Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

Lost in transition: knowledge acquisition and knowledge loss in interpersonal exchanges

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Abstract

In this paper, we focus on two distinct dimensions underpinning the effectiveness of knowledge transfer in organizations: ease of knowledge acquisition, and amount of knowledge loss. In particular, considering 3,429 knowledge-sharing ties among 313 employees in a data solution company we explore the determinants of ease of acquisition and loss of knowledge in terms of specific features of individuals? network of contacts. Results indicate that while frequent interactions facilitate knowledge acquisition and reduce the amount of knowledge lost in interpersonal exchanges, interacting with a diverse set of contacts facilitates knowledge acquisition but increases, at the same time, the amount of knowledge lost. Frequency of interaction further moderates the relationship between diversity of contacts and knowledge loss. By observing a ?cost? to diversity of contacts in terms of lost knowledge, we suggest that more attention should be paid not only to the advantages, but also to the liabilities of different network positions when they are used as mechanisms to explain effective knowledge transfer among individuals.

Jelcodes:D83,D85

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INTRODUCTION

Effective knowledge transfer in organizations is considered a relevant pre-condition for firms' ability to achieve competitive advantage (Argote & Ingram, 2000; Szulanski, 1996). In either manufacturing firms (Epple, Argote, & Murphy, 1996), or service firms (Baum & Ingram, 1998; Darr, Argote, & Epple, 1995; Hansen & Haas, 2001; Mors, 2010), for the generation of innovations (Dahlander & Frederiksen, 2012; Fleming, Mingo, & Chen, 2007; Hansen, 1999; Tortoriello & Krackhardt, 2010), or to increase individuals' creativity and innovative potentials (Gruber, Harhoff, & Hoisl, 2013; Kleinbaum & Tushman, 2007; Perry-Smith, 2006; Sosa, 2011), effective transfer of knowledge and expertise among individuals in organization matters.

Organizational literature on knowledge transfer has suggested that knowledge transfer occurs and that it is *often incomplete* (Argote & Ingram, 2000, p. 163) and extensive efforts have been devoted to understand the mechanisms underpinning the transfer process at different levels of analysis (Argote, 2012). However, while the majority of empirical research so far has invested in identifying and studying the enablers of successful transfer of knowledge (Argote, 2012; Borgatti & Cross, 2003; Darr et al., 1995; Reagans & McEvily, 2003), comparatively less attention has been devoted to what might make those transfers *incomplete*. This lack of attention to what restricts the amount of knowledge flowing from a source to a recipient reflects the tendency of much empirical work on knowledge management to treat knowledge transfer as a discrete phenomenon that either happens and it is observed through concrete performance outcomes, or that does not happen at all. For instance, since measuring knowledge transfer is hard, researchers have often considered objective performance outcomes as key dependent variable, and inferred knowledge transfer as the theoretical mechanism linking knowledge exchanges and performance (Fleming et al., 2007; Hansen, 1999). In those instance in which scholars have tried to measure knowledge transfer treating it as the dependent variable of the study (Reagans & McEvily, 2003, 2008; Tortoriello, Reagans, & McEvily, 2012) they focused on the ease of transfer/acquisition as a function of the sender/recipient position in the overall patterns of knowledge flows without questioning the possibility that knowledge exchanges, whether smooth or difficult, could be at least in part incomplete. And, in those cases in which researchers have focused explicitly on the impediments to successful transfer of knowledge identifying different drivers of friction, or stickiness of knowledge (Ghosh & Rosenkopf, 2014; Hansen & Haas, 2001; Szulanski, 1996), the implications of these impediments in terms of actual loss of knowledge in dyadic exchanges have not been directly examined.

In this paper we focus on two important dimensions of the knowledge transfer process which have been treated interchangeably by past research: ease of knowledge acquisition, and amount of knowledge loss in interpersonal exchanges. If we consider the system of knowledge exchanges defined among individuals as a web of pipes through which knowledge and information flows, incomplete transfers of knowledge would occur to the extent that some of those pipes are "leaky". In case of a leaky pipe, in fact, much of the knowledge to be transferred would still make it from the source to the recipient, but part of it would get lost during the transfer phase. Our contention in this paper is that past research on knowledge transfer has developed under the tacit assumption that no leaky pipes exist and, as a result, once on its way, all of the knowledge that A transfers to B will successfully reach its destination. Our objective is to challenge this view by explicitly identifying knowledge loss as an important phenomenon that has received to date only limited attention from knowledge management scholars. In particular, our goal is to introduce and study the concept of knowledge loss and to focus on its relationships with other more established constructs in knowledge management research such as knowledge transfer and properties of the network structure (Argote, McEvily, & Reagans, 2003). To do that, we consider in our theoretical development and empirical analysis two distinct dependent variables: the ease of knowledge acquisition *and* the amount of knowledge lost in dyadic knowledge-sharing interactions.

In particular, considering 3,429 knowledge sharing ties among individuals in a large data solution company we observe that while frequent, repeated interactions among two parties ease the acquisition of knowledge and reduce the amount of knowledge lost, the diversity of knowledge sharing partners eases the acquisition process but *increases*, at the same time, the amount of knowledge lost in interpersonal exchanges. Our analysis further shows that the positive association between diversity of contacts and knowledge loss is reduced when the frequency of interaction with diverse contacts is taken into account; i.e. having a diverse network of contacts with whom one interacts unfrequently increases the loss of knowledge whereas having a diverse network of contacts with whom one interacts frequently reduces the amount of knowledge loss.

THEORY

Knowledge transfer, ease of acquisition and knowledge loss

Prior research on knowledge transfer tends to treat successful sharing of knowledge as a binary outcome that either occurs completely or does not occur at all. While some scholars have touched upon potential reasons for difficulties in transferring knowledge, such as knowledge complexity (Szulanski, 1996) knowledge tacitness (Nonaka, 1994), unwillingness or inability to transfer knowledge (Reagans & McEvily, 2003), these problems are usually examined indirectly by looking at factors that drive success (Hansen, 1999). Consequently, extant research has primarily focused on the antecedents of *successful* transfer and/or factors *facilitating the sharing* of knowledge between a source and a recipient (Argote, 2012; Borgatti & Cross, 2003; Darr et al., 1995; Reagans & McEvily, 2003) without explicitly considering the case of *incomplete* transfers of knowledge, meaning, specific instances in which some parts of the knowledge are successfully transferred from a source to a recipient, while some other parts are lost in the process. This lack of attention to knowledge loss and its drivers can at least in part be attributed to how knowledge transfer has been conceptualized and captured empirically in previous studies. For instance, since knowledge transfer has been defined as a "change in a recipient unit's knowledge/performance" (Argote & Ingram, 2000, p. 151; Van Wijk, Jansen, & Lyles, 2008), to the extent that any positive effect on the recipient level of knowledge and/or performance is observed, the transfer of knowledge is considered successful. Indeed, given the conceptualization of knowledge transfer as a change in a recipient's knowledge/performance level, it is theoretically possible that even when *most* of the knowledge gets lost in the sharing process, if *some* effect on the recipient's performance and/or level of knowledge is observed, successful transfer is assumed. This approach leaves knowledge loss not only unobserved but theoretically un-acknowledged.

And yet, there are logical reasons to expect that knowledge loss can be a more common and pervasive phenomenon than what implied by past research. As noted by Ghosh and Rosenkopf (2014) the metaphor of network as pipes through which knowledge flows, has probably contributed to take too far the assumption according to which knowledge flows between a source and a recipient is in fact unrestricted. Instead, they argue, "frictions" are likely to exist in dyadic relationships that preclude complete knowledge transmission from a source to a recipient. For instance, even when a source and a recipient are perfectly willing and able to share what they know with each other (Reagans & McEvily, 2003) some loss of fidelity during the transfer process could easily occur because of unintentional errors, language diversity, or inherent knowledge complexities. Research that has examined the ease of knowledge transfer among individuals (i.e. focusing on the process rather than the outcome of transfer) does not speak to the possibility of incomplete transfers either. For instance, although in their studies of knowledge transfer in an R&D service organization, Reagans and McEvily (2003) acknowledge that some types of knowledge might be more difficult to share than others, they do not explicitly take loss of knowledge into account. So, if the only variable considered is the ease or difficulty of sharing knowledge, short of assuming that ease of transfer is a proxy for how complete the transfer of knowledge is (for instance assuming that easy sharings of knowledge result in complete transfers while difficult ones in complete losses of knowledge), knowledge loss can happen and still go undetected.

Whether looking at objective outcomes presumed to be the result of successful transfer, or at the ease of knowledge transfer itself, existing research has not yet taken into account the possibility that some knowledge sharing interactions might result in incomplete transfers of knowledge. An important implication of this fact is that we know very little about *what* determines losses of knowledge when knowledge is flowing from a source to a recipient and how to reduce these unintended losses.

