This study examines the influence of the structure and composition of a firm’s alliance network on its exploratory innovation—innovation embodying knowledge that is novel relative to the firm’s extant knowledge. A longitudinal investigation of 77 telecommunications equipment manufacturers indicated that the technological diversity of a firm’s alliance partners increases its exploratory innovation. Further, network density among a firm’s alliance partners strengthens the influence of diversity. These results suggest the benefits of network “closure” (wherein a firm’s partners are also partners) and access to diverse information can coexist in an alliance network and that these combined benefits increase exploratory innovation.

A core area of research on strategic alliances concerns their influence on firm performance (Gulati, 1998). Within this domain of inquiry, researchers have often characterized alliances as wellsprings of innovation and new capabilities (e.g., Hamel, 1991; Leonard-Barton, 1995). Many studies have shown the alliance networks in which firms are embedded can enhance firm learning and innovation (e.g., Ahuja, 2000; Shan, Walker, & Kogut, 1994; Smith-Doerr et al., 1999; Soh, 2003). Despite this evidence, substantial opportunity exists to expand understanding of how and under what conditions alliance networks influence firm innovation. A review of nearly 40 years of research published in 12 leading management and social science journals (Phelps, Heidl, & Wadhwa, 2010) showed the literature on alliances and firm innovation is limited in at least four important respects.

First, although some research has examined the influence of alliance network structure on firm innovation, the composition of firms in these networks has received little attention. Network structure refers to the pattern of relationships that exist among a set of actors, and network composition refers to the types of actors in a network characterized in terms of their stable traits, features, or resource endowments (Wasserman & Faust, 1994). Recent research has recognized that alliance network studies have largely ignored network composition and has called for more attention in network research to the heterogeneity of the resources of firms in networks (Lavie, 2006; Maurer & Ebers, 2006). The few studies that have examined both structure and composition have focused on the depth of partner technological resources and found that they improve a firm’s innovation performance (Baum, Calabrese, & Silverman, 2000; Stuart, 2000). Although dyad-level research has examined the influence of technological differences between partners on firm innovation (Sampson, 2007), research has largely overlooked the influence of network-level technological diversity—the technological differences between a firm and its partners and among the partners. Such compositional diversity is relevant to a current debate in the social network and alliance literatures.

Second, research has yielded conflicting results about the influence of alliance network structure on firm innovation. Research that examines the influence of social networks on creativity and innovation has stressed the benefits actors derive from network structure and explored how these benefits, or “structural social capital” (Nahapiet &
Ghoshal, 1998), influence knowledge creation. In particular, the configuration of an actor’s set of direct ties (i.e., the actor’s “egocentric network structure”) has received some attention. This research has focused on triadic closure (i.e., whether an actor’s partners are partners), but two competing perspectives exist, each with different causal mechanisms linking network structure to innovation. The argument of one view is that disconnected networks increase creativity and innovation because they provide actors with timely access to diverse information (Burt, 1992, 2004). An alternative view suggests dense networks, in which triads are closed and “structural holes” (unconnected partners) are absent, provide social capital because such structures generate trust, reciprocity norms, and a shared identity, which increase cooperation and knowledge sharing (Coleman, 1988; Portes, 1998). Research has found support for both views, yielding conflicting results. Although studies have found structural holes in a firm’s network enhance its knowledge creation (Hargadon & Sutton, 1997; McEvily & Zaheer, 1999), other research has suggested that network closure improves knowledge transfer and innovation (Ahuja, 2000; Dyer & Nooteboom, 2000; Schilling & Phelps, 2007).

One plausible reason for these conflicting results is that most studies have examined the influence of network structure and largely overlooked network composition. An examination of network composition may help resolve these conflicting results and lead to a better understanding of how alliance networks influence firm innovation. Another possible explanation is that different studies have examined different types of ties, different institutional contexts, and different outcome variables. It is unlikely a particular network structure is universally beneficial (see Adler & Kwon, 2002). Research has suggested that the value of open versus closed networks for innovation and creativity is contingent on the type of task (Hansen, 1999), type of tie (Ahuja, 2000), and particular institutional environment (Owen-Smith & Powell, 2004). In contrast, network structure may act as a contingency variable and moderate the influence of network composition on firm innovation. Moreover, this effect may depend on the type of learning and innovation actors pursue. Both of these contingencies have been largely unexplored in prior research and are examined in this study.

