particular, while some studies have analyzed the transfer of knowledge from one point to another (e.g., Gupta & Govindarajan, 2000; Szulanski, 1996; Zander & Kogut, 1995), they have excluded the logically prior phase of searching for knowledge or have not empirically disentangled the two phases of search and transfer (Hansen, 1999). Scholars therefore do not know much about the extent to which different factors explain search and transfer. Moreover, in the few studies on search for knowledge, researchers have tended not to distinguish between the decision to seek knowledge and the ensuing search process (e.g., Borgatti & Cross, 2003; Hansen, 1999).

These shortcomings in existing research are problematic. Existing findings may be biased or incomplete to the extent that explanatory properties that have a positive or negative effect on outcomes in one phase, such as transfer, may have the opposite or no effect on outcomes in other phases. There is therefore a need for research that explores the extent to which different properties explain outcomes associated with the various phases of knowledge sharing.

To address this gap in extant research on knowledge sharing, we pose this research question: Do properties of social networks explain the outcomes of the three phases—deciding to seek knowledge, searching for knowledge, and transferring knowledge—in different ways? By social networks, we refer to subsets of established informal relations that exist within teams and across subunits in an organization. We delineate the application of this multiple network approach to an analysis of one type of task units, new-product development teams, and examine the impacts of teams' subsets of social networks on whether they seek knowledge

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across subunits, their interunit search costs, and the costs of knowledge transfer.

MULTIPLE NETWORKS, MULTIPLE PHASES

Scholars adopting a relational approach to knowledge sharing have mainly focused on the characteristics of established informal relations that facilitate or impede the sharing of knowledge in an organization. This body of research has, however, focused on quite different subsets of relations. Some research has focused on analyzing informal relations within teams and organization subunits (e.g., Levin & Cross, 2004), whereas other studies have focused on teams' and individuals' external informal relations (Ancona & Caldwell, 1992; Cummings, 2004) or on relations between subunits in an organization (e.g., Gupta & Govindarajan, 2000). Furthermore, while some research has analyzed properties of a subunit's *total* set of interunit relations (e.g., Hansen, 1999; Tsai, 2001), other studies have focused exclusively on the properties of *dyadic* relations involving one providing and one receiving unit in a transfer event (e.g., Gupta & Govindarajan, 2000; Szulanski, 1996).

Apart from a few studies that have begun to address multiple subsets of relations (e.g., Nohria & Ghoshal, 1997; Schulz, 2001), this body of research has not carefully analyzed the potentially different roles of various subsets of relations, yielding an incomplete understanding of what particular subsets of relations affect the decision to seek knowledge across subunits, search costs, and costs of transfer. To address this shortcoming, we develop a multiple network perspective that addresses three subsets of networks that exist *prior* to the start of a focal project: established relations between members of a team located within a focal subsidiary (a *within-team network*); a team's *total set* of established relations with those in other subsidiaries, irrespective of whether it transfers knowledge from those contacts (an *intersubsidiary network*); and a team's *dyadic relations,* involving only subsidiaries providing it with knowledge (a *transfer network*). The latter two subsets both refer to *direct contacts or relations* that a team in a focal subsidiary has with other subsidiaries. The difference between these two subsets is that an intersubsidiary network includes all direct contacts that a team has, whereas a transfer network includes only direct contacts with subsidiaries from which it is transferring knowledge.

We argue that these three informal networks affect a team's decision to seek knowledge, search costs, and costs of transfers in different ways, and we explore two overarching theoretical mechanisms for why this may be the case. First, as prior research on social networks and communication patterns in product development projects has shown, established informal relations tend to channel actors' time and energy in the direction of established contacts—actors interact with those whom they have interacted with before (e.g., Gulati, 1995; Katz & Allen, 1988). This channeling mechanism implies that different subsets of networks may channel teams' time and energy in different directions. Second, building on prior research that has shown that an actor's different social relations have different utilities (e.g., Podolny & Baron, 1997), we argue that the three different subsets of relations serve different purposes. Intersubsidiary relations are more beneficial for search across subsidiaries than are within-team relations, whereas dyadic transfer relations are more useful for transfer than a team's total set of intersubsidiary relations. This utility mechanism implies that properties of the three networks that we analyze should have different impacts on the outcomes of the three phases.

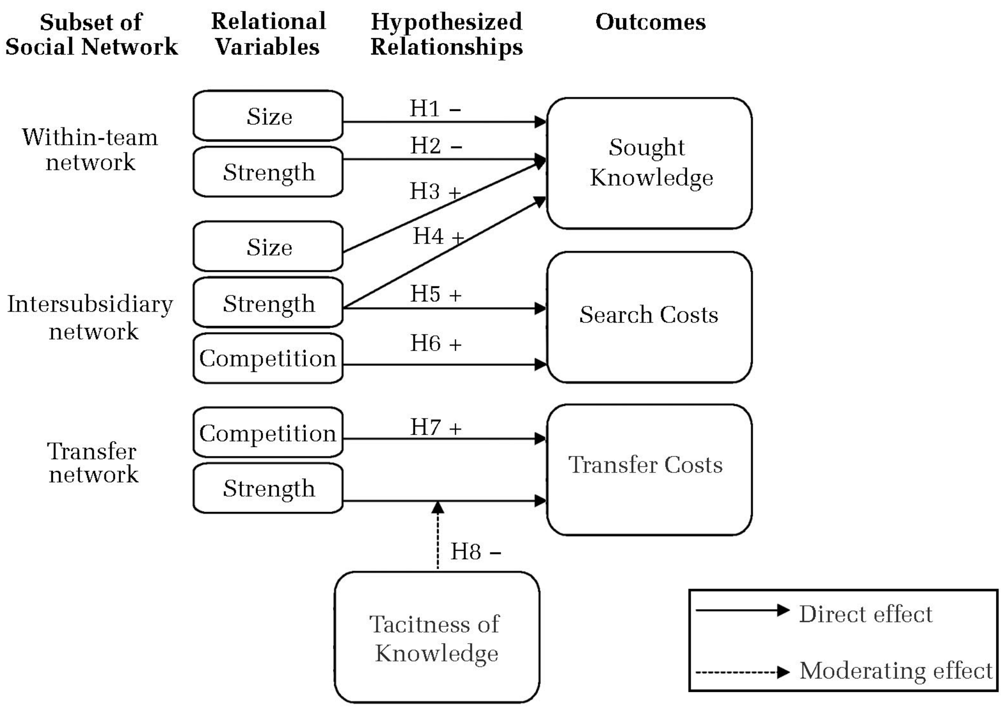
On the basis of these two overarching theoretical mechanisms, we develop a set of hypotheses, which are depicted in Figure 1. We focus on three relational variables that have received attention in knowledge-sharing research: the extent of a network as given by its size (e.g., Hansen, 2002), the strength of relations (e.g., Hansen, 1999), and the degree of perceived competition inherent in relations (e.g., Tsai, 2002).

Deciding Whether to Seek Knowledge across Subsidiaries

In the first phase, teams may decide to seek knowledge in other subsidiaries. Assuming that a team's decision to seek knowledge results in attempts to seek knowledge, an outcome of this phase is thus whether a focal team in a focal subsidiary contacts other subsidiaries to inquire about potentially useful knowledge for a project. Irrespective of teams' varying needs to seek knowledge from subsidiaries other than their own, a team's decision to seek knowledge across subsidiaries may be affected by established relations that exist both within teams and across subsidiaries.[1]

[1] We assume that project development tasks are not purposefully decomposed into subtasks whereby other subsidiaries provide components to the focal project and subsidiary, thereby preordaining intersubsidiary interactions.

