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Forgotten Third Parties: Analyzing the Contingent Association Between Unshared Third Parties, Knowledge Overlap, and Knowledge Transfer Relationships with Outsiders

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Forgotten Third Parties: Analyzing the contingent association between unshared third parties, knowledge overlap and knowledge transfer relationships with outsiders.

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Abstract

Third parties play a prominent role in network-based explanations for successful knowledge transfer. Third parties can either be shared or unshared. Shared third parties signal insider status and have a predictable positive effect on knowledge transfer. Unshared third parties, however, signal outsider status and are believed to undermine knowledge transfer. Surprisingly, unshared third parties have been ignored in empirical analysis, and so we do not know if or know how much unshared third parties contribute to the process. Using knowledge transfer data from an online technical forum, we illustrate how unshared third parties affect the rate at which individuals initiate and sustain knowledge transfer relationships. Empirical results indicate that unshared third parties undermine knowledge sharing and they also indicate that the magnitude of the negative unshared third party effect declines the more unshared third parties overlap in what they know. Our results provide a more complete view of how third parties contribute to knowledge sharing. The results also advance our understanding of network-based dynamics defined more broadly. By documenting how knowledge overlap among unshared third parties moderates their negative influence, our results show when the benefits provided by third parties and by bridges (i.e., relationships with outsiders) will be opposed versus when both can be enjoyed.

1. Introduction

Successful knowledge transfer is essential for a host of organizational processes and performance outcomes, including but not limited to improvements in learning rates and overall organizational efficiency (Argote et al. 1990; Darr et al. 1995), new product development (Hansen 1999; Carlile 2002) and technological innovation (Ahuja 2000; Tortoriello and Krackhardt 2010). As market competition has increased, sharing knowledge has become even more important because knowledge transfer influences a firm's ability to improve and develop new products and work routines (Rosenkopf and Almeida 2003; Sørensen and Stuart 2000). Indeed, in a dynamic market context, the ability to share knowledge is viewed as a distinct source of competitive advantage (Kogut and Zander 1996).

Explanations for successful knowledge transfer often emphasize the importance of two contextual factors – knowledge overlap and network context. While distinct, knowledge overlap and network-based explanations for knowledge transfer emphasize complementary processes and dynamics. In particular, prevailing theoretical arguments cast knowledge overlap as a key variable defining transfer costs. And this is so because individuals often learn new ideas by associating those ideas with what they already know (Cohen and Levinthal, 1990; Simon 1991). Thus, when defined in terms of time and effort, transfer costs are lower when a knowledge source and potential recipient overlap in what they know and as transfer costs decline, the likelihood of successful transfer increases. Different network features such as tie strength, shared third parties, and network range are conceptualized as social resources that facilitate knowledge sharing activities by offsetting transfer costs (Tortoriello, Reagans, and McEvily, 2012). A network connection is strong when a source and recipient either communicate frequently and/or feel emotionally invested in their interaction. Shared third parties indicate the number of mutual contacts a source and recipient have in common and network range captures the extent to which the network which surrounds a focal individual draws on contacts from different parts of a larger network. A number of studies have documented the importance of

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these network features for successful knowledge transfer (Phelps, Heidl, and Wadhwa, 2012 provide a systematic review). For example, prior research has shown that a knowledge source is more likely to share what he knows with a recipient when the two are connected by a strong relationship either directly or indirectly through mutual shared third party interactions. Strong network connections facilitate pro-social behavior such as knowledge transfer by increasing the reputation costs associated with failing to assist fellow members of a group or community (Granovetter 1985; Coleman 1990).

Network and knowledge overlap-based explanations for successful knowledge transfer emphasize complementary processes and dynamics. Prevailing theoretical arguments cast knowledge overlap as a key variable defining transfer costs and view different network features as resources that facilitate knowledge sharing activities by rendering transfer costs less relevant. The complementary nature of the two processes suggests that it would be worthwhile to consider how the two factors combine to shape knowledge sharing outcomes and activities (Tortoriello, Reagans, and McEvily, 2012). We explore this issue by examining how knowledge overlap moderates the influence of a network feature that has been overlooked in network-based explanations for successful knowledge transfer. In particular, we examine how unshared third parties to an interaction affect the likelihood that a knowledge transfer relationship will be initiated and maintained over time and we also consider how the degree of knowledge overlap among unshared third parties potentially moderates their influence.[1]

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[1] Our focus on knowledge overlap and different network features isn't to suggest they are the only determinants of successful knowledge transfer. Prior research had identified a number of factors that can influence knowledge transfer (Argote et al. 2003; Phelps et al. 2012), including physical proximity (Hansen and Løvås 2004; Salomon and Martin 2008), social similarity (Loyd et al., 2010), and even properties of the knowledge being shared (Szulanski 1996). Some of those factors shape transfer costs while others like different network features introduce resources that can render those costs less relevant. While we have focused on knowledge overlap and network features in our argument, we believe it would be worthwhile to consider how cost and resource-based factors combine to influence knowledge sharing activities. For example, sharing tacit knowledge is more demanding than sharing codified knowledge even after one has controlled for how much a source and recipient overlap in what they know. And so properties of knowledge should also moderate observed network effects. Features of the source and recipient could also play a role. Sharing an identity can also increase an individual's willingness to engage in the knowledge transfer process (Kane, Argote, Levine 2005), even when it is costly to do so.

While it is generally understood that third parties can be shared and unshared, unshared third parties have been ignored in previous research analyzing network effects on knowledge sharing activities. The stylized network in Figure 1 illustrates the difference between shared and unshared third parties. The focal interaction is the Sarah-Roy connection. Sarah is the knowledge source and Roy is the recipient. Alvin and Allen are connected to Sarah and Roy and so represent shared third parties to the Sarah-Roy interaction. A large number of studies have established the positive influence that Alvin and Allen can have on the Sarah-Roy relationship in general (see Portes and Vickstrom 2011 for a review) and for knowledge transfer in particular (see Phelps, Heidl, and Wadhwa 2012 for a review). The relationships that connect Sarah with Bob, Bill and Ben, however, represent unshared third parties to the Sarah-Roy interaction because Roy is disconnected from the individuals in group B. For members of group B, Roy is an outsider and the relationships that Sarah has with members of group B can make it difficult for Sarah to maintain her relationship with Roy. The point is that same third parties that promote interactions between in-group members can make it more difficult for an individual to productively interact with individuals from outside of that group (Granovetter 1973; Burt and Knez 1995; Labianca et al. 1998).

Third parties can shape network dynamics by influencing how people allocate their limited network time and energy. For example, if Sarah decides to spend more time helping her contacts in group B, her decision can have implications for her relationsnhps with individuals in group A. When her time is limited, if she decides to spend more time with contacts in group B, Sarah must also consider limiting the amount of time she spends with Alvin, Abe, Allen, and Roy. Her relationships with Allen, Abe, and Alvin have the support of third parties, so reducing network time and energy in any one of those relationships could be problematic for her reputation. Sarah's relationship with Roy has less third party support and so as Sarah starts to allocate more time to contacts in group B, she could very well decide to end her relationship with Roy. In general, individuals have a limited budget for network activities. And time

consuming activities like knowledge transfer can exhaust that budget more quickly (Levine and Prietula 2012). This suggests that the negative influence that unshared third parties can have on relationships with outsiders will be especially pronounced in the context of knoweldge transfer relationships.