A third limitation of research on alliances and firm innovation concerns an often-used, yet largely unexamined, assumption about the benefits of structural holes. Although a principal benefit attributed to structural holes is timely access to diverse information (Burt, 1992), structural holes are neither a necessary nor a sufficient condition for such access (Reagans, Zuckerman, & McEvily, 2004). The informational benefits contacts provide can be directly observed by examining the extent to which they specialize in different domains of knowledge (Reagans & McEvily, 2003; Rodan & Galunic, 2004). Observing differences in competencies also allows a finer-grained measure of diversity than simply counting structural holes. Because competencies are stable and durable properties of firms (Patel & Pavitt, 1997), they are a compositional variable. Ties to partners with dissimilar knowledge stocks provide a firm with access to diverse information and know-how, independent of the structure of its local network. Thus, the social control benefits of network closure and access to diverse information and know-how can coexist.

Research on interfirm alliances (Ahuja, 2000) and interpersonal networks (Rodan & Galunic, 2004) has shown network density and knowledge diversity are empirically distinct. However, alliance research has not examined the independent and interactive effects of network structure and network knowledge diversity on firm innovation.

A final limitation of research on alliance networks and firm innovation is that it largely ignores the novelty of the knowledge created and embodied in the innovations measured. Instead, studies have focused on the amount of innovation indicated by survey items or counts of new products and patents. This approach implicitly rests on the assumption that innovations are similar in their knowledge content. Although research has suggested firms typically search for innovative solutions to problems in the domains of their existing expertise (“local search”) and produce “exploitive” innovations that represent incremental improvements to their prior innovative efforts (e.g., Dosi, 1988; Martin & Mitchell, 1998), some research has shown firms vary in the scope of their search and the exploratory content of their innovations (Ahuja & Lampert, 2001; Rosenkopf & Nerkar, 2001). A few studies have examined how organizational design decisions influence exploratory knowledge creation (Jansen, Van Den Bosch, & Volberda, 2006; Sigelkow & Rivkin, 2005). However, with the exception of some qualitative case study research (Dittrich, Duysters, &

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1 Burt (1992) also argued structural holes allow actors freedom from the normative expectations of others in a network, yet research into the influence of network structure on innovation and creativity has stressed informational benefits, rather than control benefits, as the primary causal motor (e.g., Ahuja, 2000; Burt, 2004; Obstfeld, 2005).
de Man, 2007; Gilsing & Noteboom, 2006), research has generally ignored the effects of alliance network structure and network diversity on exploratory knowledge creation.

The purpose of this study is to address these limitations. I do so by examining the influence of the structure and composition of a firm’s network of horizontal technology alliances on its exploratory innovation. I focus on horizontal technology alliances for theoretical clarity. Exploratory innovation is the creation of technological knowledge that is novel relative to a firm’s extant knowledge stock. Research has often portrayed exploration as a process (March, 1991), yet the manifestation of this process can be observed by examining the exploratory content of a firm’s innovations (Benner & Tushman, 2002; Rosenkopf & Nerkar, 2001). Exploratory innovations embody knowledge that differs from knowledge used by the firm in prior innovations and shows the firm has broadened its technical competence (Greve, 2007; Rosenkopf & Nerkar, 2001).²

Understanding the origins of exploratory innovation is an important endeavor. Because the results of exploration (versus exploitation) typically take longer to realize, are more variable, and produce lower average returns, organizations generally pursue exploitative innovation at the expense of explorative innovation (March, 1991). They face a fundamental challenge: although exploitation improves an organization’s short-term performance, exploration increases its long-term adaptability and survival (Levinthal & March, 1993). This formulation does not suggest that exploratory innovation is preferred over incremental innovation, only that a balance is necessary (March, 1991). The strong incentives to pursue exploitation at the expense of exploration raise the question of how and when firms are able to explore effectively. Research has documented the propensity of firms to pursue local search and exploitative innovation (e.g., Dosi, 1988; Helfat, 1994), but much less is known about how and when firms overcome this predisposition and develop exploratory innovations. Explaining the production of exploratory innovations should provide a better understanding of how organizations are able to thrive and survive.