FIGURE 1
Effects of Subsets of Social Networks on Outcomes of Three Phases of Knowledge Sharing



Within-team network. Product developers may have formed enduring relations among themselves, including friendship and advice-seeking informal relations, that develop over time and exist *prior* to the start of a particular product development project (Podolny & Baron, 1997). When developers join a common project team, these established relations may channel their time and energy toward the team: when confronted with new project-specific problems, they may seek to solve them by interacting and sharing knowledge with team members. Given that teams typically have a finite number of problems to solve, this preference is likely to reduce the need to seek knowledge outside the teams, including knowledge resident in other subsidiaries.

Existing theory suggests three reasons why this channeling may occur. First, within-team relations may be associated with an in-group bias. Social psychologists have studied the tendency of some group members to systematically overvalue group members and undervalue nonmembers (e.g., Brewer, 1979; Tajfel & Turner, 1986). Scholars studying research and development (R&D) activities in organizations have reported a similar tendency among engineers, known as the "not-invented-here" syndrome, which refers to the bias in a group of engineers of valuing their own knowledge more than that of others and henceforth rejecting knowledge held by others outside their group (Hayes & Clark, 1985; Katz & Allen, 1988). These biases often develop when group members have spent considerable time interacting with one another, a scenario that restricts the inflow of new viewpoints and differences and reinforces commonly held beliefs (Oakes, Haslam, Morrison, & Grace, 1995; Wilder, 1978).

Second, established relations may be associated with a team's inward-looking absorptive capacity (Cohen & Levinthal, 1990). Product developers who interact regularly with one another may, over time, assimilate one another's knowledge, thus developing a common knowledge base and a common specialized set of terminologies. Through established relations, they may also develop a capacity for mutual problem solving (Uzzi, 1997). These interaction benefits in turn make it easier for team members to absorb one another's knowledge, leading to a preference to work and share knowledge with each other as opposed to seeking knowledge resident in subsidiaries other than their own.

Third, established within-team relations may give team members increased awareness of each other's knowledge, including awareness of knowledge that may be relevant to project-specific tasks (Austin, 2003; Schulz, 2003). This awareness may lead team members to focus on this body of knowledge when seeking solutions and further reduce the chances that the team will seek knowledge from subsidiaries other than their own.

Members of a team who have a number of ongoing established relations with one another prior to the start of a project may therefore channel their time and energy toward the team and not toward other subsidiaries. The density of the within-team network (i.e., the number of ongoing established relations among team members, divided by the total possible number of such relations)[2] and the average strength of relations (i.e., the frequency and intensity of interactions) may positively affect this channeling tendency. The chance of an in-group bias forming is likely to increase because of the enhanced opportunity for members to jointly emphasize the value of their own skills and reinforce commonly held beliefs afforded by extensive, frequent, and intense past interactions. Furthermore, teams that have high density and average strength of within-team relations are likely to have a larger common knowledge base than teams with low density and strength of relations, increasing the preference for relying on team members. And finally, the more extensively, frequently, and intensively team members have interacted in the past, the more chances they have had to become aware of the extent and type of knowledge held by other team members. This should increase their preference for seeking solutions inside the team and not outside. We therefore predict:

Hypothesis 1. The higher the density of a within-team network, the less likely the focal team is to seek knowledge across subsidiaries.

Hypothesis 2. The higher the average strength of relations in a within-team network, the less likely the focal team is to seek knowledge across subsidiaries.

Intersubsidiary network. The within-team network may channel members' time and energy inside their team, while the team's established relations in its intersubsidiary network may "pull" it outward. The causal mechanisms that lead teams to seek solutions and knowledge within themselves may also explain why some teams tend to look outward. First, a team's intersubsidiary network may mitigate the effect of in-group biases. Teams that are isolated from outside interactions may form negative perceptions about others, thereby increasing the risk that an in-group bias is forming (Tajfel & Turner, 1986). The larger a focal team's intersubsidiary network (i.e., the higher the number of direct intersubsidiary relations), the *lower* this risk should be, as team members have had more chances to interact with engineers in other subsidiaries and thereby have been exposed to different views and skills. Moreover, the higher the average strength of these established relations, the lower the risk should be, as more frequent and intense interactions will have increased the exposure of team members to other views and skills, thereby reducing their negative perceptions of others and increasing the chances that they will seek knowledge in other subsidiaries.

Second, established intersubsidiary relations may also be associated with a focal team's capacity to absorb knowledge from those contacts, as there have been a number of interactions in the past in which focal team members have had opportunities to learn to engage in mutual problem solving and develop a common knowledge base with engineers in those subsidiaries (Cohen & Levinthal, 1990; Uzzi, 1997). The larger a team's intersubsidiary network and the more frequent and intense interactions have been, the more such opportunities have been given to team members, enhancing their absorptive capacity and hence their preference for seeking knowledge from engineers in these other subsidiaries.

Third, as the size and average strength of a focal team's intersubsidiary network increase, the team members' awareness of knowledge held by engineers in this network should increase, because team members have had more extensive, frequent, and intense opportunities to learn about this knowledge (cf. Austin, 2003). With increased awareness about the knowledge available in other subsidiaries, including knowledge that is relevant for completing project-specific tasks, a focal team should be more likely to seek knowledge across subsidiaries. In short, we predict:

Hypothesis 3. The larger a focal team's intersubsidiary network, the more likely the team is to seek knowledge across subsidiaries.

Hypothesis 4. The higher the average relation strength in a focal team's intersubsidiary network, the more likely the team is to seek knowledge across subsidiaries.

Search Costs

A team in a focal subsidiary that has decided to seek knowledge needs to search for it, an activity that involves looking for, identifying, and evaluat-

[2] The total possible number of relations in a within-team network is defined as $N \times (N - 1)$, where N is the number of team members (Wasserman & Faust, 1994).

ing knowledge resident in other subsidiaries. During this phase, teams incur search costs, which in our context are measured as the number of engineering-months that a product development team spends on search.

Because the search phase in our definition precedes the identification of useful knowledge, team members may not know ex ante which subsidiaries possess novel and useful knowledge for a particular project. In such a situation, a team's *total* set of intersubsidiary relations may be useful as it provides an initial search position from which a team in a focal subsidiary can draw on several intersubsidiary relations to launch a search for knowledge.

As social network research has shown, however, it is not the sheer number of direct relations in a network that provides an advantageous search position but, rather, the extent to which those direct relations provide access to novel knowledge (cf. Burt, 1992; Granovetter, 1973; Hansen, Podolny, & Pfeffer, 2001). In particular, a set of intersubsidiary relations with *low* average strength (i.e., relations involving infrequent and nonintense interactions) is more likely than a set with high average strength to enable team members to access direct contacts that possess novel knowledge. A set of relations with high average strength tends to involve direct contacts that are themselves connected, because they are likely to have been introduced to each other through their common strongly tied actor (Burt, 1992; Granovetter, 1973). Direct contacts that are themselves connected tend to circulate knowledge among one another and thereby possess similar knowledge, reducing the probability that a focal team will identify novel knowledge when contacting several of them. Thus, for a given amount of novel knowledge being sought, a team may have to make a number of contacts, as each one is likely not to have much knowledge that differs from what the other contacts have. In contrast, when the average strength of the relations in a team's intersubsidiary network is low, the team's direct contacts are less likely to be connected themselves and thereby are less likely to possess the same knowledge. In this situation, the team is likely to identify more novel knowledge for each contact it makes and thereby lower search costs for a given amount of novel knowledge sought.[3] We thus predict:

Hypothesis 5. The higher the average relation strength in a focal team's intersubsidiary network, the higher the focal team's search costs.