The proceeding discussion highlights how unshared third parties can undermine knoweldge sharing activities and therefore why it is important to consider unshared third party effects in empirical anlaysis. Given the complementary nature between networks and knowledge overlap, it is also important to consider knowledge overlap among unshared third parties overlap because the degree of knowledge overlap among unshared third parties could determine how difficult it is for an individual to meet their requests for help and assistance. And if this is so, the degree of knowledge of knowledge overlap among unshared third parties could offset any negative effect that unshared third parties could have on an individual's ability to maintain relationships with outsiders. For example, as members of group B begin to overlap in their knowledge and expertise, instead of responding to a diverse set of requests for help and assistance, it is more likely that Sarah will need to respond to a smaller set of questions, which should make it easier for her to satisfy those requests, leaving more network time and energy for interactions with contacts outside of group B. This line of thinking suggests that as unshared third parties become more similar in their knowledge and expertise, any negative influence that unshared third parties can have on relationships with "outsiders" like Roy should be diminished. We develop this argument in greater detail in the next section.

We test our argument among knowledge workers from a Fortune 1000 IT services firm. Global Business magazine, Fortune, reported that this firm is one of the fastest growing firms in the United States. Market success allowed the firm to expand rapidly to different cities, countries and continents. Knowledge transfer was critical for firm success but during the expansion little attention was paid to how members of the firm would continue to share knowledge with each other. As a result, different pockets of knowledge emerged between

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locations over the years. Senior members of the firm recognized that the absence of knowledge transfer was undermining the firm's performance and the firm took several Enterprise 2.0 initiatives to encourage knowledge sharing among employees across locations, including the knowledge sharing forum analyzed in this study.

The firm launched the online forum in 2006 and it was adopted across different locations. The forum is technical in nature and employees primarily posted technical queries. Once a query was posted, however, anyone in the firm could post an answer to the forum. The forum provided knowledge seekers with greater access to a much larger knowledge pool than what would have been possible in the absence of such a forum. The firm did not provide any direct incentive to participate in the technical forum. However, over approximately a year, approximately 17,000 questions were posted to the forum which received more than 20,000 responses. The forum kept track of individuals who sought assistance and the names of individuals who responded to their requests. As a result, we can measure the network context in which knowledge transfer occurs. Queries were posted to specific subjects and domains and individuals who responded to queries posted in a specific domain revealed their knowledge and expertise. Thus, in addition to measuring shared and unshared third party ties, we can also measure how much people overlap in what they know and therefore we can also examine how knowledge overlap moderates any association between unshared third party ties and the likelihood a knowledge transfer relationship is initiated and sustained over time.[2]

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[2] The widespread use of electronic data in network analysis has been met with some skepticism. Some worry about the extent to which "online" data actually corresponds to relationships "offline." Analysis of email data suggests that there is (Wuchty and Uzzi 2011; Quintaine and Kleinbaum 2011). A related issue is the extent to which network processes and dynamics that have been documented offline occur in online settings. We are assuming they do, and there is empirical evidence in support of our position (Aral and Van Alstyne 2011; Burt 2012). This isn't to suggest that all "social" networks are the same. Social media networks like Facebook or Twitter often have features that make them distinct from offline social networks. It would, therefore, be a mistake to reduce social media networks to social networks (Kane et al., 2014). Indeed, there is growing body of research describing how platform features can both constrain but also enable effective knowledge transfer online (Majchrzak et al., 2013). Research findings to be presented suggest the "online" forum we study exhibits network-based dynamics and processes similar to "offline" social networks studied in the past.

To preview our empirical results, we find that unshared third parties reduce the likelihood that a knowledge transfer relationship would be initiated and sustained over time and we also find that the magnitude of this negative effect declines as unshared third parties became more similar in their knowledge and expertise. Our results provide a more complete view of how third parties affect knowledge sharing. While prior research has emphasized the positive influence shared third parties can have on knowledge sharing, our results illustrate how the same third parties that promote interactions with insiders can also make it more difficult for an individual to share knowledge with outsiders. Our results also advance our understanding of network-based dynamics defined more broadly. For example, the Sarah-Roy relationship in Figure 1 is a bridge and prior research has shown that bridges provide a number of information and knowledge-based benefits (Granovetter, 1973; Burt, 1992; Reagans and Zuckerman, 2008a), especially when they are strong (Burt, 1992). Indeed, strong bridges are essential in high information and knowledge environments because weak bridges lack sufficient bandwidth to support successful transfer (Aral and Van Alstyne, 2011). But as we have described above, third parties can make it difficult for an individual to initiate and maintain bridges (Granovetter, 1973). And thus, the benefits provided by bridges and third parties are often viewed in opposition. The benefits created by one can be expected to come at the expense of the benefits introduced by the other. By illustrating how knowledge overlap among unshared third parties moderates the negative effect that unshared third parties can have on relationships with outsiders, our results show when the benefits provided by third parties and by bridges will be in stark opposition versus when both network-based benefits can be realized and enjoyed.

2. Third Parties: Shared and Unshared

Shared Third Parties, Collaboration, and Reputation Costs

The importance of shared third parties in the context of knowledge transfer has been established across a number of studies, including individual knowledge workers (Gargiulo,

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Gokhan, and Galunic 2009), hotel managers (Ingram and Roberts 2000), design engineers (Obstfeld 2005), and individuals working in research and development (Tortoriello and Krackhardt 2010). Shared third parties are important because they can help to align individual behavior with more collective goals and objectives (Granovetter 1985; Coleman 1988; Grief 1989). In any group or organization, conflicts of interest can develop between what is best for the organization and what is best for each individual member of the organization. For example, the successful transfer of knowledge can be beneficial for a recipient and the broader organization, but sharing knowledge can be costly for the source. At a minimum, a source must spend time sharing what he knows (Reagans and McEvily 2003). Successful knowledge transfer can also be costly for the recipient who must dedicate time and effort to figuring out how to use whatever knowledge he has acquired in his work context (Tortoriello, Reagans, and McEvily 2012). Indeed, successful knowledge transfer can introduce dynamics that undermine subsequent transfer because the more two individuals overlap in what they know, the more they potentially compete against each other for status and attention inside the group or larger organization. A focus on status-based competition helps to explain why individuals often prefer knowledge originating from outside of their organization or organizational unit (Menon and Pfeffer 2003; Menon et al. 2006).

Shared third party ties facilitate pro-social behavior by raising the reputation costs associated with failing to provide help and assistance. When two individuals in an interaction are connected to the same third parties, news of uncooperative behavior travels among those third parties quickly (Coleman 1988). And those very same shared third parties are positioned to sanction an offending party, for example by refusing to cooperate with him in the future (Grief 1989). Thus, when shared third parties are present, individuals collaborate in general and share knowledge in particular out of a desire to protect their reputation. In the context of knowledge transfer, this means that individuals share what they know, in part, to preserve their rights to request assistance from their colleagues in the future.