I derive two predictions about the effect of horizontal technology alliances on firm exploratory innovation. First, in highlighting the role of network composition, I draw on the recombinatory search literature (e.g., Fleming, 2001) and examine the benefits and costs of increasing network technological diversity for exploratory innovation. I predict network diversity has an inverted U-shaped effect on firm exploratory innovation performance. Second, building on interfirm learning and network research, I argue that the extent to which a firm’s partners are densely interconnected generates trust and reciprocity, which enhance the benefits of network diversity and mitigate some of its costs. I predict the density of a firm’s alliance network positively moderates the effect of network diversity on the firm’s exploratory innovation performance.

In the empirical work reported here, I tested these predictions on a panel of 77 leading communications equipment manufacturers during 1987–97 and found partial, yet robust, support for both hypotheses. A positive linear effect of network diversity emerged, rather than a curvilinear effect, and a positive linear interaction between diversity and density, rather than a curvilinear interaction. This study contributes to the alliance and innovation literatures by addressing significant gaps in research on the influence of alliance networks on firm innovation. This is the first study of which I am aware that investigates the influence of alliance network structure and composition on firm exploratory innovation. The results show the technological diversity in a firm’s alliance network and the density of the network increase exploratory innovation, independently and in combination. The results also suggest the presence of structural holes in a firm’s network is not a necessary condition for providing the firm with access to diverse information. The extent to which an actor’s network is composed of alters with diverse knowledge bases provides it access to diverse information, independent of network structure. The benefits of network closure and access to diverse information and know-how can coexist in a firm’s alliance network, and combining the two increases the firm’s exploratory innovation. Because I find network diversity begets diverse innovations (Kauffman, 1995), the results suggest that dense networks populated by diverse actors generate more, rather than less, diverse knowledge.

**THEORY AND HYPOTHESES**

To understand when alliances influence a firm’s exploratory innovation, I build on two complementary theoretical bases: recombinatory search and
social capital. The recombinatory search literature casts innovation as a problem-solving process in which solutions to valuable problems are discovered via search (Dosi, 1988). Search processes leading to the creation of new knowledge typically involve the novel recombination of existing elements of knowledge, problems, or solutions (Fleming, 2001; Nelson & Winter, 1982) or reconfiguring the ways knowledge elements are linked (Henderson & Clark, 1990). Search is uncertain, costly, and guided by prior experience (Dosi, 1988). Over time, feedback from past search efforts becomes embodied in organizational routines, which efficiently guide current search efforts (Nelson & Winter, 1982).

Firms create knowledge by engaging in local and distant search (March, 1991). Local search, which is synonymous with exploitation, produces recombinations of familiar and well-known knowledge elements and is often the preferred mode of search (March, 1991; Stuart & Podolny, 1996). In contrast, distant search, or exploration, involves recombinations of novel, unfamiliar knowledge and involves higher costs and uncertainty (March, 1991). Although distant search can be less efficient and less certain than local search, it increases the variance of search and the potential for highly novel recombinations (Fleming, 2001; Levinthal & March, 1981).

Innovation search research has primarily focused on where firms search for solutions (i.e., local versus distant); the interfirm learning literature, on the other hand, has emphasized how firms search. According to this research, interfirm relationships are a mechanism for search and a medium of knowledge transfer (Ingram, 2002). Because knowledge is widely and heterogeneously distributed (von Hayek, 1945), the exchange of knowledge is necessary for recombination (Nahapiet & Ghoshal, 1998). Yet the nature of knowledge involved in innovation poses challenges to exchange. Technical innovation involves tacit and socially embedded knowledge (Dosi, 1988). Technology is knowledge embedded in communities of practitioners (Layton, 1974) who develop tacit understandings of how to solve problems related to its use and reproduction (von Hippel, 1988). Such knowledge is also stored in organizational routines (Nelson & Winter, 1982). The specialized, tacit, and embedded nature of technical knowledge makes market trading for it subject to severe exchange problems (Teece, 1992). Firms that can identify potentially useful elements of technological knowledge, conceive of how these elements can be fruitfully combined, and effectively access and assimilate this knowledge increase their potential for knowledge creation (Galunic & Rodan, 1998). Strategic alliances are important in each of these aspects of successful recombination.