From a theoretical standpoint, there are several reasons why knowledge transfer can happen *and* be incomplete at the same time. For example, individuals could (a) be limited with regard to resources in terms of time and attention devoted to specific interactions, (b) lack common language or mutual knowledge with others, or (c) have cognitive limitations in terms of understanding and processing all the knowledge received. The issue of time and attention stems from the fact that the higher the number of connections to be maintained, the lower the amount of time that can be spent with each (Ahuja, 2000). The common language or knowledge overlap issue could arise in the contexts of interactions among individuals assigned to different units or functions which tend to have different (technical) languages or understandings of the same situation (Bechky, 2003; Carlile, 2002, 2004; Dougherty, 1992; Tortoriello & Krackhardt, 2010). Having a different understanding of a common problem or a different interpretive scheme of the challenges faced or the type of knowledge required will increase the likelihood that colleagues do not get *everything* their counterpart are trying to convey because they are hailing from different functional backgrounds, or different business units that rely on substantively different technical languages. Individuals' cognitive limitations suggest similar problems and lead into the discussion of boundary spanning roles (Hargadon & Sutton, 1997; Obstfeld, 2005), and the mutual knowledge problem (Carlile, 2002, 2004; Cramton, 2001).

To address these issues, we argue that the amount of knowledge lost in the communication process is primarily a function of the particular knowledge-sharing relationship that exists between a source and a recipient and of the system of relationships in which this connection is embedded. For example, there could be structural properties of a network that might result in greater (smaller) levels of loss when knowledge gets passed from a source to a recipient, so that loss could be a function of specific features of the focal relationship between two individuals, and, of the network context in which this relationship is embedded.

Understanding the drivers of knowledge loss has important implications for achieving a more fine-grained understanding of knowledge sharing processes. For instance, without knowing how much knowledge gets lost in any specific interaction, it is hard to judge how beneficial a given interaction really is. If the objective of knowledge sharing is to increase creativity by bringing together different knowledge reservoirs (Argote & Ingram, 2000), losing a great portion of the knowledge transferred might not be an issue because "some" new knowledge can still be enough to spark new ideas and trigger innovation. However, if the objective is the implementation of an innovation or the solution of a complex technical problem, every bit of knowledge counts and even minimal losses might compromise the ability to replicate solutions developed somewhere else (Darr et al., 1995).

To study those instances in which knowledge transfer does happen while, at the same time, is incomplete, we propose to investigate the properties of the knowledge sharing relationships defined among individuals in an organization. Consistent with recent studies in this area of research (Reagans & McEvily, 2003, 2008; Tortoriello et al., 2012) we focus on frequency of interactions, as well as on the diversity of connections among individuals as potentially relevant drivers of the knowledge sharing process. In addition to that, we jointly consider the effects of frequency of interactions and diversity of connections on both the ease of knowledge acquisition and, on the amount of knowledge loss in interpersonal exchanges.

Frequency of interaction, ease of knowledge acquisition and knowledge loss

Recent research on informal networks and knowledge management provides evidence for the fact that frequent interactions between two individuals facilitate the knowledge-sharing process (Reagans & McEvily, 2003, 2008). From a theoretical standpoint one of the main driving mechanisms behind the ease of knowledge transfer associated with frequent interactions is the greater willingness of the parties involved to engage in extra-effort during the transfer process. Sharing knowledge, in fact, is a costly activity that requires time and effort for both the provider and the recipient. On the one hand, the provider of knowledge has to devote time and effort to communicate what he/she knows to the recipient and, on the other hand, the recipient has to be willing to engage in the exchange process by taking the newly provided knowledge into account, translating and adapting it to his/her specific context. This greater motivation to be of help and assistance brought about by frequent interactions (Granovetter, 1982: 113) supports and facilitates the sharing of knowledge among individuals (Hansen, 1999).

Following this line of reasoning, frequent interactions should also help to reduce the amount of knowledge that might get lost during the knowledge sharing process. For instance, two individuals who interact repeatedly tend to develop heuristics, common languages, and common knowledge that facilitate their ability to interpret and understand each other (Uzzi, 1997). Without the adoption of a common language and the development of shared understandings, individuals might be using different terms to refer to the same thing, and/or use the same term to indicate different things (Bechky, 2003; Dougherty, 1992). In either case, communication problems of this kind might end up multiplying the opportunity for misunderstandings, thus increasing the likelihood that important parts of knowledge would be lost in the communication process. Frequent and repeated interactions among individuals lead to the formation of a common language and a shared knowledge base between the parties involved. A common language and a shared knowledge base not only reduce possible ambiguities and margins of errors but, at the same time, facilitate the complete and accurate transfer of knowledge from a sender to a recipient.

Another relevant aspect of repeated and frequent interactions between a sender and a recipient of knowledge is the increase in the depth of the relationship, the greater familiarity between the parties involved and eventually the creation and development of trust about each other's motives and intentions (McEvily, Perrone, & Zaheer, 2003). Familiarity and trust can further facilitate the solution of possible misunderstandings and doubts that might arise during the sharing process (Levin and Cross, 2004). In fact, asking a colleague for advice amounts to an act of deference toward the knowledge and expertise of this colleague which, particularly in highly competitive organizations, might have non-trivial costs in terms of status and reputation. For instance, evidence suggests that individuals might prefer to access and use knowledge provided by external experts to avoid unfavorable social comparisons implicit in the act of asking for help to internal organizational sources (Menon & Pfeffer, 2003). This reluctance to show one's vulnerability by asking for knowledge to internal contacts is likely to affect knowledge loss in important ways. If the decision to ask an internal contact for knowledge is weighted against possible costs that this act entails in terms of status, asking repeatedly, for instance to clarify something that was not entirely clear the first time, becomes quite unlikely. If the fear of losing status in the eyes of a colleague acts as an impediment to follow-up and clarification questions required to dissipate doubts and to correct misunderstandings, the amount of knowledge lost when interacting with contacts inside the organization might become substantial.

Familiarity and trust generated by frequent interactions, however, facilitate access to the expertise of colleagues in the organization by reducing fears that asking and, if necessary, asking again, might translate into a negative evaluation of the knowledge seeker's competence or expertise. When familiarity and trust develop between two individuals, the knowledge-seeker will be more willing to show his "vulnerability" admitting what he/she does not know (Rousseau, Sitkin, Burt, & Camerer, 1998) and less concerned about possible negative implications of reiterated requests that might become necessary to dissipate doubts, to eliminate misunderstandings, and to ensure complete and accurate transfer of knowledge. Based on the foregoing arguments, and consistent with previous research on knowledge sharing, we predict that frequency of interaction will facilitate the understanding, and promote the assimilation, and absorption of knowledge transferred between a source and a recipient, and at the same time, will reduce the amount of knowledge loss in any given knowledge sharing interaction.

H1a: Frequency of interaction between two individuals will increase the ease of knowledge acquisition in knowledge sharing interactions

H1b: Frequency of interaction between two individuals will reduce the amount of knowledge lost in knowledge sharing interactions

Diversity of contacts, ease of knowledge acquisition and knowledge loss

In addition to the effects of the *depth* of relationships achieved through frequent interactions on the ease of knowledge acquisition and on the reduction of knowledge loss, previous research also suggested that the *breadth* of network relationships should also have a positive effect on the *ease* of knowledge transfer (Reagans & McEvily, 2003, 2008). When individuals occupy a network position that allows them to interact with a broad and diverse set of contacts, they are able, through these interactions, to span a variety of knowledge domains. This diversity of contacts, knowledge, and perspectives provides in turn the opportunity to develop a greater capacity for interaction with a broader set of people and for sharing knowledge (Hargadon & Sutton, 1997). For instance, the constant exposure to different sources of knowledge, languages, and mindsets "trains" individuals to develop special skills in terms of understanding, assimilating, and absorbing knowledge coming from different areas. By interacting with contacts that use different languages and that belong to different thought worlds, individuals become accustomed to frame the same problem in different terms. This increases an individual's capacity to translate knowledge and information in a way to be understood in different domains and it facilitates the application of that individual's knowledge in different contexts. This ability to translate knowledge and information in a language that can be understood by individuals who belong to different areas of expertise and have different knowledge backgrounds is an essential part of the knowledge sharing process (Bechky, 2003; Carlile, 2002; Dougherty, 1992). Occupying network positions characterized by breadth of interactions offers more frequent opportunities to cultivate theses skills and abilities than having a concentrated and redundant set of contacts within the same group of people. Consistent with these arguments, research has shown that breadth of interactions facilitates not only the transfer of knowledge (Reagans & McEvily, 2003) but also the acquisition of knowledge across formal organizational boundaries, where diversity of knowledge and impediments to sharing it tend to be greater (Tortoriello et al., 2012).