Unshared Third Parties, Self-Interests, and Decay

Third parties can also be unshared. The available empirical evidence indicates that unshared third parties make it difficult for an individual to maintain a strong relationship with outsiders (Burt and Knez 1995; Labianca et al. 1998). Cognitive factors could account for the negative influence that unshared third parties can have on relationships with outsiders (Heider 1946). For example, Sarah has strong ties with Roy and Bob, but Roy and Bob are disconnected. If the relationships in figure 1 are friendships, it is cognitively more demanding for Sarah to be friends with Roy and Bob who are not friends than it is for Sarah to be friends with Bob and Ben who are friends. The Sarah-Bob, Sarah-Ben, and Bob-Ben interactions are balanced, while the Sarah-Bob, Sarah-Roy, and Bob-Roy interactions are not. Imbalanced relationships are more difficult to maintain and one way to restore balance would be for Bob and Roy to become friends. Balance would also be restored if Sarah ended her relationship with either Roy or with Bob. Since Sarah's relationships around Bob are more balanced than her relationships around Roy, if she is forced to select one, she is more likely to end her relationship with Roy.

The negative effect that unshared third parties can have on relationships with outsiders could be rooted in more self-interested behavior. For example, the third parties in group B could be interested in continuing to receive whatever benefits their relationship with Sarah provides, and as their relationships with each other become stronger; they are in a better position to demand more from her, including requests for more knowledge and information. And if we assume that Sarah has a limited amount of time and effort she can allocate to sharing knowledge, providing more assistance to contacts in B should increases the odds that one or some or her relationships in group A will end. But some of Sarah's relationships with people in group A are in a more stable position than others. The reputation costs associated with ending a relationship with an insider are higher than the reputation costs associated with ending a relationship with an outsider. If Sarah is forced to withdraw from any relationship in A as

demands in B increase, she is more likely to withdraw wherever the reputation costs associated with doing so are lower. The reputation costs associated with withdrawing from her relationship with Allen or Abe are higher than the costs associated with withdrawing from the relationship with Roy. And this fact means that the relationship that Sarah has with Roy is more likely to end, as the requests for help and assistance in group B increase.[3] Thus, consistent with prior research on the negative influences of unshared third parties, we expect for unshared third parties to have a negative effect on the knowledge transfer process.

While we have discussed and will analyze the association between unshared third parties and knowledge transfer, we are primarily interested in how overlap in knowledge among unshared third parties moderates the negative effect unshared third parties can have on knowledge transfer relationships with outsiders. The negative unshared third party effect could be rooted in balance or the fact that third parties are interested in continuing to secure whatever resources a contact provides. In the current empirical context, knowledge workers are concerned with being productive and acquiring knowledge can improve their productivity. If the contacts in group B are primarily concerned with receiving knowledge from Sarah, increasing knowledge overlap within group B should moderate the negative effect that strong ties within group B can create for relationships with people from outside of B. In particular, as knowledge overlap among members of group B increases, the number of distinct demands that each person in B represents for Sarah should also decline. For example, if individuals only possess

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[3] An additional mechanism which also assumes self-interested third parties is gossip (Burt and Knez 1995). According to this argument, the third parties surrounding Sarah are primarily concerned with maintaining their relationship with her, and out of a desire to maintain that relationship, simply echo back whatever she wants to hear. In particular, whenever difficulties occur in an interaction, the relationship is at risk for decay. Unshared third parties exacerbate the problem. Since they are primarily concerned with maintaining their relationship with Sarah, if she should ask their opinion about the offending party, they are likely to echo back whatever negative emotions she is experiencing at that particular moment in time. The end result is to undermine the relationship with the offending party even more. Mutual or shared third parties act to restore a relationship after a difficult encounter and primarily because they are interested in maintaining their relationships with both parties. Sarah's relationship with Bob is surrounded by shared third parties, which help to maintain and restore the relationship after a difficult event. Sarah's relationship with Roy lacks this kind of support and so if Sarah should share negative emotions after a difficult interaction with Roy, they echo them back which serves to undermine Sarah's relationship with Roy. We focus on third parties who are interested in securing resources, as opposed to simply maintaining relationships, because it seems like a more plausible explanation in our empirical context.

expertise in one domain, when the members of group B are completely heterogeneous, Sarah must satisfy increasing requests with respect to three knowledge domains. When the members of group B overlap completely, Sarah must satisfy increasing demands with respect to one domain. While it is certainly the case that meeting increasing demands in one domain will make it difficult for her to maintain knowledge transfer relationships outside of group B, it is also true that meeting increasing demands across multiple knowledge domains will make it even more difficult to maintain external knowledge transfer relationships. This line of argument leads to the following prediction.

H1: The negative effect that unshared third parties have on knowledge transfer becomes less negative as the degree of knowledge overlap among them increases.

3. Methods and Measures

Technical workers at a Fortune 1000 IT services firm were our study population. Market success had allowed the original firm to expand geographically to multiple cities, countries and continents. With the expansion, firm performance started to suffer. Managers understood that knowledge transfer had been essential for early success and were looking for activities to encourage the transfer of knowledge between people in different geographic locations. The firm took several Enterprise 2.0 initiatives to encourage knowledge sharing among employees across locations, including the knowledge sharing forum analyzed in this study.

The online forum was launched in 2006 with the explicit intent of encouraging transfer across the different locations. The forum was technical in nature and employees primarily posted technical questions. Questions were posted to specific topics and once a question was posted, anyone in the firm could post a response. The forum provided knowledge seekers with greater access to a much larger knowledge pool than what would have been possible in the absence of such a forum. We have data on all questions and responses from April 2006 until August 2007. During the 16 month period, 17,386 questions were posted and those questions

received 20,421 responses. The forum kept track of individuals who sought assistance and the names of individuals who responded to their requests. So the identities of individuals were visible on the forum. Moreover, these archival records allow us to observe a knowledge transfer network evolving over the 16 month period. A knowledge transfer relationship exists between two individuals when one had responded to a question posted by the other. Our knowledge transfer network was updated daily so knowledge transfer relationships were allowed to develop and grow stronger but could also decay over time.

Dependent Variable – Sharing Knowledge. The dependent variable, Y_{srq}, is an indicator variable which equals 1 if a potential knowledge source s responds to the question q posted by potential knowledge recipient r and 0 otherwise. We focus on the likelihood of an individual responding to a colleague's question. Most responses were posted within a few hours and differences in time zones made it difficult to measure the time lapse between when a potential knowledge source was exposed to a question and when he or she posted a response. While individuals could have responded to a question more than once, this was very rare. Individuals responded to the same question more than once only thirty-nine times. While the typical person only posted a single response, like most technical forums more than one person could have responded to a question. And since more than one person can respond to a question, we have more answers than questions.

Independent Variables

Third Parties: We examine how an increase in the relative number of unshared third parties will affect the likelihood that an individual with respond and continue to respond to a colleague's requests. The workers in our study population can belong to more than one network neighborhood and so the stylized network in figure 1 is again useful for illustrating different kinds of third parties. The focus relationship is the relationship between Sarah (s) and Roy (r). s and

r share a number of third parties in group A but s is involved in a number of relationships in group B that represent unshared third parties for the s-r interaction.