Strategic alliances are a means of accessing knowledge a firm does not have and can be an effective medium of knowledge transfer and integration (Hamel, 1991). Alliances provide a firm with direct and repeatable access to its partners’ organizational routines, which reduces its ambiguity about a partner’s knowledge and increases the efficacy of its transfer and assimilation (Jensen & Szulanski, 2007). Because of the increased social interaction and enhanced incentive alignment and monitoring features they provide, alliances are institutions better suited than market transactions for the repeated exchange of tacit, routine-embedded knowledge (Teece, 1992).

Although alliances provide access to external knowledge, they do not guarantee its effective detection, transfer, and assimilation. These processes, and thus the odds of successful recombination, are influenced by the incentives partners have to cooperate and share knowledge with each other (Hamel, 1991). Because the risk of opportunism is pronounced in horizontal technology alliances, effective cooperation and knowledge sharing are difficult to achieve (Gulati & Singh, 1998). Alliance research has typically emphasized the role of formal governance mechanisms—such as detailed contracts, the use of equity as a “hostage,” and joint venture structures—in curbing opportunism and increasing cooperation (e.g., Kogut, 1988; Mowery, Oxley, & Silverman, 1996; Sampson, 2007). Other research has suggested that mutual trust and reciprocity norms between partners provide effective and efficient informal governance (Dyer & Singh, 1998; Kale, Singh, & Perlmutter, 2000).

Trust and reciprocity serve as social control mechanisms that mitigate opportunism and safeguard exchange in alliances (Dyer & Singh, 1998). As such, they are forms of social capital, because they represent resources that are instrumentally valuable for, and appropriate by, partners in a social exchange relationship (Coleman, 1988). The extent to which social capital exists in a firm’s network of alliances can increase the firm’s access to its partners’ knowledge, the motivation of its partners to transfer knowledge, and the efficiency of knowledge exchange and transfer (Inkpen & Tsang, 2005), resulting in more successful recombinations (Galunic & Rodan, 1998). In the next two sections, I build on the recombinatory search literature and research on interfirm networks and social capital to develop predictions about how and when network technological diversity and network density influence a firm’s exploratory innovation performance.
Network Technological Diversity

Diversity refers to the extent to which a system consists of uniquely different elements, the frequency distribution of these elements, and the degree of difference among the elements (Stirling, 2007). Thus, I define alliance network technological diversity as the extent to which the technologies pursued by a firm’s alliance partners are different from one another and from those of the focal firm. Although network diversity provides benefits for a firm’s exploratory innovation efforts, it also poses significant costs. Diversity affects the relative novelty of knowledge available in a network and the ease with which a firm can recognize, assimilate, and utilize this knowledge.

Increasing network diversity increases the relative novelty of the knowledge a firm can access. Because exploratory innovations embody relatively novel knowledge, a necessary condition for firm exploratory innovation is access to dissimilar knowledge (Greve, 2007; Jansen et al., 2006). Diversity increases the number and variety of possible combinations and the potential for highly novel solutions (Fleming, 2001). The “value of variance” (Mezias & Glynn, 1993) in distant search is that though it increases failures, it also increases the number of highly novel solutions (Levinthal & March, 1981). In contrast, individuals and organizations that exploit established competences in their innovative problem-solving efforts typically experience more certain and immediate returns, but produce mostly incrementally innovative solutions (Audia & Goncalo, 2007; Dosi, 1988). Searching diverse knowledge domains challenges existing cognitive structures, including premises and beliefs about cause-effect relationships (Duncker, 1945), which can promote new associations and lead to highly novel insights and solutions (Simon, 1999). By searching diverse and novel domains, firms can develop multiple conceptualizations of problems and solutions and apply solutions from one domain to problems in another (Hargadon & Sutton, 1997). Diverse knowledge sources also provide firms with access to diverse problem-solving heuristics (Page, 2007), which can increase the exploratory content of new combinations of knowledge (Audia & Goncalo, 2007). Finally, searching diverse, nonredundant knowledge can stimulate intensive experimentation with new combinations, leading to highly novel innovations (Ahuja & Lampert, 2001).