One aspect that has not yet been considered, however, has to do with the possible tradeoffs associated with having a broad and diverse set of contacts. Previous research suggests that individuals with a broad network of contacts should have a greater capacity to translate knowledge than those lacking such diversity of connections. However, the benefits of being invested in a wide-spread system of diverse network relationships might come at a cost. Having a wide-spread network facilitates interactions with a diverse set of contacts (Burt, 1992). Nevertheless, the efforts required to developing and maintaining this breadth of network connections might end up reducing the depth of knowledge exchanges that can be achieved in any specific interaction. If such a trade-off between breadth and depth of network connections exists (Aral & Van Alstyne, 2011), a middleman sharing knowledge with a diverse set of contacts can still successfully communicate with and share knowledge among different contacts thanks to his/her greater ability to communicate with individuals who belong to different knowledge domains. On average, however, the amount of knowledge he/she is able to acquire through each contact could be significantly reduced because of his/her lack of proficiency with any one knowledge domain. Using Simmel's metaphor of cosmopolitans vs. locals (Simmel, 1950), a cosmopolitan is better positioned to interact with people who speak different languages than a local is. Yet, in each of these interactions, a cosmopolitan will never achieve the depth of understanding that two locals can achieve when they interact with each other. In the context of knowledge sharing relationships inside organizations, someone with a lot of diverse connections might be able to interact, at a basic level, with colleagues of different knowledge background and expertise. However, his ability to capture (and convey) the knowledge acquired from (transferred to) colleagues with diverse knowledge backgrounds, would never reach the precision and accuracy with which two colleagues with the same knowledge and expertise can share knowledge with one another.

In their discussion of trade-offs associated with being a middleman between otherwise disconnected others, Reagans and Zuckerman (2008, p. 932) acknowledge that "gaining access to information does not mean that such information will actually be absorbed", for instance because an individual who is not part of a cluster might find it difficult to obtain "complex and sensitive information from clusters of which she is not a member". As a result, individuals with a diverse set of network connections might struggle to acquire relevant knowledge and end up capturing only a fraction of it. But even assuming that knowledge available in a given cluster will be made fully available to an individual acting as the bridge across different knowledge clusters, there is still the risk that he/she will not be proficient enough to capture it. This implies that individuals with a diverse set of contacts might end up losing a sizable amount of the knowledge they acquire during the sharing process. Becoming minimally proficient in different domains is a pre-condition to acquire and share knowledge acquired in those domains, however, not being knowledgeable enough in all of those domains might increase the amount of knowledge that is lost when two individuals try to share it.

Based on the foregoing arguments, we predict that a diverse network of contacts will facilitate the transfer of knowledge between a source and a recipient, but, will also, at the same time, increase the amount of knowledge lost in any given knowledge sharing interaction.

H2a: Having a diverse network of knowledge sharing interactions will increase the ease of knowledge acquisition

H2b: Having a diverse network of knowledge sharing interactions will increase the amount of knowledge lost

Diversity of network connections, frequency of interactions and knowledge loss

While individuals who cultivate relationships with a broad set of contacts might end up connecting with colleagues located in diverse knowledge domains, the frequency with which they interact with others located in different clusters might vary substantially across relationships. For instance, if we consider the ties through which a focal node has access to diverse clusters, it is reasonable to expect that not all those ties, bridging across different parts of the network, are equal. In particular, individuals' bridging ties are likely to differ from one another in terms of their strength, so that some bridging is done through (comparatively) more frequent interactions, while some bridging is done through (comparatively) less frequent interactions. This intuition is supported by recent research that has started to call into question the assumption that all bridging ties are equal (McEvily, Jaffee, & Tortoriello, 2012), and, more to the point, it is also consistent with past research according to which the strength of a bridging tie has been identified as a mechanism to facilitate knowledge transfer when knowledge is more difficult to share, for instance because of its tacit nature (Hansen, 1999). In particular, while bridging *per se* has traditionally been considered a necessary and sufficient condition for obtaining network advantages (Zaheer & McEvily, 1999), a more recent view suggests that bridging might be a necessary but not a sufficient condition to realize the benefits provided by access to diverse knowledge and novel information. For instance, Tortoriello and Krackhardt (2010), analyzing different types of bridging ties (i.e. simple, strong, and embedded) defined across several research and development laboratories in a multinational high-tech company, show that only a specific subset of those are conducive to the generation of innovations. Given the diversity of knowledge accessed through bridging ties, the ability to combine different sources of knowledge to generate innovation was found to be contingent upon the "embedded" nature of those bridges (i.e. Simmelian bridging ties).

The foregoing discussion suggests that the effects of diversity of contacts on knowledge loss should also be evaluated in the light of how frequently the focal actors interact with any given contact. In fact, while network diversity might amplify knowledge loss by increasing the amount of knowledge and information that leaks through network connections, the frequency of interactions through which this diverse network is build could partially moderate the positive effects that breadth of contacts has on knowledge loss. Accordingly, we predict that:

H3: Frequency of interactions will moderate the effect of network diversity on knowledge loss by reducing the amount of knowledge lost in knowledge sharing interactions

METHODS

For this study we surveyed 313 individuals working in a global data solution company, henceforth "Datacorp". Datacorp employs over 4,000 people in 50 different offices at different locations in the US and Europe and provides data solutions in terms of navigation maps, weather reports, optimal routes, etc. to a wide range of customers in the global transportation industry. With the help of senior executives at the company we identified 313 individuals who were involved in projects that were "strategically" relevant for the company. Survey participants vary considerably in terms of their seniority, level of education, gender, and job grade. About forty-six percent of participants (145) were located in the EU headquarter while the remaining fifty-four percent were located in the US headquarter (168).

After several extensive interviews with company's senior managers and company informants with different job grades from both the US and EU sites, we developed a survey questionnaire to measure knowledge sharing relationships among individuals in our sample. We pre-tested the survey tool for both method and content on six individuals who then would not participate in the actual data collection process. The knowledge sharing data was collected using a combination of name generating and name interpreting questions. More precisely, respondents were first presented an alphabetically ordered list of all the 313 study participants and asked to identify the names of those colleagues *"with whom they have worked on a project in the past two years, or, even if they have not directly worked with them on a project, colleagues who have been in the past two years an important source of knowledge or information for the work they do at Datacorp"*. Once respondents identified their contacts, they were then asked to describe the relationships with each cited contact in terms of communication frequency, ease of knowledge acquisition and knowledge loss.

The decision to focus on knowledge loss as a distinct dimension of the transfer process was corroborated by the fact that during our interviews, company informants, at middle and senior executive levels, constantly referred to difficulties in successfully sharing knowledge among individuals in the company. In particular, the interviewees put emphasis on the fact that most transfer attempts were not immediately helpful to knowledge recipients because these attempts were perceived as "incomplete". For instance, in the words of one of the company directors "Datacorp doesn't make it easy to communicate". Elaborating on this point, a sales director stated that since engineers did not have direct contact with customers but several steps mediated this relationship, there was a "loss of knowledge and information all the way down in the organization". Another sales director explained that many different parts of the organization are involved in the development of new products but that there is “no good way to share knowledge and information from customers and market information [throughout the organization]”. A total of 134 individuals (or about 43% of the study population) completed the entire survey. Given that the response rate we obtained is slightly lower compared to similar network studies, we conducted a number of tests to identify possible systematic differences between respondents and non-respondents. In particular, we conducted a series of t-tests to examine differences in terms of job grade, geographical distribution, size of the project, priority of the project, and being a project leader. Across all these dimensions we did not detect any statistically significant difference between respondents and non-respondents. On average, respondents identified approximately 25 contacts which is slightly greater than the number of contacts observed in similar studies. For example, respondents interviewed by Reagans and McEvily (2003) listed 16 contacts on average. The higher number of contacts in our study population could result from a number of factors, including the fact that individuals in our sample could choose from a list of 313 co-workers whereas in the case of Reagans and McEvily (2003) there were only 100 study participants.

The survey data was complemented with archival data provided by the company. Archival data allowed us to measure a number of individual characteristics, including each respondent’s assigned project, job grade, project leadership, organizational tenure, gender, and geographical location. Table 1 contains descriptive statistics and bivariate correlation for the variables presented below.

********* INSERT TABLE 1 about here **********

Dependent variables: knowledge acquisition and knowledge loss

Since we are interested in comparing the effects of frequency of interaction and knowledge diversity on ease of knowledge acquisition and amount of knowledge loss in interpersonal exchanges, we modeled our dependent variables at the dyadic level of analysis. Previous studies have argued that not all ties are equal for triggering the generation of creative ideas (Sosa, 2011), or for facilitating the acquisition (Tortoriello et al., 2012) and transfer of knowledge (Reagans & McEvily, 2003, 2008). Similarly, we were interested in capturing variation at the level of the specific interaction, since the same individual might be able to successfully obtain one hundred percent of the knowledge she receives from some of her contacts, while systematically losing substantial parts of the knowledge she receives from other contacts. In order to measure ease of knowledge acquisition and knowledge loss we took the perspective of the knowledge recipient and relied on her idiosyncratic assessment of how easy it was to acquire knowledge from her contacts, and what percentage of knowledge got lost in each of these interactions. One could have possibly considered the point of view of the knowledge provider as well, yet we reasoned that while the provider of knowledge could be in a position to assess how easy of difficult it was to communicate knowledge to a counterpart, it might be hard for the provider to also assess what part of the knowledge transmitted was understood and assimilated by the recipient and what part went lost in the process. Consequently, following studies using a similar dyadic set up (Sosa, 2011; Tortoriello et al., 2012), we opted for recipients' self-reported assessment of ease of knowledge acquisition and amount of knowledge loss in interpersonal exchanges. Although this measurement strategy raises the issue of which portion of variability is meaningfully comparable across individuals, and which portion is due to idiosyncratic differences of individuals' perceptions we reasoned that knowledge recipients are still the best judges of how easy or difficult it was to acquire knowledge from a counterpart, and of what part of the knowledge provided by a counterpart they effectively understood and retained and which part they couldn't get (or couldn't *entirely* get). Moreover, as detailed in the analysis section below, we took several steps to econometrically control for individuals' idiosyncratic variations that could add noise to our measurement strategy.