To measure the intensity of shared and unshared third party ties, we first calculated the strength of the direct ties in the knowledge sharing network. The individuals in our study population can act as knowledge sources and recipients in our knowledge transfer relationships. A knowledge transfer relationship exists between s and r if either one has responded to a question posted by the other. Thus the data are counts. We know the number of times s has responded to a question posted by r and we know the number of times that r has responded to questions posted by s. To measure the strength of the relationship s has with r, we first sum the number of times s has responded to r and the number of times r has responded to s. $Nsrt +$ $Nrst$ is the level of the relationship between s and r at time t. It is important to remove volume or level from our network measures (Burt and Carlton 1989). One approach is to express each interaction as a function of the maximum interaction involving the focal individual at time t, which for individual s is $\max(Nsqt + Nqst)$ (Reagans and McEvily 2003; Tortoriello et al. 2012). Thus, the marginal strength of the relationship from s to r at time t is calculated as

$Z_{srt} = \frac{Nsrt+Nrst}{\max(Nsqt+Nqst)}$, where N_{srt} is the number of times s has responded to questions posted by r at time t and N_{rst} is the number of times r has responded to questions posted by s at time t and max$(Nsqt + Nqst)$ is the strongest relationship s has with anyone on the forum at time t. These marginal strength relationships were used to calculate our network measures.[4] Our shared third party variable increases to the extent there are individuals like q who have strong connections with s and r. If our network data were binary, our shared third party variable would simply be the number of third parties that s and r have in common (Burt 2007).

$$Shared\ third\ parties = STP_{srt} = \sum_{q} Z_{sqt}Z_{rqt}$$

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[4] We measure tie strength using marginal relationships to be consistent with prior research (Reagans and McEvily 2003; Tortoriello et al. 2012). Empirical results to be presented lead to the same substantive conclusions if we measure tie strength using the original count data.

Our measure of unshared third parties increases to the extent the focal individual s had strong ties to contacts q and k and those colleagues were disconnected from the focal contact r. Again with binary network data, our unshared third party variable would be the number of "Simmelian" or closed triads (Krackhardt 1999) surrounding s that do not involve the focal respondent r.[5]

$$Unshared\ third\ parties = USTP_{srt} = \sum_{k \neq r} \sum_{q > k, q \neq r} Z_{skt} Z_{sqt} Z_{kqt}$$

We have called our two network measures the number of shared and unshared third parties but it is important to emphasize that both variables are indicators of triadic closure. Our shared and unshared third party variables are conceptually identical to the triadic closure measures used by Krackhardt (1999, pg. 108), Burt (2007, pg. 14), and other scholars who study network effects on individual, team and organizational outcomes. Triadic closure measures are rooted in the idea that group dynamics occur in collectives of three or more people. An issue, of course, is how triadic effects aggregate as the size of the collective increases. Consistent with prior work, we assume triadic effects are additive.

Knowledge Expertise: Questions on the technical forum were posted to specific topic areas or domains. There were eighty-nine topics on the forum. An individual "expressed" or signaled his or her knowledge and expertise based on where he or she posted answers. We constructed a vector of expertise, V_s, for each individual based on the questions he or she has answered. The value corresponding to element $V_s(e)$, represents the number of questions on topic e answered by individual s.[6] We constructed the vector V_s using information on how s responded to questions posted on the forum during the 16 month time period. Thus our knowledge or

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[5] Our network variables are unadjusted in the sense we do not divide our shared third party variable by the number of contacts maintained by the focal individual s and we do not divide our unshared third party variable by the number of closed triads surrounding s that did not involve the focal respondent r. We have focused on the unadjusted network variables because we believe the extent of these interactions is as important as their average strength. However, we reach the same substantive conclusions if we adjust our shared third party variable by the number of contacts and our unshared third party variable by the number of unshared closed triads.

[6] Empirical results to be presented lead to the same substantive conclusions if we define an individual's expertise as a function of where he or she has posted questions and answers.

expertise variable was not time dependent. We can relax this assumption and assume an individual only has expertise on a topic if he or she has responded to a question on the topic prior to the day when a focal question was posted. The time dependent expertise variable and time constant variable are correlated at 0.99 and results based on either measure lead to the same substantive conclusions.

Knowledge Overlap: We calculate the level of dyadic knowledge overlap (DKO_{sr}) between two individuals *s* and *r* as the un-centered correlation of their knowledge expertise vectors (Jaffe 1986). Dyadic knowledge overlap varies from zero to one, with a value of one indicating maximum knowledge overlap.

$$Dyadic\ Knowledge\ Overlap = DKO_{sr} = \frac{V_s V_r'}{\sqrt{(V_s V_s')}\sqrt{(V_r V_r')}}$$

Knowledge Overlap among Third Parties: Knowledge overlap among third parties can vary from high to low. We expect for the magnitude of the estimated third party effects to vary with the amount of knowledge overlap among them. We calculated knowledge overlap at the network level using triads. To calculate knowledge overlap among shared third parties, we calculate the average dyadic knowledge overlap among s, r, and q for every q connected to s and r. We sum across every such q to define the level of shared triadic knowledge overlap.

$Knowledge\ Ovlerap\ among\ Shared\ Third\ Parties = KOSTP_{sr}$

$$= \sum_q 1/3 \left[\frac{V_s V_r'}{\sqrt{(V_s V_s')}\sqrt{(V_r V_r')}} + \frac{V_s V_q'}{\sqrt{(V_s V_s')}\sqrt{(V_q V_q')}} + \frac{V_r V_q'}{\sqrt{(V_r V_r')}\sqrt{(V_q V_q')}} \right]$$

To calculate knowledge overlap among unshared third parties, we calculated the average dyadic knowledge overlap among s, q, and k for every q and k connected to s and but not connected to r and we summed across every such q and k.[7]

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[7] As with our network variables, our measures of knowledge among shared and unshared third parties were not adjusted by the number of contacts maintained by the focal individual s or the number of closed triads surrounding s that did not involve the focal respondent r, respectively. We have focused on the unadjusted knowledge variables for

$$Knowledge\ Overlap\ among\ Unshared\ Third\ Parties = KOUSTP_{sr}$$

$$= \sum_{k \neq r} \sum_{q > k; q \neq r} 1/3 \left[\frac{V_k V_s{}'}{\sqrt{(V_k V_k{}')}\sqrt{(V_s V_s{}')}} + \frac{V_s V_q{}'}{\sqrt{(V_s V_s{}')}\sqrt{(V_q V_q{}')}} + \frac{V_k V_q{}'}{\sqrt{(V_k V_k{}')}\sqrt{(V_q V_q{}')}} \right]$$

Control Variables

In addition to the intensity of shared third party relationships, prior research has established the importance of tie strength and network range for knowledge transfer. Recall that tie strength was measured as the marginal strength of the relationship from s to r at time t.

$$Tie\ strength = Z_{srt} = \frac{Nsrt + Nrst}{\max_q (Nsqt + Nqst)}$$

Our indicator of network range was information centrality (Stephenson and Zelen 1989; Brandes and Fleischer 2005; Tortoriello, Reagans, and McEvily 2012). Like closeness centrality, information centrality is a function of the path distance between any two actors. Unlike closeness centrality, however, which gives maximum weight to the shortest path between two actors, information centrality considers all paths and assigns greater weights to shorter paths. Individuals who were high on information centrality were connected to nonequivalent contacts in the knowledge transfer network, and thus individuals who were high on information centrality were more likely to be connected to non-redundant knowledge and expertise. We control for the centrality of the source and recipient in our analysis.