The previous discussion rests on the assumption that direct contacts in a focal team's intersubsidiary network are motivated to help the focal team identify useful knowledge, but this may not be the case. One reason for a lack of motivation to aid search is intersubsidiary competition (Tsai, 2002). A team and its subsidiary may compete with another subsidiary in the sense that both subsidiaries sell products to the same external markets and seek to develop the same types of products and technologies. In such a situation, one subsidiary's product development efforts may constrain the opportunities of a competing subsidiary to the extent that new products and technologies "crowd out" the available market and technology opportunity set for the competing subsidiary (Sorenson, 2000).

If subsidiaries that a focal team contacts in its search for knowledge perceive that the focal team presents such a competitive threat, the contacted subsidiaries may hide what they know (so that the focal team will not identify useful knowledge), declare only parts of their related knowledge (so that the team only benefits partially), or fail to point the focal team to other subsidiaries that may have useful knowledge (making search more difficult). Although they may be inaccurate, these perceptions may nevertheless govern contacted subsidiaries' responses and are likely to increase a focal team's search costs, as team members may need to expend additional effort searching to obtain a given amount of useful knowledge. Thus, focal teams whose direct contacts perceive high levels of competition are more likely to have higher search costs than teams whose direct contacts perceive low levels of competition between them and the focal subsidiary:

Hypothesis 6. The higher the average level of competition perceived by subsidiaries in a focal team's intersubsidiary network, the higher the focal team's search costs.

Transfer Costs

Once a focal team has identified potentially useful knowledge, it has to be transferred from the providing subsidiary to the team, a process that involves modifying, editing, and incorporating the knowledge into the team's product (Szulanski, 1996; Zander & Kogut, 1995). In this phase, teams

[3] Having a high average relation strength may be especially problematic for teams pursuing very novel projects. In the empirical part of our study, we included an interaction term involving average intersubsidiary relation strength and project novelty, but results for this term were not significant, suggesting that this was not the case in our data set.

incur transfer costs, which we measure as the number of engineering-months spent on this activity.

While a focal team's intersubsidiary network confers a search position, a transfer event most likely does not involve the total set of a team's intersubsidiary contacts but only those that end up providing knowledge. Despite having agreed to provide knowledge, however, providing subsidiaries may have various degrees of motivation to aid the transfer effort, in part depending on the level of perceived competition between them and the focal subsidiary. A providing subsidiary may believe that a transfer of knowledge to a team in a competing subsidiary will diminish its own opportunities for developing products and technologies based on the knowledge being provided to the focal team (cf. Galunic & Eisenhardt, 2001). As a result, the providing subsidiary may "drag its feet" and be more guarded about what knowledge—and how much knowledge—it transfers than it would be if no competition existed. In this situation, the focal team has to spend more time negotiating with the providing subsidiary, increasing the time and effort required to transfer knowledge.

The effect of competition on transfer costs primarily concerns the extent of competition perceived by the *providing subsidiary,* not by the focal team or the focal subsidiary. Providing engineers who perceive that a focal team and subsidiary pose a significant competitive threat are likely to be more guarded and less forthcoming than are providing engineers who do not perceive the same extent of competition. Stated in a hypothesis:

> *Hypothesis 7. In a dyadic transfer relationship, the more a providing subsidiary perceives that it competes with a focal subsidiary, the higher the focal team's transfer costs.*

Although the extent of perceived competition affects the motivation to transfer knowledge to a focal team, other factors affect the *ability* of a providing subsidiary and the focal team to carry out a transfer smoothly. Prior research has demonstrated that tacit knowledge—knowledge that is difficult to articulate or that can only be acquired through experience—is difficult to transfer smoothly (e.g., Hansen, 1999). When knowledge is tacit, engineers in the providing subsidiary will find it more difficult to explain its content and nuances to members of the focal team, who in turn may find it difficult to understand, thereby making the tasks of modifying and incorporating the knowledge into the product difficult. Because of these difficulties, transferring tacit knowledge is likely to be more cumbersome, take a longer time, and thus be more costly than transferring nontacit knowledge (Zander & Kogut, 1995).

As prior research has shown, however, the difficulty of transferring knowledge can be alleviated to some extent if the two parties to a transfer know each other well and thus have learned to work together (Hansen, 1999; Uzzi, 1997). When two parties to a transfer have developed a strong relation prior to the transfer effort, they have likely developed a shared communication frame whereby each party has come to understand how the other party uses subtle phrases and ways of explaining difficult concepts (Uzzi, 1997). Such strength in a dyadic transfer relation should therefore reduce transfer costs by reducing the time and effort required to understand and incorporate knowledge into the focal project. In particular, as the tacitness of the knowledge that a subsidiary provides to a focal team increases, an existing shared communication frame afforded by established strong dyadic transfer relations is likely to become more important, as the two parties to a transfer can rely on it to articulate, modify, and incorporate the subtle and implicit aspects of the tacit knowledge, thereby reducing transfer costs:

> *Hypothesis 8. Knowledge tacitness will modify the main negative effect of dyadic relationship strength on a focal team's transfer costs: the effect will be stronger when tacitness is high and weaker when tacitness is low.*

METHODS AND DATA

We tested the hypotheses using a data set of 121 new-product development teams and 41 subsidiaries of a large high-technology company. The company, which had annual sales of more than $5 billion at the time of the study, was involved in developing, manufacturing, and selling a range of industrial electronics and other high-technology products and systems. It was structured into 41 fairly autonomous subsidiaries that were responsible for their own new-product development, manufacturing, and sales and thus had considerable freedom in choosing which other subsidiaries to contact to access useful knowledge. For the purposes of this study, we considered a new-product development team in a focal subsidiary to be engaged in intersubsidiary search and transfer if it contacted and obtained knowledge from one or more of the other 40 subsidiaries. Having negotiated access to the company through three senior corporate R&D managers, we visited 14 subsidiaries and conducted open-ended interviews with more than 30 project engineers and managers to better understand the context and to develop survey instruments to test our hypotheses.

To select product development teams, we used the firm's databases on projects to develop a list of projects that the subsidiaries undertook and identified 147 projects. We administered three different survey instruments to create the variables: a network survey distributed to the R&D managers in each of the 41 subsidiaries, asking about relations across the subsidiaries (a 100 percent response rate was achieved); a survey distributed to the 147 project managers of each of the product development teams included in the study, asking about sources of knowledge for the project (an 82 percent response rate); and a survey distributed to 510 individual members of the projects, asking about their own personal relations with colleagues (a 51 percent response rate).

The final sample included 121 projects that took place in 27 different subsidiaries. We used the information on projects from the databases to analyze response rates but found no differences between the final 121 projects and the 26 projects for which the survey was not returned in terms of number of engineers, budget, and project age. In addition, we took several steps to minimize potential common method biases (Podsakoff & Organ, 1986). This concern was reduced substantially because we relied on three different sets of respondents. Furthermore, as recommended by prior research, we focused on behavioral measures and not on perceptual ones, which are prone to common method biases (Gatignon, Tushman, Smith, & Anderson, 2002).

Dependent Variables

Sought knowledge. We asked each project manager to indicate whether team members had sought knowledge in any of the other subsidiaries except the focal one. Project managers were able to answer this question reliably, as they kept detailed logs on how engineers on the project spent their time. Fifty-five project managers (45%) reported that their teams had sought knowledge in at least one of the other 40 subsidiaries. We coded this dependent variable, *sought knowledge,* as 1 if a team had sought knowledge from another and 0 otherwise.