To capture dyadic level variation in the ease of knowledge acquisition we used a combination of items that mapped into different dimensions of successful acquisition of knowledge (Table 2). For each one of their contacts, respondents assessed the four items reported in Table 2 on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The four items loaded on a single factor with the first principal component explaining 75% of the variance. Factor loadings on the first principle component ranged from 0.8 to 0.91. Cronbach's alpha for the four items was 0.89. We used the average of the four items in Table 2 to define the level of successful knowledge acquisition although similar results are obtained using factor loadings instead of averages.

To capture dyadic level variation in the perception of knowledge loss, we relied on the respondent's assessment of the amount of knowledge that is perceived to be lost when interaction with her contacts. In particular, we asked participants the following question: "Sharing knowledge or information is important but difficult. On the one hand, it is important because it could help getting things done more efficiently or effectively. On the other hand, it is difficult because sometimes individuals use different terminology, or sometimes use technical language that is hard to understand, or simply because the content of their knowledge or information is often complex and inherently hard to transmit. As a result of these difficulties, some amount of knowledge or information might get "lost" when two individuals try to share it. *In your personal experience with the individuals listed below, what amount of knowledge or information "gets lost" in the sharing process as a function of diversity of terminology, use of technical language, and/ or complexity of knowledge or information transferred?"* Using a drop-down menu, respondents could answer this question by choosing among 11 different options for each one of their contacts. The options ranged from "0%: all of the knowledge and information is perfectly transferred" to "76-100%: most of the knowledge and information is lost in the process" with the possibility to identify different percentages of lost knowledge in-between these two extremes.

A tabulation of the answers obtained (Table 3) reveals that although the distribution is skewed toward limited perceived amounts of knowledge loss, over 75% of the dyads in our sample entail some amount of knowledge loss.

********* INSERT TABLE 2 & 3 ABOUT HERE **********

This is not only consistent with our theory about the importance and magnitude of the phenomenon, but also corroborates the indications emerged during our interviews with company informants who identified knowledge loss as a major issue preventing the effective circulation of knowledge and information within the company.

Explanatory variables

Frequency of interaction. In addition to the ease of acquisition and amount of loss of knowledge experienced in knowledge sharing interactions, respondents were also asked to describe how frequently they interacted with each cited contact. In particular, we captured communication frequency by asking the following question: "Please indicate how often you generally communicate with <name of the person> for knowledge or information on work-related topics".

Prior research has shown that frequency of interaction is an important component of the "strength" of a tie. Consistent with that, we used the relational assessment provided by respondents about how frequently they interacted with their contacts. This measure ranges between 1 (interact rarely, or less than once a month) and 5 (interact frequently, or multiple times per day). The values considered had an average of 2.31 and a standard deviation of 1.31.

Diversity of contacts. To measure diversity of contacts, we considered the structure of relationships that each individual has with his/her network of contacts. In particular, we relied on Burt's measure of effective size (Burt, 1992) which we computed using Ucinet VI (Borgatti, Everett, & Freeman, 2002). Conceptually the effective size is given by the number of people a focal actor is connected to, minus the redundancy in that actor's network. In this way, effective size captures the non-redundant elements of an actor's network which presumably provides access to non-overlapping knowledge bases. Formally:

$$\textit{Effective size for } i = \sum_j \left[1 - \sum_q p_{iq} m_{jq} \right]$$

This measure, which ranges from zero to one, is defined considering all the j contacts that actor i has, and the amount of redundancy defined in i's network (q being every third person other than i or j in i's ego network). The quantity ($p_{iq}m_{jq}$) in the brackets captures the level of redundancy between ego and a particular alter, j. The term p_{iq} is the proportion of actor i's relations that are spent with alter q and m_{jq} is the marginal strength of contact j's relation with common third party q (basically j's interaction with q divided by j's strongest interaction with any other third party). The sum of the product $p_{iq}m_{jq}$ measures the portion of i's relation with j that is redundant to i's relation with other direct connections. Individuals with high effective size scores tend to be connected to mostly non-redundant contacts, while individuals with low scores on this measure tend to be connected to contacts who are themselves connected (i.e. who are redundant).

Control Variables

As respondents in our sample are assigned to two different locations, one in the US and one in the EU, one important element to consider when studying access and loss of knowledge is the actual location of the individuals involved in the exchange. In our case, we created four different categories based on the geographical location of respondents: (1) both located in the US, (2) knowledge-recipient located in EU and knowledge-source located in the US, (3) knowledge-recipient located in the US and knowledge-source located in EU, and (4) both located in EU. Interactions among respondents located in the US equal to the baseline category. In addition to being assigned to two main locations, individuals at Datacorp are also assigned to different project teams. The organization of work and the nature of objectives assigned to each project provide individuals who belong to the same team with more opportunities to interact and share knowledge with each other. Thus, belonging to the same project team is a potential confound of frequency of interactions and diversity of network contacts. To control for this possibility, we created a shared team membership indicator variable that was set equal to one if the respondent and the focal contact were assigned to the same team and remained equal to zero otherwise.

We also controlled for similarity with respect to demographic variables that could affect the likelihood of interaction and ease of acquisition/amount of knowledge lost from a source to a recipient. We have demographic data with respect to gender, tenure, job rank and project leadership (i.e., the individual is the responsible in charge of the project). We created four category variables with respect to project leadership: (1) both leaders, (2) both non-leaders, (3) knowledge-recipient leader knowledge-source non leader, and (4) knowledge-recipient non leader knowledge-source leader, with interactions among non-leaders providing the baseline category. We also created four control variables with respect to gender: (1) both female, (2) both male, (3) female knowledge-recipient, male knowledge-source, and (4) male knowledge-recipient, female knowledge-source, with interactions among female respondents providing the baseline category. To control for the effects of experience and familiarity with the organization on individuals' ability to limit knowledge loss we include in our model a variable capturing the tenure of respondents. Job-rank in our data ranged across five levels. To control for the effect of individuals' job-rank on the likelihood of knowledge loss we included dummy variables for the job-rank of knowledge recipients as well as dummy variables for the job-rank of knowledge sources. In terms of network variables, we primarily controlled for network size considered in terms of the log of the number of contacts each respondent has. The sheer size of each respondent's network could in fact determine a confounding effect with respect of the focal individual's ability to successfully acquire knowledge and information from his/her contacts. We also controlled for structural configurations of respondents' ego-networks by considering the extent to which a given knowledge sharing relationship was embedded in a dense web of third party ties (Gargiulo, Ertug, & Galunic, 2009). Previous research has investigated the impact of network cohesion on ease of knowledge acquisition as a structural effect defined over and above the property of the focal knowledge sharing relationship (Reagans & McEvily, 2003; Tortoriello et al., 2012), We controlled for this possible confound using a measure of indirect dyadic constraint (Burt, 1992, pp. 54-56). Formally:

$$c_{ij} = \sum_q p_{iq}\, p_{qj}$$

Where p_{iq} represents the proportion of i's interaction devoted to colleague q and p_{qj} reflects the proportion of q's network time and energy allocated to contact j. Considering all the common third-party interactions q, c_{ij} indicates the extent to which the focal relationship between i and j is embedded in a dense system of strong common connections. When c_{ij} is high, the network surrounding i and j's relationship is characterized by closure, or cohesion, when c_{ij} is low, the network surrounding i and j's relationship is sparse (Reagans & McEvily, 2003). Lastly, we included a control for structural equivalence (i.e. the extent to which two individuals have similar patterns of interactions) and a control to distinguish reciprocated ties from non-reciprocated ties. These are especially relevant in our context because individuals with similar contacts might find it easier to share knowledge with each other, and because to the extent that interactions between two individuals are reciprocal (i.e. one receives knowledge from the other and vice versa) they might become increasingly able to understand each other and develop a common language which would allow them to facilitate knowledge sharing while minimizing the amount of knowledge lost in any given interaction.