Prior research has also established that similarity with respect to demographic characteristics, such as age, gender, and tenure can affect knowledge sharing behavior. Our demographic data is limited. We only have demographic data for gender. To control for any effect gender-based similarity can have on the knowledge transfer process, we created two indicator variables, both female and both male. The both female indicator is set equal to one if

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the same reason we focused on the unadjusted network variables. However, models that use the adjusted network and knowledge variables lead to the same substantive conclusions as the models that use the unadjusted network and knowledge variables.

the recipient and source were both female and remained equal to zero otherwise. The both male indicator variable was set equal to one if the source and recipient were both male and remained equal to zero otherwise. Interactions involved men and women were the excluded category in our analysis. We also controlled for similarity with respect to work roles and responsibilities. The firm formally distinguished forty-seven job classifications (e.g., data analyst, SAS programmer, director, Senior IT Security Specialist). While we know each individual's classification, we do not know exactly the activities each job classification entails. With more detailed information on what each work activity entailed, we could construct an indicator of how much two individuals overlapped in their work roles and responsibilities and therefore, the extent to which they were potentially more relevant as knowledge exchange partners. To control for any influence that task similarity could have on knowledge sharing, we created an indicator variable for pairs of classifications (e.g., SAS programmer and data analyst). Three hundred and eighty-two of the job classification pairs had a sufficient number of observations to be included as controls in our models. The indicators variables are estimated in our model but are not displayed in the tables.

We know where each individual worked and so could control for the extent to which two individuals worked at the same geographic location. It is important to control for geographic proximity because two individuals who are in close proximity have more opportunities to develop stronger network connections or to simply become more aware of each other. Either dynamic could increase the odds of a knowledge source responding a question posted by a potential recipient. Our same geographic location variable is set equal to one if the potential recipient and source work at the same location and remains equal to zero otherwise.

17,386 questions were posted to the technical forum during the 16 month period we studied.[8]

1,201 individuals could have responded to each question. The 17,386 X 1,201 question-source

pairs are the units of analysis. We have multiple observations for each potential recipient r and

we have multiple responses from each knowledge source s. The observations are clustered

within knowledge sources and within potential recipients. Clustering can artificially reduce the

size of our standard errors and inflate our significance tests. To adjust our standard errors for

clustering, we introduced a random effect for each knowledge source and for each knowledge

recipient. The crossed random effects adjust our standard errors for clustering. The individual

random effects also allow us to control for the influence of unobserved and unmeasured factors

(e.g., age, and tenure) could have had on the knowledge transfer process. While the crossed

random effects controlled for unmeasured features of an individual either as a source or a

recipient, they do not control for unobserved features of a relationship between two individuals

that could have affected the likelihood they would initiate and continue to share knowledge with

each other. To control for unmeasured features of each relationship that could have affect

knowledge transfer, we also introduced a dyadic random effect for every pair of individuals

(Reagans 2011).

Given the dyadic random effects specification and the large size of our data

(approximately 20 million rows), the total amount of computation time was large. This is a

challenge that is often encountered in large scale dyad-level studies of networks (e.g., Braun

and Bonfrer 2011; Kleinbaum, Stuart, and Tushman 2013). Further, an estimation approach

based on random sampling was not practical with our data since the instances where a potential

source replied to a recipient was extremely rare. For approximately 20 million observations

there were only 20421 instances where the dependent variable equaled 1. Hence, to deal with

the computational requirements of our dyad-level model with time-varying covariates, we

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[8] Our empirical results lead to the same substantive conclusions if we ignore the first 6 months of the technical forum.

estimated our model with the recently proposed Weighted Exogenous Sampling with Bayesian

Inference (WESBI) (Lu et al 2013).

To employ WESBI, we collected all of the instances where the dependent variable was

one, and randomly sampled 15% of the observations where the dependent variable equaled

zero. By combining these two sets of observations, we constructed a much smaller dataset

("sampled data"). And then, we used the weighted log-conditional-likelihood function for

Bayesian inference over our sampled data (Lu et al. 2013). The intuition behind the weighted

log-conditional-likelihood is to weigh each sampled observation by the population elements it

represents in order to make the choice-based sample simulate a random exogenous sample.

The WESBI method reduces the time of estimation by an order of magnitude, while still

providing consistent estimates.

4. Empirical Results

The estimation results are provided in Table 1. While we are concerned with how

unshared third parties affect the knowledge transfer process, the estimates for shared third

parties are informative. We considered two distinct kinds of interactions in our empirical

analysis. We first considered how our network variables affected the likelihood an individual

would initiate a knowledge transfer relationship and then we considered how the same network

variables affected the likelihood a knowledge transfer relationship would be sustained over time.

The individuals in column 1 had never shared knowledge with each other. The estimate for

shared third parties in column 1 is positive and significant. The estimate indicates that a

knowledge source was more likely to respond to a request posted by a network neighbor. The

results in model 2 focus on individuals who had shared knowledge with each other in the past.

And since we control for the relative number of times they have shared knowledge with each

other in the past, one can interpret the estimates as capturing the rate at which their relationship

is getting stronger over time. The results indicate that shared third parties increased the

likelihood a knowledge source would sustain a knowledge transfer relationship. The estimates

in models 1 and 2 illustrate the positive effect shared third parties can have on the knowledge

transfer process. Shared third parties made it more likely that a knowledge source would

respond to a question posted by a colleague and would continue to respond to future requests.

The estimates from models 3 and 4 illustrate the negative effects unshared third parties can

have on external relationships. The individuals in column 3 were disconnected while the

individuals in column 4 had shared knowledge with one another in the past. The estimate for

unshared third parties is negative and significant in models 3 and 4. Unshared third parties

made it less likely that a source would respond to a question and even if the source had

responded to a previous request (perhaps formed when the intensity of unshared third parties

was lower), that he or she would continue to respond to future inquires. Overall, the results in

models 1-4 illustrate the positive and negative influences associated with third parties. Third

parties facilitate knowledge transfer among insiders but undermine sharing knowledge with

outsiders. We are interested in how knowledge overlap among unshared third parties

moderates the magnitude of their negative influence but it is worth noting that while the

unshared third party effect is generally understood, the negative unshared third party effect is

rarely documented empirically.