Network diversity also influences a firm’s relative absorptive capacity. As the technological distance between partners increases, their ability to recognize, assimilate, and apply each other’s knowledge declines (Lane & Lubatkin, 1998), increasing the costs of recombinatory innovation (Weitzman, 1998). A firm must expend greater effort and resources to understand and integrate dissimilar knowledge (Cohen & Levinthal, 1990). This can manifest in costly, excessive, and inconclusive experimentation (Ahuja & Lampert, 2001). A firm’s cognitive capacity constraints and its relative inexperience with dissimilar knowledge components will limit its ability to comprehend increasingly complex interactions among these components (Fleming & Sorenson, 2001). Moreover, integrating novel knowledge from dissimilar sources often requires changing existing patterns of communication and social exchange, which is difficult in established organizations (Kogut & Zander, 1992). Attempting to assimilate and integrate highly diverse knowledge components can lead to information overload, confusion, and diseconomies of scale in innovation efforts (Ahuja & Lampert, 2001). Thus, as a firm’s network diversity increases, its costs of absorbing and utilizing this knowledge greatly increase.

Given these benefits and costs of network diversity, I expect it to exhibit a curvilinear effect on a firm’s exploratory innovation. At low levels of diversity, a firm has a high degree of relative absorptive capacity in its portfolio of partners, but the knowledge to which it has access provides little novelty. At high levels of network diversity, absorptive capacity costs are likely to outweigh the benefits of highly novel knowledge. Although increasing diversity exponentially increases opportunities for novel recombinations (Fleming, 2001), an organization is greatly constrained in its ability to process an abundance of potentially novel recombinations into usable innovations (Weitzman, 1998). Research has shown that as knowledge components become more diverse, the chance of their recombination into useful innovations declines, with excessive diversity reducing innovation (Fleming & Sorenson, 2001). In contrast, at a moderate level of network diversity a firm’s exploratory innovation efforts benefit from a balance of access to a moderate degree of novel knowledge and moderately efficient relative absorptive capacity. Thus, some degree of diversity is valuable for exploratory innovation; too much can be detrimental.

Hypothesis 1. The technological diversity in a firm's alliance network has an inverted U-shaped relationship with the firm's subsequent degree of exploratory innovation.

Network Density

Although an alliance provides access to a partner’s knowledge, it does not guarantee the effective
detection, transfer, and assimilation of this knowledge (Hamel, 1991). The tacit and embedded nature of technological knowledge makes it difficult for partners to detect, transfer, and assimilate (Teece, 1992), reducing its potential for successful recombination (Galunic & Rodan, 1998). Increasing network diversity worsens this problem, since a firm’s absorptive capacity in relation to its partners will decline (Lane & Lubatkin, 1998). Greater diversity reduces the odds partners share a common understanding of technical issues, a language for discussing them, and an approach to codifying knowledge (Cohen & Levinthal, 1990). The exchange hazards in horizontal technology alliances compound these problems. Because partners have incentives to compete, the risk of opportunism is elevated. Such alliances are also inherently uncertain and pose large measurement and monitoring problems (Pisano, 1989). Partners are at risk of involuntary knowledge leakage, the withholding of effort and resources needed to achieve alliance goals, misrepresentation of newly discovered knowledge, and challenges in transferring tacit knowledge developed during the relationships (Gulati & Singh, 1998). Network diversity also compounds these problems. Increasing diversity increases the relative novelty of knowledge and the variety of tacit knowledge, thereby increasing the amount of unique tacit knowledge. High novelty and tacitness increase partner uncertainty and contractual hazards (Pisano, 1989). Technological diversity increases coordination problems and the potential for costly contractual renegotiations (Sampson, 2004). These exchange hazards can reduce cooperation and knowledge sharing, hindering a firm’s recombination efforts.

The extent to which a firm’s alliance partners are densely interconnected mitigates some of the costs and amplifies some of the benefits of increasing network diversity, thus positively moderating its effect on exploratory innovation. Dense networks facilitate the production of trust and reciprocity among networked firms, which decrease exchange hazards in alliances, increase cooperation among partners, and mitigate absorptive capacity problems. These problems become more challenging, and thus more important to resolve, as network diversity grows.