Search costs. The preliminary interviews informed us that one of the most salient search costs for these projects was engineering-months spent looking for, identifying, and evaluating knowledge from other subsidiaries and that project managers kept track of the number of engineering-months spent on this activity. The company defined an *engineering-month* as the equivalent of a product developer's full-time work for one month. We asked the project managers, "How many engineering-months did the team spend searching for (looking for, identifying, and evaluating) the technical advice, software and hardware that the team wanted from other subsidiaries?" The responses ranged from 0.1 to 15 (or from approximately 1 to 22 percent of total engineering-months for a project), with a mean of 4.39 (or 5 percent of total engineering-months). To compute the variable *search costs,* we used the absolute number of engineering-months spent on search.

Transfer costs. To measure transfer costs, we asked the project managers, "How many engineering-months did the team spend modifying, editing and incorporating the technical advice, software and hardware that came from the other subsidiaries?" Project managers kept a close eye on engineering-months spent on this activity and thus could provide reliable answers to this question. The responses ranged from 0.1 to 40 (or approximately 1 to 57 percent of total project engineering-months), with a mean of 7.94 (or 10 percent of total engineering-months). To compute the variable *transfer costs,* we used the absolute number of engineering-months spent on transfer. Five projects did not report transfer costs, and we thus had to drop these from the analysis (there were no significant differences between these five and the other projects).

These search and transfer costs variables do not specify the benefits of using knowledge from other subsidiaries. To control for the benefits that the teams obtained by spending time searching and transferring, we entered a control variable denoting the amount of knowledge obtained from other subsidiaries (described in the section about control variables). This way we measured search and transfer costs given a certain *amount of knowledge obtained.*

Within-Team Network Variables

Within-team network density. To test Hypothesis 1, we used responses from the individual team member survey. Following accepted procedures from the social network literature for soliciting a person's network contacts (e.g., Podolny & Baron, 1997), we asked each team member three questions: "Looking back over the last year, are there any persons in your subsidiary: (i) from whom you regularly sought information and advice to help your project work, (ii) to whom you would go on a regular basis to get buy-in for your work, or (iii) with whom you interacted informally as a friend?" Each respondent entered the names of individuals described by either of these three choices, and we then counted the number of contacts these individuals had with other members of the respondent's team.

In addition, to avoid recording relations that were created *after* the start of a focal project, we asked each respondent how long each relation had been in existence and excluded relations that commenced after the start of the focal project. We computed *within-team network density* as the number of existing relations divided by the number of possible asymmetric relations, which is given by $N \times (N - 1)$, where N is the number of team members (Wasserman & Faust, 1994). This measure ranges from 0 ("no relations exist") to 1 ("all possible relations exist").[4]

Within-team relation strength. To test Hypothesis 2, we asked team members two questions: "How frequently have you interacted with this person over the past year?" (1, "once a day," to 7, "once every 3 months") and "How close are you to this person? (1, "very close," to 7, "distant"). We reverse-scored the two dimensions and took the average of these two dimensions to create *average within-team relation strength*. The Cronbach alpha for this scale was .81.

Intersubsidiary Network Variables

Intersubsidiary network size. To test Hypothesis 3, we constructed a measure of the number of intersubsidiary relations. We asked the subsidiary R&D managers, "Over the past two years, are there any units [i.e., subsidiaries] from whom your unit [i.e., focal subsidiary] regularly sought technical and/or market-related input?" The question was followed by a list of the 41 subsidiaries included in the study, and the manager could then check the appropriate subsidiaries. We asked the respondents to indicate the age of each relation and excluded those that had commenced after the start of focal projects. These relations thus vary among the projects within a subsidiary. Finally, we assigned the appropriate intersubsidiary relations to each focal project and computed the number of established relations with other subsidiaries that existed prior to the start of the focal project, labeling the variable *intersubsidiary network size*.

Intersubsidiary relation strength. We asked the subsidiary R&D managers to answer the following for each of the relations he or she listed on the survey: "How frequently do people in your [subsidiary] interact with this [subsidiary]?" (1, "once a day," to 7, "once every 3 months") and "How close is the working relationship between your [subsidiary] and this [subsidiary]?" (1, "very close, practically like being in the same work group," to 7, "distant, like an arm's length delivery of the input"). We reverse-scored and averaged the two items, which were highly correlated (r = .83; α = .92). To test Hypotheses 4 and 5, we computed an average for each team, *average intersubsidiary relation strength*.

Intersubsidiary perceived competition. To measure the level of perceived competition between subsidiaries, we asked each subsidiary R&D manager to indicate, for each relationship he or she listed on the survey, "How would you describe the competitive nature between your [subsidiary] and this [subsidiary]?" (1, "non-competitive: never compete for markets and technologies," to 7, "competitive: frequently compete for markets and technologies"). These perceptions are asymmetric: an R&D manager in subsidiary A may perceive subsidiary B as a competitive threat to A, but the R&D manager in subsidiary B may not perceive subsidiary A as a threat to B. Because all 41 R&D managers completed the survey and indicated the level of perceived competition with subsidiaries with which they had relations, we were able to obtain information on how *other* subsidiaries perceived a focal subsidiary.

We used this information to construct two measures of perceived competition in each team's intersubsidiary network. First, to test Hypothesis 6, we computed the average value of direct contacts' responses to the above question. This variable, *direct contacts' average perceived competition,* measured how all subsidiaries with which a focal team had established relations perceived the subsidiary to which the team belonged. Second, we computed *focal subsidiary's average perceived competition*—that is, how each subsidiary's R&D manager perceived the level of competition with direct contacts.

Transfer Network Variables

Perceived competition in transfer. To test Hypothesis 7, we followed the same procedures but limited the measure to only those subsidiaries that provided knowledge to a focal team. The average value of their responses to the question about perceived competition was the variable *providers' perceived competition*.

Dyadic transfer relation strength and tacitness of knowledge. We limited this relational variable to subsidiaries that provided knowledge to a focal team. Using the scale for intersubsidiary relation strength described above, we constructed the measure *dyadic transfer relation strength* (0, "no established relation," to 7, "very strong relation"). For this measure, we subtracted the mean from the values to reduce the correlation with the interaction effect. To measure the tacitness of transferred

[4] Because this information was missing for eight teams, we created a dummy variable that took on a value of 1 for missing information and 0 otherwise.

knowledge, we asked each project manager to indicate, for the knowledge transferred from each providing subsidiary: (1) "How well documented was the knowledge?" (1, "It was very well documented," to 7, "It was not well documented"); (2) "Was all of this knowledge explained to your team in writing?" (1, "All of it was," to 7, "None of it was"); and (3) "What type of knowledge came from this unit?" (1, "mainly reports, manuals, documents, self-explanatory software, etc.," to 7, "mainly personal practical know-how, tricks of the trade"). To compute the variable, we averaged the responses and then subtracted the mean from the values. The Cronbach alpha for this variable was .81. To test Hypothesis 8, we interacted the tacitness variable with the variable denoting the strength of dyadic transfer relations *(tacitness × transfer relation strength).*

Control Variables

Need to seek knowledge. We entered three variables to control for teams' need or inclination to seek knowledge outside their own subsidiary. First, a team engaged in tasks that depart significantly from its subsidiary's knowledge base may be more motivated to search outside than teams that can draw on their subsidiaries' existing knowledge. We measured the extent to which each team drew on its subsidiary's knowledge base via project managers' logs of the sources of the software and hardware used in their projects. The variable, *existing ware,* was the fraction of all the software and hardware used in a project that had already been developed and existed in the subsidiary to which the project belonged.