Our predictions are tested in models 5 and 6. The individuals in model 5 had never

shared knowledge, while the individuals in model 6 had. Model 5 contains an interaction

between unshared third parties and the degree of knowledge overlap among unshared third

parties. Model 6 includes a three-way interaction between our tie strength variable, unshared

third parties and the degree of knowledge overlap among unshared third parties because the

source and recipient had shared knowledge previously. It can be difficult to interpret two-way

and three-way interactions, so we calculated the simple slope for unshared third parties when

knowledge overlap among unshared third parties was high (i.e., 1.5 standard deviations above

its mean) and low (1.5 standard deviations below its mean) (Aiken et al. 1991). The results for

the estimates in model 5 are in Table 2. When we focus on individuals who have never shared

knowledge, the results indicate that the negative unshared third parties effect was less negative

when the degree of knowledge overlap among unshared third parties was high versus when it

was low. We observed similar results when we focused on individuals who had shared

knowledge before. In addition to calculating the simple slope for unshared third parties when

knowledge overlap among unshared third parties was high and low, we also calculated the

simple slope when tie strength was either high and low. The results are in Table 3. The

negative effect that unshared third parties had on continuing to share knowledge was less

negative when knowledge overlap among unshared third parties was high versus low. The

magnitude of the negative unshared third parties effect doesn't appear to vary with the strength

of the relationship between the knowledge source and recipient. Overall, the results provide

support for our predictions. Unshared third parties undermined knowledge transfer and the

magnitude of their negative influence declined when they overlapped in their knowledge and

expertise.

Robustness Checks

The empirical results reported above provide empirical support for our argument. In addition to

the models discussed above, we estimated a number of models to evaluate the robustness of

our conclusions to different assumptions about our dependent and independent variables. For

example, we have focused in our analysis on the likelihood a knowledge source would respond

to a potential recipient. We also estimated models in which our dependent variable was length

of response (i.e., the number of words used in response to a question), conditional on

responding to a question. Estimates from those models led to the same conclusions as the

findings discussed in our results section. While length of response might seem more

appropriate because it could capture strength of connection (i.e., number of words used in a

response could indicate how much time and effort an individual allocated to answering a

question), length of response could also introduce noise in our outcome variable. Length of response could have varied with features of the question, who asked (some people are more verbose and more verbose questions could have generated more verbose responses), or who responded. Given these issues we focused in our primary analysis on less fine-grained binary outcome variable.

Second, we included in our models dyadic random effects to adjust our estimates for unmeasured features of each interaction that could have affected the likelihood a knowledge source responded to a recipient. The dyadic random effects in our model were assumed to be uncorrelated with the predictors in our regression equations. Estimating a model with dyadic fixed effects would have allowed unmeasured features of each dyad to be correlated with our predictors. While we would have preferred to estimate models with dyadic fixed effects, we lacked sufficient variation at the dyad level to do so. Our data, however, did allow us to let a subject of our predictors to be correlated with our dyadic random effects (Hausman and Taylor 1981). We had sufficient variation at the dyadic level to allow our network centrality variables to be correlated with our dyadic random effects. Empirical results from these models lead to the same conclusions as the models discussed above.

Third, the online technical forum we analyzed cut across different geographic locations. We controlled for geographic proximity in our analysis but it is possible that geographic proximity interacted with our network variables. In particular, it is possible that our effects primarily held for individual who worked in different locations while our network variables had no effect when two individuals could communicate with each other offline. To examine this issue, we estimated models in which we split our analysis by our same geographic location variable. We found that the estimated network effects were larger when two individuals worked in different geographic locations versus when they worked in the same location. But in each instance, however, the coefficients led to the same substantive conclusions as the coefficients

discussed in the text. The coefficients provide some support for a potential substitution effect but the potential substitution effect appears to be modest.

Our final robustness check considered an alternative specification for our shared third party variable. Our shared third party variable is an indicator of triadic closure. It is essentially a count of the number of contacts two individuals have in common. Our shared third party however, ignores the potential influence of relationships *between* shared third parties. It is possible that a potential knowledge recipient r will be even more successful in motivating a knowledge source s to share knowledge if s and r share many contacts and if those contacts are connected to each other. Put differently, the influence that a shared third party q has on the s-r interaction can also vary with the presence of another shared third party k, how strongly s and r are connected to q and k and the strength of the q-k relationship. To capture this potential influence, we modified our shared third party variable:

$$Shared\ third\ parties = STP_{srt} \ = \ \sum_q (Z_{sqt} Z_{rqt} + \alpha \sum_k Z_{skt} Z_{rkt} Z_{qkt})$$

Closure around the s-r interaction increased with the presence of many shared third parties, especially when those third parties are also strongly connected to each other. We do not modify our unshared third party variable because that variable already captures the potential influence that a relationship between two people outside of the s-r interaction can have on how s interacts with r. The second part of the equation above is the modification and its influence (i.e., α) on knowledge sharing was estimated empirically. The empirical results using this modified shared third party variable were informative. Without the modification, we found that shared third parties increased the likelihood that s would start to share knowledge with r and the estimate equaled .779. We also found that shared third parties increased the odds that s would continue to share knowledge with r over time and the estimate equaled 1.439. The modified shared third party variable allows us to distinguish the triadic closure effect from an effect that while correlated with triadic closure was in fact due to the influence of relationships with and between

the third parties s and r share. Using the modified variable, we found that with respect to initiating a relationship, the effect for triadic closure equaled .684 and the estimated α effect equaled .094. With respect to continuing a relationship, the effect for triadic closure equaled 1.294 and the estimated α effect equaled .120. The results suggest that in addition to triadic closure, relationships to and among mutual third parties also contributed to initiating and sustaining knowledge transfer relationships. Relationships between third parties are often implicit in network theorizing but are rarely estimated empirically. Our modification represents one way to capture the potential influence of relationships between shared third parties.

5. Summary and Discussion

Third parties play a prominent role in network-based explanations for successful knowledge transfer. When two people share a large number of contacts, refusing to help one another could damage their reputation. Third parties to an interaction, however, are often unshared and unshared third parties can make it more difficult for two individuals to work collaboratively. But with a few notable exceptions (Burt and Knez 1995; Labianca et al. 1998), unshared third parties have been ignored in empirical analysis. Any potential negative unshared third party effect is often equated to forgoing any potential shared third party effect. Our findings illustrate the value of considering shared and unshared third parties in empirical analysis. In our analysis of an online technical forum, we found that shared third parties made it more likely that a knowledge sharing relationship would be initiated and maintained over time, while unshared third parties had a negative influence on the same process. We also found that the degree of knowledge overlap among unshared third parties limited the magnitude of the negative unshared third party effect. This suggests that satisfying unshared third parties was more demanding when there was less knowledge overlap among them; meeting multiple demands exacerbated the negative influence unshared third parties had on knowledge sharing. Our research findings have a number of managerial and theoretical implications.