ANALYSIS

The 134 individuals who completed the survey were involved in a total of 3,429 knowledge sharing relationships. These observations, however, are not independent because for each respondent and each contact there are multiple observations. This special type of co-dependency can reduce the size of standard errors, thereby artificially increasing the significance of our tests. To adjust standard errors for this type of clustering, we used mixed-effect models ('mixed' models in STATA) combining fixed and random effects for the individuals in our sample. This approach is one solution to the non-independence problem that dyad-level analyses introduce (Krackardt, 1987; Krackhardt, 1988; Reagans & McEvily, 2003; Tortoriello et al., 2012) and it also provides, at the same time, an additional control for idiosyncratic features of respondents that might make cross-individual comparisons hard to justify. In addition to the lack of independence of our observations due to the data structure, another possible source of bias associated with our dyadic approach is given by the fact that we only analyze observed knowledge-sharing relationships. This represents a particular instance of sample selection bias (Heckman, 1979) since there are different elements that determine, in the first place, why individuals form knowledge sharing relationships with some colleagues and not with others. To take this bias into account we estimated a two-stage Heckman correction model. In the first stage we modeled the probability of observing a knowledge sharing relationship using a Probit model in which we considered as risk-set all the 97,656 theoretically possible dyads (313 * 312)[1]. In this model we used all non-network variables available in our dataset that come from archival company sources for both respondents and non-respondents (i.e. gender, job grade, project leader, and physical location) to predict the likelihood of observing a knowledge sharing tie out of all the theoretically possible dyads. Based on these results, we computed an Inverse Mills Ratio (IMR) to capture the probability of observing a knowledge sharing tie as a function of those variables, which we then used as an additional control in our mixed- effects models predicting ease of knowledge acquisition and perception of loss[2].

[1] The same procedure was done considering only actual respondents and associated risk set of 134 * 312 = 41,808 possible dyads obtaining substantively similar results.

[2] In addition to that, we also estimated a Probit model considering all the 97,656 possible dyads as a risk set in which we used only job grade to predict the likelihood of observing a knowledge sharing tie. Job grade is significantly associated with the likelihood of observing a tie (individuals with same job grade are more likely to interact with one another), but it

For both dependent variables covariates of theoretical interest are first introduced in stepwise fashion one by one and then tested jointly in the final model (Model 4 and Model 9 respectively). Model 1 presents only control variables for ease of knowledge acquisition, and subsequent Models 2, 3, and 4 present frequency of interaction, diversity of contacts, and both frequency of interaction and contacts diversity jointly considered, respectively. Model 5 presents only control variables for perception of knowledge loss, and subsequent Models 6, 7, 8 and 9 frequency of interaction, diversity of contacts, joint consideration of frequency of interaction and diversity of contacts and the interaction term, respectively.

********* INSERT TABLE 4 & FIGURE 1 about here **********

As can be seen in Table 4, when introduced one by one, each of our variables of interest achieves statistical significance according to what we predicted in hypothesis 1a, 1b, 2a, and 2b. Similarly when all the variables of interest are introduced together (Model 4 and 8), they also remain statistically significant. This suggests support for Hypotheses 1a and 1b according to which frequency of interactions increases the ease of knowledge acquisition and reduces knowledge loss in the perception of the recipient, and Hypotheses 2a and 2b according to which having a diverse network of contacts increases the ease of knowledge acquisition, while, at the same time also increases knowledge loss. Finally, in Model 9 we test for the moderating effect of frequency of interaction on the positive relationship between diversity of contacts and perception of knowledge loss. As can be seen in this model, the coefficient for the interaction term is negative and statistically significant, suggesting that when diversity of contacts is adjusted by the frequency of interactions, the perception of the amount of knowledge lost is significantly reduced.

To shed light on the magnitude and significance of this interaction term, we ran a simple slope analysis to test for the range of frequency values along which the effects of diversity of contacts on

is unrelated to knowledge acquisition and loss. When computing the IMR using estimates from this model our results do not change.

knowledge loss are significantly reduced. Results of this analysis show that the relationship between diversity of contacts and perception of knowledge loss, while remaining positive, is progressively reduced when frequency of interaction goes from its minimum to its maximum value (Figure 1). Furthermore, the analysis reveals that the moderating effect of frequency of interaction on diversity of contacts is statistically significant for 99% of our observations. This confirms that the positive moderating effects of frequency of interaction on the relationship between diversity of contacts and perception of knowledge loss are statistically significant over a range of frequency values that is substantively meaningful in our dataset.

Robustness Checks

One issue that warrants further discussion is the relatively low response rate and how it might affect and/or bias the findings of our analysis. As previously detailed, we could not detect any statistically significant differences between respondents and non-respondents comparing the two samples in terms of all the variables obtained from archival data provided by the company. In addition to that, we ran some additional analysis to take into account possible differences in terms of key network metrics between respondents and non-respondents. Primarily, we compared network in-degree of respondents with the in-degree of non-respondents observing no statistically significant differences ($p = 0.19$). Second, to assess the representativeness of our responses we took into account time trend evolution of survey participation. Common practice in survey research suggests that the time-line of respondents' survey participation can be used to extrapolate the magnitude of non-response bias. The key assumption behind this approach is that "late" respondents are more similar to non-respondents than to "early" respondents (Armstrong & Overton, 1977). In our case we computed a set of standard network metrics for early respondents and for non-respondents and tested for significant differences across the two samples. In particular we considered individuals' out-degree, in-degree, network size, tie strength and effective size for the two samples and could not find any statistically significant difference between early and late respondents. Finally, we checked for LinkedIn memberships as an indicator of individuals' networking attitude and observed that no statistically significant differences existed between respondents and non-respondents in terms of the proportion of people with a LinkedIn account. In addition to that, for those with a LinkedIn account we further considered the number of contacts they had on this social network and observed no statistically significant differences in the number of contacts of respondents vs. the number of contacts of non-respondents[3]. This set of additional analysis provides further corroborating evidence for the fact that no statistically significant differences should exist in our case between respondents and non-respondents.

However, even in the absence of systematic biases, our analysis could still be affected by the low response rate in a way that could spuriously interfere with our conclusions. To address this residual possibility we adopted two different estimating approaches to further establish the robustness of our findings.

In one first set of analysis, we zeroed in on the variation in our data in terms of reciprocated vs. unreciprocated dyads. One risk of low response rates in network surveys, is that several relationships show up as un-reciprocated not because of lack of reciprocity (which is possible even in complete datasets and depends on the distribution of network ties), but because of the fact that several participants did not fill in the questionnaire. To dig into this issue we replicated our analysis on different subsets of the observed sample. Primarily, we reran our models limiting the analysis to reciprocated ties only (i.e. dyads are retained in the regression model only if *i* indicated *j* as a contact and *j* indicated *i* as a contact), and we obtained exactly the same patterns of relationships as those

[3] Due to LinkedIn's restrictions we could not compare respondents vs. non-respondents in terms of the number of connections they had within the company. However, this supplemental analysis using LinkedIn's data was intended as a proxy for individuals' networking orientation and not as a substitute for their actual networking behaviors.

reported in Table 4. In addition to that, we reran our models considering only non-reciprocated ties (i.e. dyads are retained in the regression model only if *i* indicated *j* as a contact and *j* did not indicate *i* as a contact), also in this case, we observed results fully compatible with those reported in Table 4. Finally, when comparing the coefficients of theoretical interest (i.e. frequency of interaction and network diversity) in the two set of models just described (i.e. models with reciprocated ties only, and models with non-reciprocated ties only), we observed no statistically significant difference among coefficients (z= 1.48, and 1.16 for frequency of interaction and contact diversity respectively in the case of ease of knowledge acquisition, and z= 0.12, 1.14, and 0.25 for frequency of interaction, contact diversity and interaction term in the case of knowledge loss) suggesting that our findings are robust to different distributions of dyadic relationships in terms of reciprocated vs. non-reciprocated ties, irrespective of the low response rate.

In one last set of analysis, to further corroborate the findings' robustness, we used the data observed to reran our models using a bootstrapping procedure generating 10,000 simulated distributions for both ease of knowledge acquisition and perceptions of knowledge loss. Since we could establish that no statistically significant difference existed between respondents and non-respondents (e.g. no discernible bias affected the observed data), to approximate the distribution of the overall population, we drew new random samples from the observed distribution and computed our analysis for each re-sampled set. The results obtained from the bootstrapping procedure for either ease of acquisition and amount of knowledge loss are, once again, fully consistent with those presented in Table 4. Although the evidence we were able to produce, from t-tests, to split-sample analysis, to bootstrapping, cannot be considered as conclusive lacking the counterfactual of a complete response rate, it provides at least suggestive evidence that the key findings presented in the paper are not systematically distorted in any discernible way because of the low response rate.

One other issue which needs to be addressed given the cross-sectional nature of dataset used is the possibility of reverse causality in the case of the frequency of interaction hypotheses. One could in fact reasonably make the argument that it is not the frequency of interactions that leads to easier transfers or lower knowledge losses, but that these two elements are in fact leading to more frequent interactions among two individuals. To address this issue we ran GLS random effect models ('xtivreg' models in STATA) in which we instrumented frequency of interaction using a set of variables that are significantly correlated with the supposedly endogenous variable (frequency of interactions) and uncorrelated with the error term of our models for ease of acquisition and amount of knowledge loss. In our dataset, we determined that network size, structural equivalence and reciprocity of relationships exhibited these properties. Using these variables as instruments for frequency of interaction we obtained substantively similar results to those presented in Table 4, furthermore, the results of the Sargan-Hansen' s test statistics ($p>0.15$ for knowledge loss, and $p>0.12$ for knowledge acquisition) further corroborate the validity of the instruments adopted. Taken together, these findings suggest that the observed positive (negative) association of frequency of interactions with ease of knowledge acquisition (amount of knowledge loss) does not change when instrumental variables are used to remove from the model error terms the part of variation that is correlated with the dependent variable suspected of endogeneity.