Network density promotes trust and reciprocity between partners because they share common third-party partners. Dense networks allow firms to learn about current and prospective partners through common third parties, reducing information asymmetries among firms and increasing their “knowledge-based trust” in one another (Gulati, Nohria, & Zaheer, 2000). Network closure also promotes trust by increasing the costs of opportunism (Coleman, 1988). Because a firm’s behavior is more visible in a dense network, an act of opportunism can damage its reputation, jeopardizing its existing alliances and reducing future alliance opportunities (Gulati, 1998). Because the costs of opportunism can outweigh the benefits, firms will refrain from such behavior. Thus, dense networks also generate “enforceable” or “deterrence-based” trust (Kreps, 1990; Raubb & Weesie, 1990). Research has provided empirical support for these arguments (Gulati & Sytch, 2008; Holm, Eriksson, & Johanson, 1999; Husted, 1994; Robinson & Stuart, 2007; Rooks, Raub, Selten, & Tazelaar, 2000; Uzzi, 1996).

Network density also generates reciprocity exchanges in which partners share privileged resources because they expect recipients will repay them with something of equivalent value (Coleman, 1988). A firm can encourage reciprocity between two of its partners by transferring reciprocal obligations one partner owes to the firm to the other partner (Uzzi, 1997). Dense networks also promote reciprocity by protecting relationships from opportunism, increasing actors’ confidence that obligations for repayment will eventually be met (Coleman, 1988).

The trust and reciprocity benefits of dense networks can mitigate some of the exchange hazards and challenges to effective interfir cooperation associated with greater network diversity. Trust and reciprocity generated by network density act as informal safeguards of dyadic exchange, supplementing formal alliance governance mechanisms (Powell, 1990). Given the challenges of formal governance in horizontal technology alliances among technologically diverse firms, informal governance becomes more important in mitigating opportunism and promoting cooperation as diversity increases. Informal governance reduces the threat of opportunism and increases each partner’s motivation to cooperate and share resources (Dyer & Singh, 1998). Trust reduces the extent to which alliance partners protect knowledge, increases their willingness to share knowledge, and increases interfirm learning and knowledge creation (Kale et al., 2000; Larson, 1992). Reciprocity norms reinforce this motivation to share, since firms can be confident partners will reciprocate (Dyer & Nobeoka, 2000). As a result, the information and knowledge shared will be less distorted, richer, and of higher quality (Dyer & Nobeoka, 2000; Uzzi, 1997).

Research has suggested dense interfir networks are better for transferring and integrating complex and tacit knowledge than networks with structural holes (Dyer & Nobeoka, 2000; Kogut, 2000).

Alliance network density also reduces absorptive capacity problems related to growing network di-
versity. Network closure promotes intense social interaction, experimentation, joint problem solving, and triangulation, which enhance a firm’s ability to absorb and apply increasingly diverse partner knowledge. The trust and reciprocity benefits of network closure promote intense interaction among personnel from partnered firms (Larson, 1992), which improves the detection and transfer of tacit and embedded knowledge (Zander & Kogut, 1995). Intense interaction can also lead to the creation of partner-specific knowledge-sharing routines that facilitate knowledge transfer (Lane & Lubatkin, 1998). The social capital produced in dense alliance networks encourages such relation-specific investments (Walker, Kogut, & Shan, 1997).

The trust and reciprocity benefits of network closure also increase partners’ joint problem-solving efforts and stimulate experimentation with different knowledge combinations, improving knowledge detection and transfer from diverse partners (Dyer & Nobeoka, 2000; Uzzi, 1997). Trust and reciprocity can also increase a partner’s motivation to “teach” (Szulanski, 1996), which is more important for student firms as partner diversity increases, since they should find it easier to learn unaided from similar partners (Szulanski, 1996). Alliance partners also provide alternative interpretations of technical problems and solutions, allowing a firm to compare, contrast, and triangulate these perspectives (Nonaka, 1994). Alternative perspectives diffuse rapidly in dense networks (Smith-Doerr & Powell, 2005) and are more valuable when partners are diverse, since a variety of perspectives increases the chances some will be useful in a firm’s recombination efforts (Nonaka, 1994). Finally, the rapid flow of information in dense networks provides firms with more opportunities to share and expand their understanding of technical issues and can help establish a shared mode of discourse (Smith-Doerr & Powell, 2005), allowing diverse partners to more efficiently communicate with and learn from one another (Kogut & Zander, 1996).