Second, we used a two-item scale to capture *project novelty,* the extent to which each project strayed from its subsidiary's technological and market expertise. Each project manager was asked, "Prior to this project, how much experience did your subsidiary have with the technologies and technical competencies that the project required?" and "Prior to this project, how much experience did your subsidiary have with the market for which the product was developed?" (1, "none of the required expertise," to 7, "all of the required expertise"). Answers to the two questions were averaged and then reversed the scale so that a high value indicated a relatively novel project (α = .66).

Third, because prior research has shown that team members' tenure negatively affects the probability of their seeking outside help (e.g., Katz & Allen, 1988), we included *team tenure,* a variable denoting the average number of years individual team members had been with the company. Because this information was incomplete for 23 out of the 121 projects, we also included a dummy variable that took on a value of 1 if this information was incomplete and 0 otherwise.

Search and transfer controls. Because it is possible that projects with many engineering-months available have more capacity to search, we used two control variables: a project's total number of engineering-months (in hundreds of months), as estimated at the beginning of the project *(project total engineering-months)* and the budget (in millions of dollars) at the start of the project *(project budget).*

We also wanted to control for the amount of knowledge sought in search and the amount of knowledge obtained during transfer. As we mentioned in the section defining search and transfer costs, knowledge obtained is a proximate measure for the benefits of transferring knowledge. Although we did not have measures of the amount of knowledge *sought,* we created a measure of the amount of knowledge *obtained* from other subsidiaries. Each project manager was asked to indicate the fraction of all his or her project's hardware and software that came from other subsidiaries (0, "no knowledge obtained," to 1, "all knowledge came from other subsidiaries"). In field interviews with project managers, we discovered that they kept close track of the amount of knowledge obtained, as this indicated the savings they could accrue and thus affected the amount of engineering hours required to complete the project. For software, for example, they would often keep track of lines of code that were provided by other subsidiaries. To compute this variable, we took the weighted average of the two fractions—one for hardware and one for software—and multiplied it by the total number of a project's budgeted engineering months. This variable, *amount of knowledge,* measured the *absolute* amount of engineering months represented by the knowledge obtained from other subsidiaries.[5]

Finally, we also controlled for each team's capacity to absorb the knowledge obtained from other subsidiaries. Because larger teams may have more

[5] Although we posit that the amount of knowledge obtained predicts search costs, it is reasonable to suspect that search costs, which may be an indication of search effort, also predict the amount of knowledge obtained. To control for this endogeneity problem, we analyzed two simultaneous equations, one specified as *search costs* = f (*amount knowledge*, all other independent variables), and one specified as *amount knowledge* = f (*search costs*, some other predictor variables). This test did not alter our results, and we are therefore reasonably confident that this type of endogeneity is not salient in our models.

skills and capacity for assimilating knowledge, we entered the variable *team size,* measuring the number of engineers spending at least 50 percent of their time working on a focal project *(team size).* For a second measure, *absorptive capacity,* we asked each project manager, "Prior to the project, did your project team have the expertise required to assimilate the knowledge that came from the other subsidiaries?" (1, "had very little of that expertise," to 7, "had very much of that expertise").

Statistical Approach

Because search and transfer costs were only relevant for those projects that sought and found knowledge, we excluded from the analysis of search and transfer costs those projects that did not seek knowledge.[6] Thus, although the analysis of whether teams sought knowledge included all 121 projects on which we obtained data, the analyses of search and transfer costs include only 55 and 50 projects, respectively. To ensure that the smaller sets of data for search and transfer costs were large enough for us to detect the expected effects, we calculated the statistical power and the effect size, and both tests showed that we had adequate sample size (Aiken & West, 1991; Cohen, 1988).[7]

In addition, because multiple project observations from the same subsidiary might not be independent, we used robust standard errors that corrected for subsidiary-specific clustering and used the robust clustering procedure as implemented in Stata 7.0 for all our models (Moulton, 1986; Rogers, 1993). We used logistic regression analysis to model whether a team in a focal subsidiary sought knowledge in one or more of the other subsidiaries and ordinary least squares (OLS) regression analysis to model the number of engineering-months spent on search and transfer. We performed tests to ensure that the OLS specification was appropriate for our data. The Kolmogorov-Smirnov test of normality revealed that the residuals were normally distributed in the OLS models. For an alternative specification, we also ran truncated regression models wherein the distributions of the search and transfer cost variables were presumed to be truncated at zero as there were no negative values. These models did not reveal any different effects and are thus not reported here.

RESULTS

Table 1 reports descriptive statistics, and Table 2 reports results pertaining to the three dependent variables. Models 1–3 in Table 2 report results on teams deciding whether to seek knowledge across subsidiaries. Model 2 shows that the within-team network density variable has a negative and significant effect on whether a team sought knowledge across subsidiaries, lending support to Hypothesis 1. As model 2 reveals, the effect for the average within-team relation strength variable is also negative but is only significant at the .10 level. To investigate further, we separated the two underlying dimensions of closeness and frequency underlying relation strength, as shown in model 3. The frequency dimension is negative and significant at the .01 level, lending support to Hypothesis 2.

Model 2 also reveals that intersubsidiary network size has a positive effect on whether teams sought knowledge across subsidiaries, lending support to Hypothesis 3. However, average intersubsidiary relation strength is not significant in model 2, and thus Hypothesis 4 is not supported.

Figure 2a reveals that the supported effects are of fairly substantial magnitudes.[8] For example, when within-team network density increases from 0.1 to 0.3, the likelihood that teams sought knowledge decreases from 0.62 to 0.31. In contrast, when intersubsidiary network size increases from 1 to 5, the likelihood of seeking knowledge increases from 0.28 to 0.59.

Models 4 and 5 in Table 2 report the results for search costs. As model 5 indicates, average inter-

[6] To control for this potential selection bias, we also ran a two-part logit model (Manning, Duan, & Rogers, 1987). In the first part, the dependent variable was whether teams sought knowledge. From this model, we calculated the predicted probability of each of the 121 teams seeking knowledge, *p (seek knowledge)*, and then entered this variable in the second part of the models for search and transfer costs. The results of this test revealed no selection bias.

[7] For a sample to be considered large enough to show expected effects, the statistical power of the analysis should be at least 0.8 (Aiken & West, 1991). In our analyses, statistical power was at a minimum 0.9 in all of the tested models. Furthermore, the effect sizes were greater than 0.35 and thus big enough to be considered large effects (Cohen, 1988). We therefore do not believe that there is any problem with the small samples for search and transfer costs.