With respect to management practice, consider a manager who would like to create a work environment that encourages the transfer of knowledge between individuals who do not overlap in their knowledge and expertise? The manager has at least two alternatives. One alternative is for the manager to create groups that are heterogeneous with respect to knowledge and encourages the members of each group to share their knowledge and expertise. Our empirical results suggest that this approach could eventually undermine knowledge sharing behavior. In particular, among our knowledge workers, shared third parties promoted knowledge transfer but the positive shared third party effect was less positive when the degree of knowledge overlap among shared third parties was low. And moreover, when knowledge overlap in a group was low, each member was less likely to initiate and sustain external knowledge transfer relationships, presumably because when knowledge overlap was low, sharing knowledge was more demanding and time consuming. Under this alternative it would be harder to create a cohesive group and if a cohesive group emerges it is likely to come at the expense of relationships outside the group. An alternative is to create homogenous groups and to encourage individuals to initiate and cultivate external knowledge transfer relationships that provide access to diverse knowledge and expertise. Our results suggest that this alternative arrangement could turn out to be more effective. Thus our findings inform management practice by helping us to understand and appreciate the conditions under which attempts to encourage the development of more diverse interactions is more likely to be successful and sustained over time.

Our findings also make a number of theoretical contributions. We contribute to a growing body of literature that has documented the importance of different network features for successful knowledge transfer. For example, prior research suggests that more frequent exposure to diverse knowledge and information can increase an individual's capacity for sharing knowledge (Reagans and McEvily 2003, 2008; Levina and Vaast 2005). If we assume that an individual is more likely to acquire a greater capacity for knowledge transfer if he or she is able

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to maintain diverse relationships longer, our findings indicate that how an individual is exposed to diverse knowledge influences the likelihood that he or she will be able to acquire a greater capacity for knowledge transfer. And thus our findings advance our understanding of the network dynamics that provide individuals with an opportunity to acquire a greater capacity for knowledge transfer.

Our research findings also contribute to a much broader literature concerned with the benefits shared third parties and bridges can introduce. The general consensus is that shared third parties and bridges (i.e., relationships with outsiders) provide access to distinct benefits and resources. Shared third parties promote cooperation and collaboration within a social group (Ingram and Roberts 2000). Bridges between groups provide access to more diverse knowledge and information and can also be sources of power and influence (Burt 1992; Burt 2010; Reagans and Zuckerman 2008a, b). While the network-based benefits are distinct, it is generally understood bridges and shared third parties can be in opposed and especially when transmission requires a strong bridge (Granovetter 1973). Shared third parties within a group represent unshared third parties to relationships that bridge groups and unshared third parties undermine the formation of strong bridges. Thus, the benefits that shared third parties introduce generally come at the expense of the benefits provided by bridges. While this belief is widespread, the empirical evidence for this tradeoff is inconclusive, with some scholars finding that unshared third parties do in fact make it more difficult for an individual to interact with outsiders (Burt and Knez 1995; Labianca et al. 1998), while other scholars have found that individuals can maintain strong ties within a group while simultaneously maintaining strong ties with individuals outside the group (Reagans et al. 2004). Our findings sharpen our understanding of when both network-based benefits will be obtained versus when we can expect for them to be traded off. For example, Aral and Van Alstyne (2011) propose a tradeoff between networks that can sustain the transfer of complex knowledge and networks that provide access to the most diverse knowledge. The successful transfer of tacit or complex

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knowledge requires a strong or high bandwidth connection. Aral and Van Alstyne illustrate their

tradeoff by contrasting a closed network with high bandwidth ties against an open network full of

low bandwidth ties (see figure 1, pg. 95 in Aral and Van Alstyne 2011). The proposed tradeoff

rests on the idea that shared third parties have a positive influence on the bandwidth of a

relationship (pg. 94-95). And yet we know that strong ties can and often do emerge when

shared third parties are absent, so much so that it is often useful to treat the two network

features as if they are only weakly correlated (Reagans and McEvily 2003; Sosa 2011). High

bandwidth ties can develop in an open network, and so open networks can provide access to

diverse knowledge while simultaneously facilitating the transfer of more complex knowledge.

The tradeoff could also be realized, however, if unshared third parties make it difficult for an

individual to have a strong tie with an outsider. Our empirical results indicate when this tradeoff

is more likely to be extreme versus more modest. Return to the relationship between Sarah and

Roy, which is a bridge. The relationships that Sarah and Roy have with Allen and Alvin

increase the odds of their relationship forming and also introduce stability into their relationship.

Bob, Bill and Ben represent unshared third parties to the Sarah-Roy interaction and make it less

likely that their bridge relationship will emerge and grow stronger over time. Indeed, the

unshared third party effects that we observed are larger than the shared third party effects.

Thus, it isn't the absence of shared third parties that prevent high-bandwidth bridges from

emerging; it is the presence of unshared third parties that reduce the likelihood of a bridge

forming or becoming high bandwidth over time, especially when those unshared third parties

make heterogeneous requests and demands. Thus, in the context of knowledge transfer, our

framework more clearly illuminates when one would expect to observe a tradeoff between the

distinct benefits that third parties and bridges can introduce.[9]

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[9] It is important to remember an additional benefit an open network can provide, which is autonomy. In an open
network, one can more freely reallocate limited bandwidth across different relationships to take advantage of
whatever immediate opportunities a specific bridge can provide. So what might appear to be a tradeoff at a single

We conclude with a final thought on brokerage. Ronald Burt has documented the numerous advantages that individuals who maintain connections that bridge network groups and communities enjoy (Burt 2010). Individuals who maintain relationships that act as bridges between groups are brokers and Burt has distinguished brokers from individuals who maintain relationships with colleagues who travel in the same group or community. While Burt has emphasized the importance of maintaining relationships that bridge different groups, David Krackhardt has called our attention to the internal structure of the bridged groups (Krackhadt 1999). Krackhardt argued that being a broker between two cohesive groups (i.e., a bowtie network) could be so difficult and demanding that an individual occupying such a position could end up being worse off than if he simply lived in a single group. We cannot test the performance implications of living in a bowtie network, but we can speak to the stability of a bowtie position. Our figure 1 is a modified version of figure 1.c from Krackhardt's 1999 article (pg. 188). Our research findings illustrate how difficult it can be to be a bridge between two internally cohesive groups. Shared third parties in one group represent unshared third parties in the other group, thereby making it more difficult to remain connected to both groups over time. Our findings also illustrate how homogeneity with respect to knowledge in those groups offset the negative influence that unshared third parties had on the stability of a relationship. While we certainly believe that knowledge homogeneity reduced the difficulties unshared third parties introduced in the context of knowledge transfer, we can also imagine that homogeneity with respect to factors and characteristics that demarcate a social identity could very well make it more difficult to be a bridge between two internally cohesive groups. We cannot address this issue with our data, but we believe that focusing on identity-based dynamics at the third party level is certainly worthwhile.

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point in time might turn out to be the strategic reallocation of a limited resource over time (Mariotti and Delbridge 2011).