DISCUSSION

In this paper we set out to explore an important but seldom studied phenomenon associated with the transfer of knowledge from a source to a recipient: the amount of knowledge that ends up being lost during the sharing process. We considered knowledge loss and ease of knowledge acquisition as two critical dimensions of the knowledge transfer process and assessed the impact of interaction frequency and diversity of contacts on these two dependent variables.

Our findings reveal that frequency of interaction increases the ease of knowledge acquisition *and* reduces the amount of knowledge lost during the sharing process. This is consistent with previous studies that have highlighted the knowledge benefits associated with tie strength in terms of ease of transfer and acquisition (Hansen, 1999; Reagans & McEvily, 2003; Tortoriello et al., 2012). Our findings also show that diversity of contacts, while increasing the ease of knowledge acquisition, simultaneously increases the amount of knowledge loss. Finally, our results also show that the greater knowledge loss determined by a diverse network is significantly reduced when network diversity is interacted with tie strength; ranging across strong ties reduces knowledge loss while ranging across weak ties increases it.

The findings associated with the effects of frequency of interaction and network diversity on knowledge loss represent an important contribution to the study of knowledge management in organizations. In particular, our results suggest that a more nuanced view of network advantages is necessary when studying knowledge sharing in organizational contexts (Burt, Kilduff, & Tasselli, 2013). For instance, while previous research has identified several benefits associated with bridging ties (i.e. ties spanning across different parts of the organizational network) in terms of innovativeness, individual creativity, ease of knowledge transfer and acquisition, our study highlight the “costs” associated with these benefits expressed in terms of knowledge loss. At a first look, the observed relationship between diversity of network contacts and knowledge loss might seem contradictory with respect to the previous body of research, suggesting positive returns to brokerage. In reality, as shown in our analysis, it is fully compatible with the extant body of work on knowledge management and networks. Having ties that range widely across different parts of the organizational network is still going to allow a focal individual to access more diverse knowledge as compared to a colleague whose connections are limited to one unit or department (Burt, 1992; Reagans & McEvily, 2003) and this is going to indirectly increase the ability to transfer knowledge. However, bridging connections are hard to create and costly to maintain (Ahuja, 2000; Tortoriello et al., 2012). Therefore, being engaged in leveraging knowledge coming from several diverse connections reduces the ability to accurately process the information and knowledge received from each contact (Tsai, 2001). Our findings warn that the greater breath of knowledge access associated through diverse contacts in the network comes at the expense of a reduced depth of the relationship so that potentially relevant bits and pieces of newly acquired knowledge might end up being lost in the process. The positive association of network diversity and knowledge loss is also compatible with research that has found positive returns on diversity of connection in terms of innovation and creativity (Burt, 2004; Perry-Smith, 2006). It raises, however, the question of how much stronger these effects could be if associated with complete knowledge transfer. For instance, while some ideas and innovation might need only limited inputs and so partial transfer of knowledge is "good enough" to trigger innovations, others might require more accurate and complete transfers of knowledge so that even a small percentage of knowledge loss might substantially reduce the innovative potential of bridging ties.

The moderating effect of frequency of interaction on the relationship between diversity of network contacts and knowledge loss is also relevant for both theoretical and practical reasons. Theoretically, this interaction is consistent with recent work suggesting that not all bridging ties are equal (Levin & Cross, 2004; Levin, Walter, & Murnighan, 2011; McEvily et al., 2012) and provides an important example of how the strength of a (bridging) tie could be a possible antidote to the loss of knowledge determined by ties spanning across different parts of the network. This is consistent with previous work showing the role of strong ties for transferring knowledge that is hard to mobilize (Hansen, 1999), but also with more recent work showing the importance of having strong/embedded relationship across organizational boundaries for the generation of innovations (Tortoriello & Krackhardt, 2010).

Taken together, our findings provide a compelling illustration of Reagans and Zuckerman (2008) discussion of the trade-offs associated with different network positions. While we know a great deal about the benefits provided by specific configurations of network structures, it becomes increasingly important to explicitly bring into the picture intrinsic limitations that each configuration has in a way to achieve a more balanced view of the advantages and disadvantages they provide.

Finally, our research also contributes to research on knowledge management and knowledge transfer, by relaxing the assumption according to which knowledge transfer is a discrete outcome, that it either happens or that it does not. In fact, inferring knowledge transfer in terms of objective performance measures, or measuring it in terms of ease of access and/or acquisition like most of previous research in this area, ends up taking our attention away from what it is that is being transferred, and, in particular, from how complete this transfer really is. Instead, a more realistic view of knowledge transfer is one according to which knowledge transfer does happen but is also often incomplete (Argote & Ingram, 2000). This suggests that there is an important amount of variation to consider in terms of how much knowledge successfully makes it from a source to a recipient when studying knowledge flows. In our empirical setting we found that while over one-fifth of the observed dyads reported a perfect and complete transfer of knowledge, the majority of the interactions we observed in our sample was associated with some amount of knowledge loss. Focusing on the network mechanisms that account for such loss of knowledge in dyadic interactions represents an important contribution to our understanding of how knowledge flows (or does not flow) in organizational networks.

Our work also has important limitations that should be acknowledged and discussed. Primarily, although we took every measure we could to deal with the response rate of our sample, it is still lower than the response rate reported in comparable network studies. That raises the question of what happens in terms of knowledge loss and acquisition in the dyads we could not capture because of a comparatively lower response rate. While it is hard to speculate about how non-observed dyads might have changed our results, we found no substantive reasons to believe that results of non-observed dyads would yield fundamentally different results. Primarily, comparing respondents with non-respondents revealed no statistically significant differences. In addition to that, the selection model we used to estimate the likelihood of observing a tie was estimated by considering the entire risk-set for tie formation. When added as an additional control to our explanatory models, the estimated likelihood of observing a knowledge sharing tie does not affect the significance of our results. Finally, results of split sample analysis (e.g. only reciprocated,\; only non-reciprocated ties) and the bootstrap analysis taking random samples of our observations provide results that are consistent with those reported in Table 4. Clearly, we cannot claim that these analyses represent conclusive evidence that would put to rest the issue of response rate. However, the consistency of results obtained across the different robustness checks we implemented offers at least suggestive evidence that no systematic bias seems to be affecting the validity of our conclusions.

Another possible contentious point is given by the strategy adopted to measure our dependent variables. Our measure is in fact based upon the perception of the recipient of knowledge, and, as such, it is likely to introduce biases associated with idiosyncratic assumptions held by different respondents about what perfect knowledge transfer means. We do not have an obvious way to directly address that issue. Indeed, respondents might vary substantially in terms of what they perceive a full transfer of knowledge should entail. In addition to that, knowledge sources might also vary substantially in terms of their ability to convey to others what they know. To partially mitigate this concern, we used a combination of fixed and random effects for the source and the recipient of the knowledge in order to take into account idiosyncratic differences in perceptions and actual abilities to provide/ acquire knowledge in interpersonal exchanges.

Finally, there is a history of past interactions and the shadow of future interactions that our models do not capture due to the cross-sectional nature of the research design. This creates legitimate concerns of endogeneity and/or reverse causality that might undermine the proposed theoretical framework. For instance, there might be unobserved variables, in addition to the explanatory variables considered, that might determine the amount of knowledge lost when two individuals interact. Or unobserved drivers of interaction frequency and diversity of connections that shape individuals position in the organization network in the first place. Although we tried to model our theoretical framework in a way to deal with possible unobserved variables and with endogenous mechanisms associated with the process of tie formation, we cannot completely rule out the possibility of other mechanisms being responsible for the findings we observed but can only statistically control for their supposed influence on the results presented.

Conclusions

In spite of the limitations associated with our design and with the nature of our data, we believe this study furthers the agenda on network and knowledge management research in important ways by focusing on the network antecedents of knowledge loss. Based on our findings, a fruitful extension of this line of inquiry could be quantifying the "costs" associated with knowledge loss in terms of actual innovation and/or ability to get things done in organizations. Indeed, we focused on the phenomenon of knowledge loss and highlighted the relationship it has with specific features of individuals' networks and system of relationships. However, we did not have data to also capture the effects of knowledge loss in terms of actual outcomes. Building upon our framework, it would be important to connect knowledge loss with concrete outcome measures in a way to provide more tangible estimates of how network features can enhance performance by reducing knowledge loss. More in general, our study shows the importance of considering explicitly the benefits *and* the limitations associated with different network configurations in the study of knowledge sharing in organizations. We believe that this dual focus is a necessary condition to improve our theories and to increase the impact of our studies on actual business practices, and hope that future research would extend this line of inquiry by considering different network configurations as well as different individual and organizational level outcomes.