[8] We computed the lines in Figures 2a and 2b by including the coefficient for the intercept and evaluating all other variables in a model at their mean values. On the basis of model 2, the two lines in Figure 2a are computed as follows:

$$\text{Prob.} = \exp^{y}/(1 + \exp^{y-6.34 \times \textit{within-team network density}}).$$

$$\text{Prob.} = \exp^{y}/(1 + \exp^{y+0.32 \times \textit{intersubsidiary network size}}).$$

TABLE 1
Descriptive Statistics for Sought Knowledge, Search, and Transer Costs[a]

Variables	Mean	s.d.	Minimum	Maximum	1	2	3	4	5	6	7
1. Sought knowledge	0.45	0.50	0.00	1.00							
2. Search costs[b]	4.39	5.17	0.10	15.00							
3. Transfer costs[c]	7.94	9.90	0.10	40.00		.70***					
4. Existing ware	0.45	0.31	0.00	1.00	−.40***	−.05	−.16				
5. Project novelty	3.12	1.55	1.00	7.00	.20*	.05	.06	−.40***			
6. Budget	1.85	4.66	0.09	45.20	.20*	.39**	.50***	−.17†	−.01		
7. Project total engineering-months	0.80	2.31	0.10	24.00	.20*	.32*	.50***	−.20*	.01	.90***	
8. Team tenure	14.13	5.47	0.10	31.00	−.04	−.26†	−.15	.01	−.04	−.03	−.18*
9. Team size	5.40	2.39	2.00	11.00	.07	.16	−.04	−.03	−.03	.10	.05
10. Amount of knowledge obtained[b]	25.00	53.4	0.43	306.00		.41**	.50***	−.25†	.02	.80***	.90***
11. Absorptive capacity[b]	4.37	1.87	1.00	7.00		−.22	−.01	−.01	−.22	.10	.19
12. Tacitness of transferred knowledge[c, d]	3.26	1.16	1.33	6.00		.33*	.17	.11	−.15	.08	.07
13. Within-team network density	0.09	0.14	0.00	1.00	−.20*	.06	−.19	.07	−.14	−.07	−.14
14. Average within-team relation strength	2.55	1.46	1.00	5.50	−.17†	.11	−.17	−.03	−.10	−.05	−.04
15. Intersubsidiary network size	5.60	2.95	1.00	14.00	.27**	.17	.17	.09	.21*	.26**	.18†
16. Average intersubsidiary relation strength	4.09	1.26	2.18	7.00	.06	.09	−.04	−.30***	−.04	−.05	−.05
17. Direct contacts' average perceived competition[b]	3.06	1.21	1.00	5.00		.26†	.18	.27*	−.28*	.01	−.06
18. Focal subsidiaries' average perceived competition	2.58	.97	1.00	6.00	.09	−.06	.02	−.09	−.10	−.15	−.11
19. Providers' perceived competition[c]	1.95	1.79	1.00	6.30		.02	.14	.12	−.18	−.01	.09
20. Dyadic transfer relation strength[c, d]	3.84	2.38	0.00	7.00		−.07	−.10	.02	−.28*	.10	.16
21. Tacitness × transfer relation strength[c]	11.57	9.92	0.00	39.69		.12	−.25†	−.26†	−.03	−.01	.03

[a] Unless otherwise stated, $n = 121$.
[b] $n = 55$ as only 55 teams entered the search process.
[c] $n = 50$ as five observations with missing information on transfer costs are omitted.
[d] Mean-deviated (precentered mean, s.d., minimum, and maximum are shown).
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

subsidiary relation strength has a positive and significant effect on search costs, supporting Hypothesis 5. The variables for the competition effects on search costs were also entered in model 5, and they show that the extent of competition perceived by direct contacts has a positive and significant effect. That is, if subsidiaries with which a team had established relations perceived the relationships to be competitive, the team's search costs increased. These findings support Hypothesis 6.

It is also interesting to note that the two powerful predictors of whether a team sought knowledge—within-team network density and intersubsidiary network size—are not significant predictors of search costs. Those factors that explain whether a team sought knowledge do not explain the costs of search.

The variables pertaining to Hypotheses 7 and 8, which concern transfer costs, were entered in models 6 and 7 in Table 2. The coefficient for the providing subsidiaries' perceived level of competition (providers' perceived competition) is significant and positive, indicating that a team's transfer costs increased to the extent that the providing subsidiaries saw the subsidiary in which the team

8	9	10	11	12	13	14	15	16	17	18	19	20
−.30**												
−.10	.13											
.29†	−.08	.10										
−.11	.01	.18	−.18									
.28**	−.30**	.01	−.01	−.13								
−.18†	.27**	.06	−.01	−.04	.40***							
−.21*	.17†	.20	−.18	−.10	−.08	−.11						
.06	−.05	−.18	.14	.04	.07	.27**	−.25**					
.11	−.07	−.09	−.09	.27*	.03	−.17†	.04	−.08				
.02	.10	−.19	.14	.07	.02	.08	.15	.04	.20			
−.08	.11	.14	.30*	.11	−.36*	−.11	−.15	−.04	−.13	.50***		
.16	.25†	.14	.26†	.17	−.13	.14	−.15	.20	−.29*	.15	.40***	
−.23	.02	.01	.18	.05	.30*	.10	−.18	.35**	−.10	−.07	−.06	−.15

was located as a competitor. This result supports Hypothesis 7. Figure 2b shows the magnitude of the effect: for example, when providers' perceived competition increases from 1 to 4 on the seven-point scale, a focal team's transfer costs go up by 4.8 engineering-months, which is a substantial jump, given that these teams spent an average 8 engineering-months on transfer.

Interestingly, as model 7 shows, the other two competition variables are not significant in the transfer models. Whether a focal subsidiary perceives relationships to be competitive (focal subsidiary's average perceived competition) has no impact on transfer costs, nor does the level of competition perceived by the total set of direct contacts in a team's intersubsidiary network. Thus, the competition variables affect the three dependent variables in different ways: while they have no effect on whether a team sought knowledge, only direct *contacts'* perceptions of competition increased *search* costs, whereas only *providers'* perceptions of competition increased *transfer* costs.

Model 7 in Table 2 also reveals that the interac-

TABLE 2
Results from Regression Analysis[a]

Dependent Variables	Model 1: Sought Knowledge	Model 2: Sought Knowledge	Model 3: Sought Knowledge	Model 4: Search Costs	Model 5: Search Costs	Model 6: Transfer Costs	Model 7: Transfer Costs
Intercept	0.11 (1.21)	0.52 (2.76)	0.03 (2.81)	6.37 (3.41)	−13.10 (10.3)	7.27 (5.14)	−12.06 (10.97)
Control variables							
Existing ware	−2.76 (1.04**)	−3.97 (1.50**)	−4.16 (1.53**)	0.62 (3.20)	3.16 (4.56)	−1.28 (3.48)	−8.17 (7.22)
Project novelty	0.02 (0.15)	−0.18 (0.21)	−0.13 (0.21)	0.28 (0.55)	0.93 (0.42*)	0.30 (1.15)	0.71 (1.16)
Budget	0.13 (0.00)	−0.03 (0.00)	−0.02 (0.00)	0.54 (0.00*)	0.35 (0.00)	0.71 (0.00)	0.41 (0.00)
Project total engineering-months	0.43 (0.01)	0.62 (0.00)	0.74 (0.00)	−0.77 (0.01)	−0.27 (0.01)	−1.82 (0.02)	0.10 (0.01)
Team tenure	0.04 (0.01)	0.08 (0.04†)	0.10 (0.04†)	−0.19 (0.13)	−0.23 (0.14†)	−0.14 (0.15)	−0.09 (0.20)
Team size	−0.03 (0.11)	−0.06 (0.16)	−0.04 (0.16)	0.09 (0.25)	0.34 (0.41)	−0.25 (0.32)	−0.73 (0.69)
Amount knowledge				0.02 (0.04)	0.03 (0.04)	0.13 (0.16)	0.03 (0.11)
Absorptive capacity				−0.46 (0.43)	−0.39 (0.49)	0.13 (0.48)	1.10 (0.73)
Tacitness of transferred knowledge[b]							1.59 (1.10)
Within-team network							
Within-team network density		−6.34 (3.13*)	−6.34 (3.13*)		2.52 (10.97)		−13.39 (16.70)
Average within-team relation strength		−0.47 (0.29†)			0.31 (1.70)		0.48 (1.20)
Average within-team closeness			0.11 (0.20)				
Average within-team frequency			−0.83 (0.30**)				
Intersubsidiary network							
Intersubsidiary network size		0.32 (0.10***)	0.32 (0.10***)		0.21 (0.28)		0.91 (0.61)
Average intersubsidiary relation strength		0.08 (0.23)	0.05 (0.25)		1.60 (0.75*)		1.71 (1.58)
Direct contacts' average perceived competition					1.86 (0.43***)		1.80 (1.43)
Focal subsidiaries' average perceived competition		0.17 (0.30)	0.21 (0.30)		−0.06 (0.38)		−0.51 (1.33)
Transfer network							
Providers' perceived competition							1.70 (0.83*)
Dyadic transfer relation strength[b]							−1.78 (0.67*)
Tacitness × transfer relation strength							−1.48 (0.50**)
Type of analysis	Logit	Logit	Logit	OLS	OLS	OLS	OLS
n	121	121	121	55	55	50[c]	50[c]
Likelihood-ratio chi-square test[d]/F		22.30***	5.01*	12.37***	230.41***	5.03**	69.49***
Pseudo-R^2/R^2	0.18	0.31	0.34	0.28	0.46	0.29	0.61