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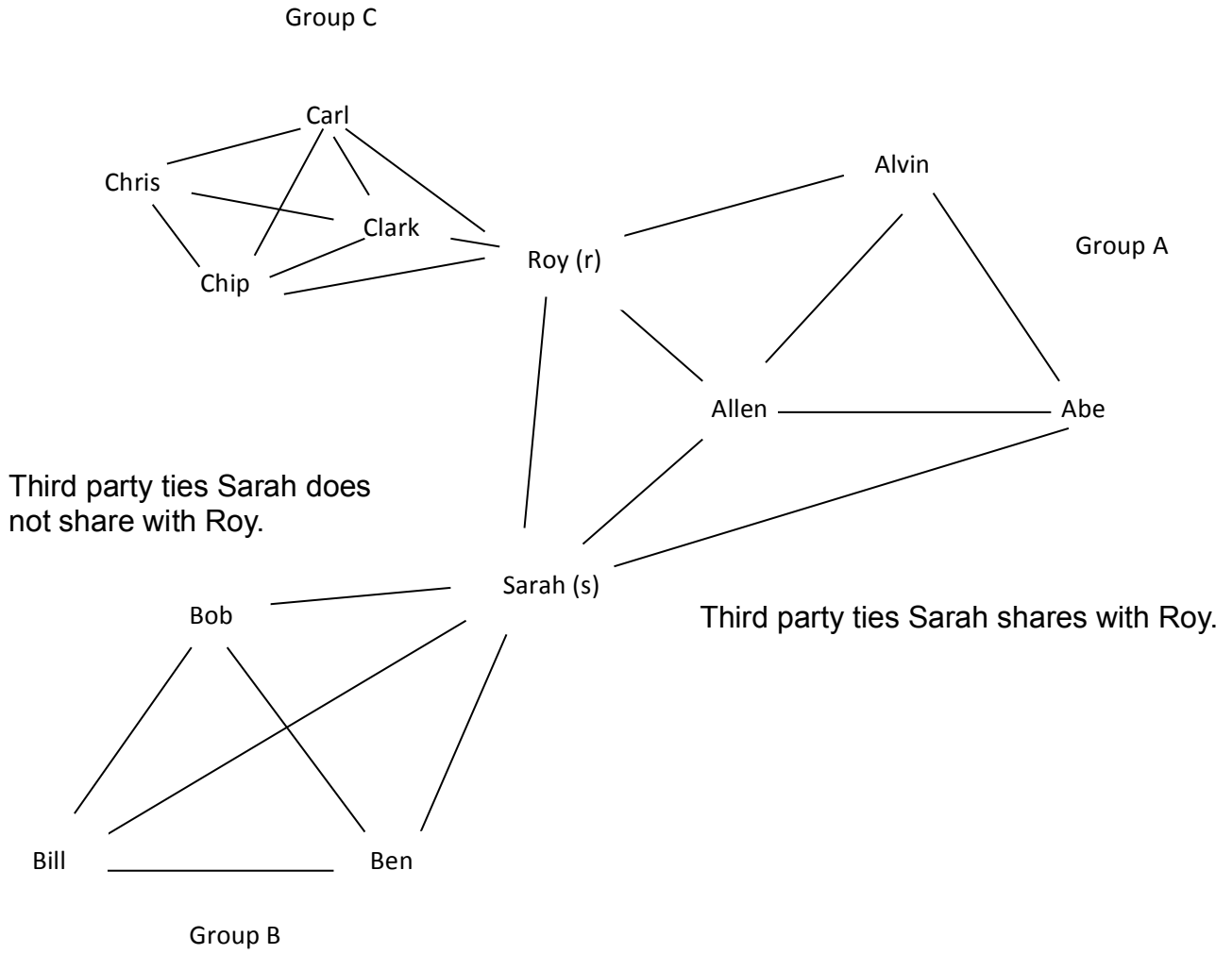
Figure 1: Third Parties

Table 1: Predictors of Initiating and Sustaining Knowledge Transfer Relationships

	Disconnected Model 1	Connected Model 2	Disconnected Model 3	Connected Model 4	Disconnected Model 5	Connected Model 6	Connected Model 7
Predictors							
Tie Strength (TS)		1.314**		1.331**		1.349**	1.394**
Knowledge Overlap							
Dyadic Knowledge Overlap (DKO)	0.691*	0.869**	0.626**	0.815**	0.649**	0.836**	0.848**
DKO X TS		0.443***		0.449***		0.425***	0.318***
Knowledge Overlap among Shared Third Parties (KOSTP)					0.557***	0.754***	0.707***
KOSTP X TS						0.273*	0.299*
Knowledge Overlap among Unshared Third Parties (KOUSTP)					-0.087	-0.251*	-0.304**
KOUSTP X TS						-0.064	-0.058
Third Parties							
Shared Third Parties (STP)	1.342***	2.273***	0.504***	2.214***	0.779***	1.542***	1.439***
STP X DKO	1.831***	2.519***	1.451***	2.375***	1.788***	2.449***	2.436***
STP X DKO X TS							0.874***
STP X KOSTP					0.587***	1.378***	1.004***
STP X TS		0.715**		0.591**		0.521*	0.463*
STP X KOSTP X TS							0.196**
Unshared Third Parties (USTP)			-5.209***	-6.268***	-3.399***	-4.136***	-4.157***
USTP X DKO			1.002***	1.404***	1.108***	1.391***	1.469***
USTP X DKO X TS							0.194
USTP X KOUSTP					0.258***	0.331***	0.291***
USTP X TS				-1.178***		-1.201***	-0.987***
USTP X KOUSTP X TS							0.079**
Controls							
Recipient's Centrality (RC)	0.559***	0.625***	0.504***	0.592***	0.501***	0.521***	0.539***
RC X DKO	0.334***	0.497**	0.298**	0.513**	0.301**	0.559**	0.532**
Source's Centrality (SC)	0.693***	0.707***	1.197***	0.719***	1.194***	0.617***	0.698***
SC X DKO	0.512***	0.895***	0.595***	0.872***	0.593***	0.995***	0.948***
Both Male	0.348	0.354	0.315	0.329	0.314	0.339	0.354
Both Female	0.421	0.431	0.385	0.461	0.385	0.454	0.451
Same Geographic Location	0.739***	0.713***	0.707***	0.694***	0.708***	0.701***	0.689***
Number of Observations	20,532,866	347,720	20,532,866	347,720	20,532,866	347,720	347,720
Model Fit (McFadden's R-Squared)	0.081	0.144	0.108	0.179	0.117	0.201	0.219
Log Likelihood	-2448287.5	-69417.4	-2156405.2	-66094.2	-1987640.2	-62195.3	-60009.1

The stars in table 1 indicate significance levels. * = p <.10, ** = p < .05, and *** = p < 001.

Table 2: Marginal Unshared Third Party Effect for Disconnected Dyads	
Knowledge overlap among unshared third parties is high	b(1) = -1.979, p < .001
Knowledge overlap among unshared third parties is low	b(2) = -4.105, p < .001
A Wald test indicates that b(1) is greater than b(2) (p < .001).	

Table 3: Marginal Unshared Third Party Effect for Connected Dyads		
	High tie strength	Low tie strength
Knowledge overlap among unshared third parties is high	b(1) = -2.162, p < .001	b(2) = -2.176, p < .001
Knowledge overlap among unshared third parties is low	b(3) = -4.551, p < .001	b(4) = -4.845, p < .001
Wald tests indicate that b(1) is greater than b(3) (p < .001) and that b(2) is greater than b(4) (p < .001).		