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Figure 1

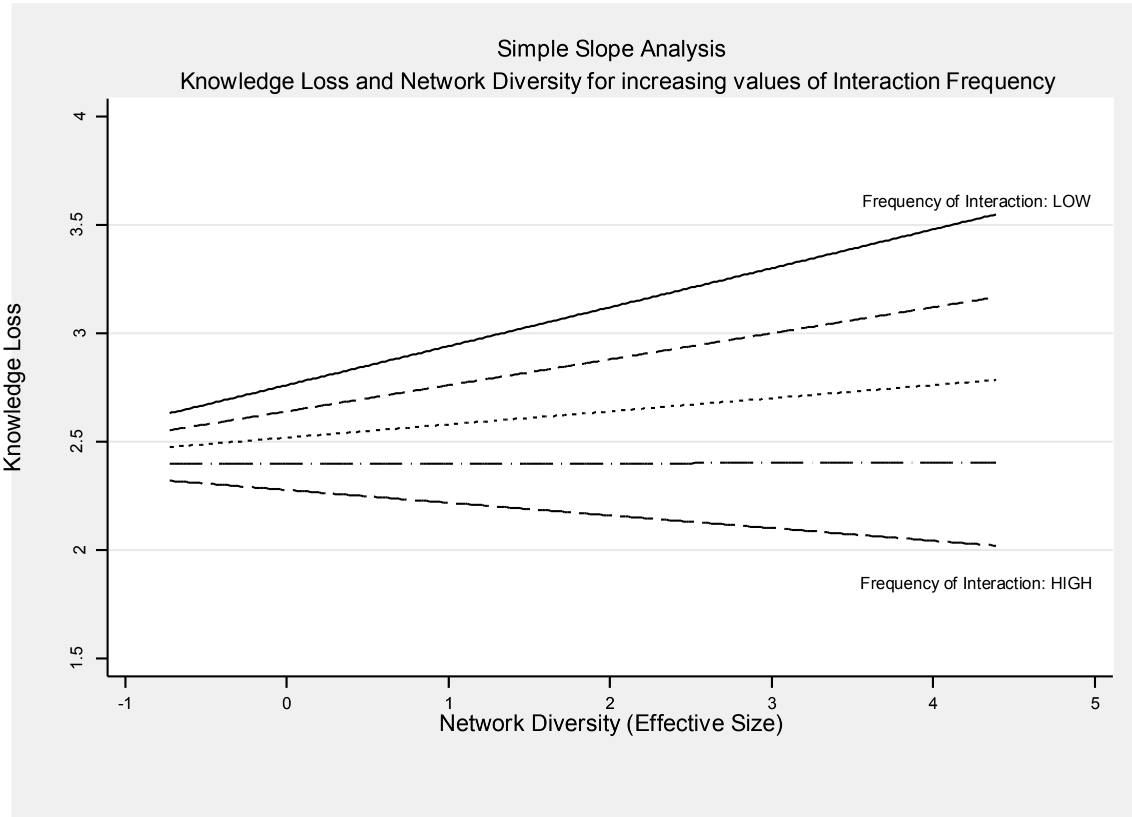
Simple Slope Analysis
Knowledge Loss and Network Diversity for increasing values of Interaction Frequency
Frequency of Interaction: LOW
Frequency of Interaction: HIGH
Knowledge Loss
1.5
2
2.5
3
3.5
4
-1
0
1
2
3
4
5
Network Diversity (Effective Size)

Table 1 - Descriptive and Correlation table

		Mean	Std Dev	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Ease of knowledge acquisition	3.30	0.89													
2	Knowledge loss	2.61	1.53	-0.474												
3	Network size (log)	3.49	0.67	0.028	0.038											
4	Network constraint	0.01	0.02	-0.014	0.020	-0.486										
5	Structural equivalence	19.81	4.70	0.017	0.014	0.626	-0.293									
6	Probability of observed ties	3.42	0.44	0.032	-0.041	-0.214	0.075	-0.156								
7	Tenure of knowledge recipient	7.06	4.91	0.184	-0.146	0.055	-0.072	0.047	0.146							
8	Reciprocal ties	0.29	0.49	0.018	-0.002	-0.074	0.374	0.015	0.035	0.047						
9	Same project affiliation	0.61	0.49	-0.061	-0.010	-0.123	0.172	-0.260	-0.080	-0.027	0.113					
10	Recipient leader-source not leader	0.06	0.23	-0.012	0.030	0.017	0.023	0.078	0.013	0.010	0.042	-0.114				
11	Recipient not leader - source leader	0.08	0.28	-0.042	0.044	0.050	-0.063	0.080	-0.349	-0.147	-0.002	-0.116	-0.075			
12	Recipient leader - source leader	0.01	0.08	0.011	-0.030	0.022	-0.016	0.052	-0.074	-0.035	-0.003	-0.098	-0.020	-0.026		
13	Recipient male - source female	0.21	0.41	-0.042	0.052	0.199	-0.110	0.129	-0.028	-0.029	-0.052	-0.077	-0.011	0.165	0.001	
14	Recipient female - source male	0.14	0.35	-0.005	0.005	-0.015	0.021	0.030	0.103	0.004	0.034	0.010	0.089	-0.048	0.022	-0.214
15	Recipient Male - source male	0.57	0.50	0.038	-0.078	-0.186	0.057	-0.145	-0.027	0.041	0.009	0.071	-0.077	-0.140	-0.048	-0.601
16	Recipient EU - source US	0.02	0.15	-0.062	0.068	-0.005	-0.005	0.017	0.472	0.008	0.039	-0.106	0.239	-0.011	0.113	0.013
17	Recipient US - source EU	0.03	0.17	-0.043	-0.009	-0.022	-0.012	-0.048	0.144	-0.085	0.008	-0.087	-0.037	0.438	0.111	0.189
18	Recipient EU - source EU	0.48	0.50	-0.062	0.063	0.268	-0.088	0.163	-0.695	-0.080	-0.032	0.142	-0.030	-0.085	-0.041	-0.123
19	Recipient Job grade 1	0.46	0.50	-0.125	0.073	0.033	-0.034	-0.047	-0.445	-0.203	-0.039	0.070	-0.044	0.090	0.008	-0.050
20	Recipient Job grade 2	0.28	0.45	0.107	-0.044	-0.121	0.069	-0.064	0.351	0.117	0.082	-0.120	0.020	-0.038	-0.012	-0.061
21	Recipient Job grade 3	0.18	0.38	0.028	-0.063	-0.068	0.024	-0.024	0.252	-0.016	-0.034	0.028	0.018	-0.012	0.019	0.042
22	Recipient Job grade 4	0.01	0.11	0.143	-0.027	0.047	-0.032	0.027	-0.034	0.113	-0.033	-0.043	0.008	-0.036	-0.010	-0.062
23	Source job grade 1	0.47	0.50	-0.048	0.030	0.129	-0.036	0.039	-0.360	-0.077	-0.040	0.083	0.012	-0.042	-0.002	-0.049
24	Source job grade 2	0.28	0.45	0.053	-0.036	-0.177	0.079	-0.084	0.307	0.050	0.068	-0.060	0.029	0.046	0.014	0.051
25	Source job grade 3	0.15	0.36	0.025	-0.034	-0.026	-0.023	-0.048	0.228	0.059	0.004	-0.028	-0.034	0.003	-0.004	0.026
26	Source job grade 4	0.01	0.09	-0.004	-0.020	0.006	0.016	-0.001	-0.041	-0.009	-0.030	-0.009	-0.023	-0.006	-0.008	-0.010
27	Frequency of Interaction	2.31	1.31	0.126	-0.114	-0.205	0.335	-0.256	-0.017	-0.021	0.187	0.272	0.007	0.061	0.034	-0.055
28	Diversity of Contacts	13.62	18.78	0.125	0.063	0.217	-0.076	0.127	-0.088	0.125	-0.018	0.002	0.032	-0.145	-0.038	0.183

		14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
14	Recipient female - source male															
15	Recipient Male - source male	-0.450														
16	Recipient EU - source US	0.071	-0.110													
17	Recipient US - source EU	-0.049	-0.167	-0.029												
18	Recipient EU - source EU	0.028	0.142	-0.146	-0.176											
19	Recipient Job grade 1	-0.024	0.077	-0.064	0.020	0.520										
20	Recipient Job grade 2	0.046	0.032	0.029	0.068	-0.412	-0.581									
21	Recipient Job grade 3	0.013	-0.065	0.077	-0.089	-0.376	-0.431	-0.306								
22	Recipient Job grade 4	-0.015	0.082	-0.018	-0.022	0.123	-0.106	-0.075	-0.056							
23	Source job grade 1	-0.021	0.095	0.031	-0.080	0.523	0.330	-0.213	-0.256	0.049						
24	Source job grade 2	0.001	-0.051	-0.019	0.094	-0.485	-0.263	0.291	0.076	-0.044	-0.593					
25	Source job grade 3	0.018	-0.095	0.014	0.035	-0.352	-0.260	0.034	0.363	-0.043	-0.401	-0.272				
26	Source job grade 4	-0.038	0.050	-0.015	-0.018	0.099	0.070	-0.060	-0.019	-0.011	-0.088	-0.060	-0.040			
27	Frequency of Interaction	-0.007	0.027	-0.038	0.005	-0.077	-0.023	0.051	-0.020	-0.011	-0.037	0.062	-0.008	0.010		
28	Diversity of Contacts	-0.062	-0.156	-0.020	-0.007	0.175	0.098	-0.027	-0.243	-0.083	0.085	-0.061	-0.101	0.031	-0.053	