[a] Dummy variables denoting missing information on total engineering-months and team tenure are not shown. All models shown with robust standard errors.
[b] Mean-deviated.
[c] Five observations are omitted owing to missing information on transfer costs.
[d] Compared with previous model.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$
Two-tailed tests for variable coefficients.

FIGURE 2a
Plot of Effects for Sought Knowledge

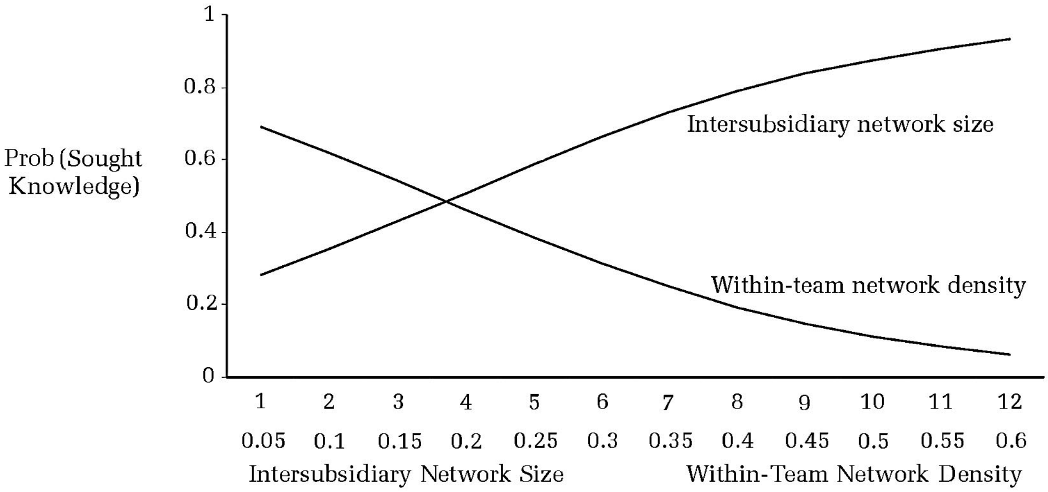
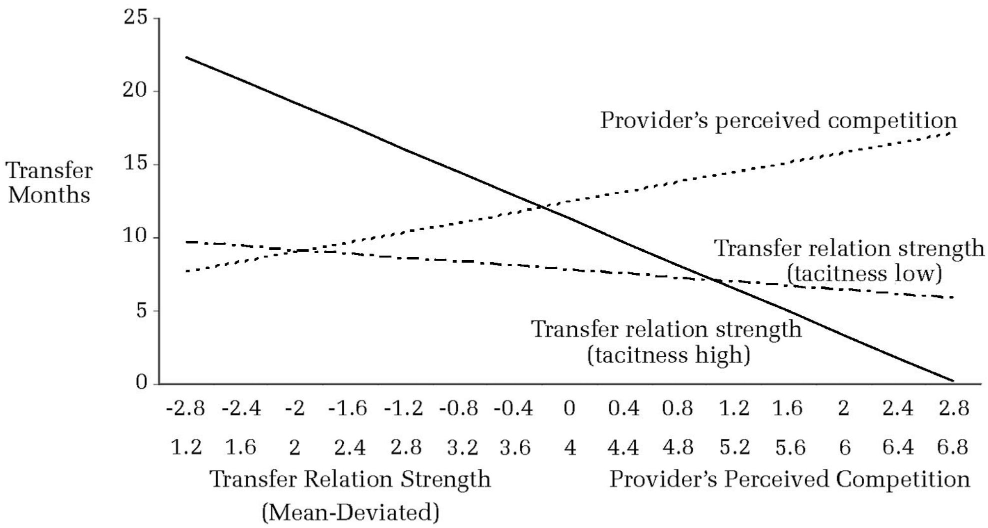


FIGURE 2b
Plot of Effects for Transfer Costs



tion effect including the tacitness and dyadic transfer relation strength variables is negative and significant, supporting Hypothesis 8. As the tacitness of the knowledge being transferred increased, an increase in the strength of the established relation between a team and the providing subsidiaries reduced the number of engineering-months spent on transfer. As Figure 2b shows, having strong established relations was especially beneficial when highly tacit knowledge was involved.[9]

Finally, model 7 in Table 2 also shows that properties of the within-team network that affected whether teams sought knowledge (that is, the density and strength of relations) and the properties of the intersubsidiary network that affected search costs (i.e., contacts' perceived competition and

[9] The lines in Figure 2b that involve tacitness were computed with results from model 7 in Table 2, evaluating the variables except dyadic transfer relation strength and the tacitness of transferred knowledge at their mean values: *transfer costs* = $-1.78 \times$ *dyadic transfer relation strength* + $1.59 \times$ *tacitness* $- 1.48 \times$ *tacitness* $\times$ *transfer relation strength,* where "tacit low" means that tacitness is –0.5 standard deviations below the mean (i.e., $-.74$), and "tacit high" means that tacitness is $+1$ s.d. above the mean (i.e., $+1.47$).

strength) have no significant effects on transfer costs.

DISCUSSION AND CONCLUSION

The main finding of this study is that teams' different subsets of networks to a large extent affected the outcomes of the three phases of deciding to seek knowledge, incurring search costs, and incurring transfer costs in different ways. The within-team network variables denoting the density and frequency of relations reduced the probability of seeking knowledge across subsidiaries but did not affect search and transfer costs. The intersubsidiary network variable capturing network size increased the probability of seeking knowledge, whereas intersubsidiary relation strength and degree of perceived competition increased search costs but did not affect transfer costs. And the variable denoting the degree of perceived competition in a team's transfer network increased transfer costs, whereas relation strength in a transfer network reduced transfer costs when transfers involved highly tacit knowledge. These effects would have been masked had we not distinguished between the three phases of knowledge sharing and decomposed teams' networks into three distinct subsets.

Before we discuss the implications of these findings, it is worth acknowledging some limitations of our study. Because we studied only one company, we cannot claim that these results would necessarily hold for all organizations. In particular, the company we studied relied quite extensively on informal relations among employees to accomplish work, implying that relational properties played an especially important role in knowledge sharing here. Other mechanisms for knowledge sharing, including reliance on headquarters' coordination and transfer prices between subsidiaries, played relatively small roles in this company, yet they may be important mechanisms in different settings.