Correlations greater than |0.038| are significant at p <= 0.05 level

Table 2. Descriptive and Factor Loadings of the Knowledge Acquisition items

Knowledge Acquisition Items	Mean	Stdv	Loading
It is easy for me to recognize the value of the knowledge and information that the following colleagues provide to me for the achievement of my work objectives at Datacorp	3.17	1.06	0.80
It is easy for me to assimilate and adapt the knowledge or information that the following colleagues provide to me so that I am able to use these, together with my existing knowledge for the achievement of my work objectives at Datacorp	3.29	1.01	0.91
If necessary, it is easy for me to transform reframe or change my existing knowledge so that I am able to use the knowledge and information that the following colleagues provide to me for the achievement of my work objective at Datacorp	3.40	1.07	0.86
It is easy for me to understand and use the knowledge and information that the following colleagues provide to me for the achievement of my work objectives at Datacorp	3.38	0.99	0.90
Items were measured on a 5-point likert scale ranging from "strongly disagree" to "strongly agree"			

Table 3. Distribution of Knowledge Loss Variable

Percentage of Knowledge Loss	Frequency	Proportion	Cumulative
0%	794	23.16	23.16
1-5%	1,185	34.56	57.71
6-15%	735	21.43	79.15
16-25%	361	10.53	89.68
26-30%	182	5.31	94.98
31-40%	80	2.33	97.32
41-50%	39	1.14	98.45
51-55%	28	0.82	99.27
56-65%	12	0.35	99.62
66-75%	11	0.32	99.94
76-100%	2	0.06	100
Total number of ties	3,429	100	

Table 4. Mixed effects estimates for Ease of Knowledge Acquisiton (Models 1 - 4) and Knowledge loss (Models 5 - 9)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	DV: Ease of Knowledge Acquisition				***DV: Knowledge Loss***				
Control Variables									
Constant term	5.915***	5.882***	5.321***	5.277***	-1.481	-1.545	-1.817	-1.875	-1.827
	(0.793)	(0.785)	(0.784)	(0.775)	(1.328)	(1.318)	(1.328)	(1.318)	(1.317)
Network size (log)	0.098**	0.080*	0.069	0.049	0.041	0.066	0.024	0.049	0.048
	(0.037)	(0.036)	(0.036)	(0.036)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Network Cohesion	1.18	-0.817	0.903	-1.146	2.152	5.134**	1.989	4.958*	4.644*
	(1.158)	(1.175)	(1.142)	(1.158)	(1.945)	(1.978)	(1.941)	(1.975)	(1.979)
Structual Equivalence	-0.01	-0.005	-0.009	-0.003	0.003	-0.005	0.004	-0.005	-0.005
	(0.006)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Probability of observed ties	-0.147	-0.125	-0.019	0.006	0.514*	0.504*	0.595*	0.583*	0.570*
	(0.151)	(0.149)	(0.149)	(0.147)	(0.252)	(0.250)	(0.252)	(0.250)	(0.250)
Tenure of knowledge recipient	0.031***	0.031***	0.028***	0.027***	-0.040***	-0.040***	-0.043***	-0.043***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Reciprocal ties	0.027	-0.032	0.034	-0.027	0.051	0.14	0.051	0.139	0.137
	(0.057)	(0.057)	(0.056)	(0.056)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)
Same project affiliation	-0.192***	-0.254***	-0.194***	-0.258***	0.076	0.169**	0.070	0.162*	0.164*
	(0.039)	(0.039)	(0.038)	(0.039)	(0.064)	(0.065)	(0.064)	(0.065)	(0.065)
Recipient leader-source not leader	-0.101	-0.198	-0.08	-0.179	1.202	1.406	1.225	1.428	1.47
	(0.845)	(0.837)	(0.833)	(0.824)	(1.375)	(1.365)	(1.372)	(1.362)	(1.362)
Recipient not leader - source leader	-0.127	-0.185	0.082	0.027	0.576*	0.681**	0.711**	0.813***	0.796***
	(0.140)	(0.139)	(0.140)	(0.139)	(0.236)	(0.235)	(0.238)	(0.237)	(0.237)
Recipient leader - source leader	-0.026	-0.22	0.194	0	0.824	1.189	0.97	1.33	1.338
	(0.880)	(0.872)	(0.868)	(0.859)	(1.438)	(1.428)	(1.436)	(1.426)	(1.425)
Recipient male - source female	-1.146*	-1.262*	-1.106*	-1.224*	1.421	1.607	1.47	1.654	1.664
	(0.567)	(0.562)	(0.559)	(0.553)	(0.953)	(0.946)	(0.951)	(0.945)	(0.944)
Recipient female - source male	-0.084	-0.085	-0.038	-0.038	-0.406**	-0.409**	-0.359*	-0.364*	-0.359*
	(0.086)	(0.085)	(0.085)	(0.084)	(0.146)	(0.144)	(0.146)	(0.145)	(0.145)
Recipient male - source male	-1.093	-1.222*	-0.991	-1.122*	1.096	1.303	1.197	1.401	1.421
	(0.568)	(0.563)	(0.560)	(0.554)	(0.955)	(0.948)	(0.953)	(0.946)	(0.946)
Recipient EU - source US	-0.991	-0.872	-1.113	-0.993	0.756	0.529	0.68	0.455	0.444
	(0.686)	(0.680)	(0.677)	(0.669)	(1.086)	(1.078)	(1.084)	(1.076)	(1.075)
Recipient US - source EU	-0.051	-0.004	-0.176	-0.131	-0.814**	-0.900***	-0.897***	-0.981***	-0.967***
	(0.159)	(0.158)	(0.157)	(0.156)	(0.270)	(0.268)	(0.270)	(0.268)	(0.268)
Recipient EU - source EU	-0.586	-0.4	-0.48	-0.287	0.969	0.689	1.028	0.749	0.696
	(0.649)	(0.643)	(0.640)	(0.634)	(1.017)	(1.010)	(1.015)	(1.008)	(1.008)
Recipient Job grade 1	0.214**	0.252***	0.311***	0.352***	0.343**	0.281*	0.370**	0.308**	0.305**
	(0.077)	(0.076)	(0.076)	(0.076)	(0.117)	(0.116)	(0.117)	(0.116)	(0.116)
Recipient Job grade 2	0.466***	0.503***	0.579***	0.619***	0.129	0.061	0.161	0.093	0.096
	(0.086)	(0.085)	(0.085)	(0.084)	(0.133)	(0.132)	(0.133)	(0.132)	(0.132)
Recipient Job grade 3	0.443***	0.508***	0.637***	0.707***	-0.053	-0.156	0.033	-0.072	-0.073
	(0.094)	(0.094)	(0.095)	(0.095)	(0.150)	(0.150)	(0.151)	(0.151)	(0.151)
Recipient Job grade 4	1.328***	1.334***	1.538***	1.547***	0.02	0.008	0.12	0.106	0.108
	(0.154)	(0.153)	(0.154)	(0.152)	(0.259)	(0.257)	(0.259)	(0.257)	(0.257)
Source job grade 1	-0.215	-0.267	-0.189	-0.241	0.046	0.132	0.061	0.145	0.176
	(0.298)	(0.295)	(0.294)	(0.291)	(0.487)	(0.483)	(0.486)	(0.482)	(0.482)
Source job grade 2	-0.311	-0.325	-0.3	-0.315	0.664	0.702	0.665	0.702	0.706
	(0.326)	(0.323)	(0.321)	(0.318)	(0.537)	(0.533)	(0.536)	(0.532)	(0.531)
Source job grade 3	-1.209**	-1.228**	-1.192**	-1.212**	1.487*	1.552*	1.495*	1.559*	1.559*
	(0.436)	(0.432)	(0.430)	(0.425)	(0.723)	(0.718)	(0.722)	(0.716)	(0.716)
Source job grade 4	0.421	0.224	0.283	0.079	-0.507	-0.184	-0.626	-0.302	-0.27
	(0.640)	(0.634)	(0.631)	(0.625)	(1.010)	(1.004)	(1.008)	(1.002)	(1.001)
Explanatory Variables									
Frequency of interaction		0.142***		0.146***		-0.213***		-0.212***	-0.212***
		(0.018)		(0.018)		(0.031)		(0.031)	(0.031)
Diversity of contacts			0.160***	0.163***			0.111***	0.109***	0.103***
			(0.017)	(0.017)			(0.029)	(0.029)	(0.029)
Freq. of interaction * Div. of contacts									-0.059*
									(0.027)
Chi-square	654.492	727.731	758.892	840.369	596.455	653.143	613.215	669.788	675.108
Number of observations	3199	3199	3199	3199	3429	3429	3429	3429	3429

* p <.05   ** p<.01   *** p < .001
Standard errors in parentheses