The company we studied was also characterized by a fairly cooperative culture in which new product developers frequently helped one another. Teams in other companies that actively encourage competition may experience outright rejection of requests for knowledge and strong resistance to transfers, which will raise search and transfer costs over what the teams in our setting incurred. This bias may be in a conservative direction, however: even though we studied an organization with a fairly cooperative culture, we still found strong effects for the competition variables, which may have an even more pronounced effect in organizations with highly competitive cultures.

Although these limitations suggest that some caution is needed in interpreting the findings, our study provides new insights into the process of knowledge sharing in organizations.

Emphasizing the Role of Competition in Knowledge Sharing

An important finding in our study is the positive and significant effect of perceived competition on both search and transfer costs. Although scholars have noted that employees often hoard knowledge (e.g., Davenport & Prusak, 1998), the mechanisms contributing to such reduced motivation to provide knowledge have not been elucidated. Our findings suggest that hoarding may in part be a result of perceived competition between users and potential providers of knowledge and that such competition is likely to vary across pairs of providers and users. The findings suggest that employees are not necessarily predisposed to hoarding knowledge; rather, their tendency to do so can be explained by interunit patterns of competition in an organization.

Furthermore, our results indicate that it matters *who* perceives competition: for search and transfer costs, it is the perceptions of the *direct contacts* in a focal actor's network and *not* the perception of the focal actor that matter. This pattern makes intuitive sense: If direct contacts perceive the searching actor to be a competitor, they are likely to be less cooperative and are more likely to hoard their knowledge or even refuse to cooperate at all, irrespective of the perceptions of the focal actor.

One implication of our findings is that research on knowledge sharing needs to address the possibly negative aspects of competition in interunit relations (cf. Tsai, 2002). This implication opens up several avenues for new research. For example, while we treated the extent of perceived competition as an exogenous variable, it may be endogenous to the process of knowledge sharing. Two units that share knowledge may, over time, begin to develop similar products and services for similar markets because they increasingly rely on the same knowledge base and ideas. This convergence, in turn, may make the relationship more competitive, triggering a process of avoiding competitive relations and forming new interunit relations to exchange knowledge (cf. Galunic & Eisenhardt, 2001). Knowledge sharing and the formation of, and possibly dissolution of, interunit relations thus coevolve in such a competitive landscape (Koza & Lewin, 1999). Although our data were cross-sectional and hence we could not disentangle these intertemporal processes, in subsequent studies researchers could use longitudinal data to analyze when knowledge sharing increases perceived competition in interunit relations and how perceived competition affects the formation and dissolution of such relations.

Multiple Networks, Multiple Phases of Knowledge Sharing

The most important implication of our findings is that research on knowledge sharing needs to fully incorporate the *phase level* of knowledge sharing in an organization and the *subset level* of social networks in order to advance a robust theory of knowledge sharing. We are not the first to conceive of knowledge sharing as consisting of multiple phases, yet our approach here represents a broader view than other perspectives. For example, although Szulanski (1996) considered various steps of knowledge *transfers,* including initiation, implementation, ramp-up, and integration of transfers, we go beyond transfer by also including the "front end" of knowledge sharing—the decision to seek knowledge in the first place, and the search process.

Despite the attention researchers have paid to different subsets of networks, such as within-team and extrateam subsets, little research compares different subsets of networks and analyzes their different impacts on various phases of knowledge sharing. Our results suggest this scarcity has impeded further insights into how and why actors share knowledge across subunits in an organization. To illustrate, consider existing work on the strength of relations and knowledge transfers. Researchers have shown that transfers of knowledge—especially tacit knowledge—between a providing and receiving unit is facilitated to the extent that the two parties have a strong established relation (Hansen, 1999; Szulanski, 1996; Uzzi, 1997). From this research one might conclude that high average relationship strength will improve knowledge sharing in an organization. Our results indicate that this hypothesis is incorrect and that it depends on the particular phase of the knowledge-sharing process being studied and which subsets of networks are being considered. Specifically, our results revealed that high average relationship strength in within-team networks led to fewer knowledge seeking attempts across subsidiaries and, thus, fewer intersubsidiary knowledge-sharing events. High average relation strength in the intersubsidiary network was also linked to higher *search costs* than low average relation strength, whereas our results validated the prediction that strong relations in a transfer situation facilitate the *transfer* of tacit knowledge. These findings provide a more nuanced perspective on the effects of relation strength on knowledge sharing that would not emerge from studying the transfer process only (measured by the number of engineering months spent on search). These findings also validate and refine results reported by Hansen (1999): while that study advanced the argument that weak interunit ties facilitate search but undermine the transfer of tacit knowledge, it had no direct measures of search and transfer outcomes but only an analysis of project task outcomes in the form of completion time. Results reported here show that weak ties (i.e., low average relation strength) benefited search by reducing search costs, while strong ties helped transfer by reducing transfer costs (that is, engineer months spent on transfer), verifying Hansen's (1999) earlier argument by measuring search and transfer costs separately.

Our results also showed that the network size has different impacts at the within-team and intersubsidiary levels of analysis. Specifically, whereas the density of relations *inside* a team decreased the likelihood that it would seek knowledge, the size of a team's network *across* subsidiaries increased this likelihood. That is, established relations at the *team* level countervailed established relations at the *subsidiary* level. This finding casts new light on research that has examined the effects of relational properties on the extent of interunit knowledge sharing and communication (Gupta & Govindarajan, 2000; Szulanski, 1996; Zander & Kogut, 1995). It is not necessarily the absolute number of established interunit relations that explains why organization members share knowledge but, rather, the *relative* number of within-team and interunit relations. For example, even though some teams in our data set had very high numbers of intersubsidiary relations (e.g., nine, which is more than one standard deviation above the mean level), a very high within-team network density (e.g., 0.60) would offset the positive effect of such a high number of intersubsidiary relations on the probability of seeking knowledge across subsidiaries.

This emphasis on the relative numbers of within-team and interunit relations raises the issue of how they relate to each other. Because we did not analyze the formation of relations, we cannot predict whether the existence of within-team relations crowds out the interunit ones (and vice versa), although this may not have been the case in our data set, as the correlation between within-team network density and intersubsidiary network size was low (–.08). Given that the time and energy that can be devoted to building and maintaining relationships may be constrained, however, we can speculate that within-team relations may come at the expense of the development and maintenance of interunit relations. If managers see developing and maintaining relations among members *within* a unit, such as a team, as a good practice and encourage it (cf. Ghoshal, Korine, & Szulanski, 1994), such a management practice may inadvertently negatively affect knowledge sharing across the organization to the extent that it leads to fewer interunit relations and thus fewer knowledge-sharing events (cf. Ghoshal & Bartlett, 1990).

In conclusion, our study shows that the problem of knowledge sharing can be usefully conceptualized as consisting of three phases that to a large extent are affected by an actor's different subsets of social networks in an organization. As the various effects of the degree of perceived competition, relation strength, and network size illustrate, disentangling interunit knowledge sharing into the three distinct phases of deciding to seek knowledge, searching, and transferring can yield significant new insights into how network variables govern the occurrence and effectiveness of knowledge sharing in organizations. By adopting a multiple network perspective on knowledge sharing, researchers can gain a fine-grained understanding of how different subsets of an actor's relations in an organization contribute to knowledge-sharing behaviors and outcomes.

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