In sum, increasing network density improves a firm’s ability to absorb and utilize knowledge from more diverse partners. I expect these benefits of network density to moderate the curvilinear effect of network diversity on firm exploratory innovation in four distinct ways. First, increasing density will increase the slope (i.e., strength) of the positive relationship between diversity and exploratory innovation (i.e., the positive slope to the left of the peak of the curve). Second, increasing density will increase the amplitude of the curvilinear effect of diversity. That is, as density increases, the maximum value of exploratory innovation achieved will increase. Third, the value of diversity that maximizes exploratory innovation will increase as density increases, shifting the peak of the curve to higher values of diversity. Finally, increasing density will reduce the slope of the negative relationship between diversity and exploratory innovation. That is, after the effect of diversity turns negative, increasing density will dampen the negative effect of diversity on exploratory innovation.

Hypothesis 2. The density of a firm’s alliance network moderates the curvilinear relationship between network diversity and exploratory innovation in such a fashion that increasing density will: (a) increase the slope of the positive effect of diversity, (b) increase the amplitude of the effect of diversity, (c) increase the value of diversity that maximizes exploratory innovation, and (d) reduce the negative effect of diversity.

METHODOLOGY

Sample and Data

The research setting for this study was the global telecommunications equipment industry (SIC 366). Firms in this industry produce and market hardware and software that enable the transmission, switching, and reception of voice, images, and data over both short and long distances using digital, analog, wire line, and wireless technology. I chose this setting for two reasons. First, during the 1980s and 1990s this industry experienced significant changes in technology and competition, resulting in a growing use of technology alliances by incumbents (Amesse, Latour, Rebolledo, & Séguin-Dudu, 2004). Second, since I used patent data, I chose to study an industry in which firms routinely and systematically patent their inventions (Hagedoorn & Cloodt, 2003; Levin, Kleverick, Nelson, & Winter, 1987).

To minimize survivor bias and right censoring, I limited the study period to 1987–97. I limited the sample frame to public companies to ensure the availability and reliability of financial data. I limited the sample to the firms in the industry with the largest sales because complete and accurate alliance data are more available for industry leaders than for smaller firms (Gulati, 1995). To minimize survivor bias, I identified the top-selling firms in the industry at the beginning of the study period rather than the end because numerous mergers, restructurings, and failures occurred during the study period (Amesse et al., 2004). To minimize the influence of right censoring, I ended the study period in 1997 to allow sufficient time for the (non)approval of patent applications that sample firms made during...
the period (also see footnote 4). Following prescriptions for establishing network boundaries in empirical research (Laumann, Marsden, & Prensky, 1983), I restricted the network to both firms and alliances that focused on the telecommunications equipment industry. Recent alliance network research has used similar network construction criteria (Rowley, Behrens, & Krackhardt, 2000; Schilling & Phelps, 2007). These sampling criteria resulted in a sample of 77 firms headquartered in 13 countries.

I used patent data to measure technological knowledge because patents are valid and robust indicators of knowledge creation (Trajtenberg, 1987). Knowledge is instantiated in inventions, and patents are measures of novel inventions externally validated through the patent examination process (Griliches, 1990). A patent application represents a positive expectation by an inventor of the economic significance of his or her invention, since getting such protection is costly (Griliches, 1990). Patents measure a codifiable portion of a firm’s technical knowledge, yet they correlate with measures that incorporate tacit knowledge (Brouwer & Kleinknecht, 1999). For these various reasons, patents are a reliable and valid measure of innovation in the telecom equipment industry (Hagedoorn & Cloodt, 2003).

Information on U.S. patents was obtained from Delphion. Using patents from a single country maintains consistency, reliability, and comparability across firms (Griliches, 1990). U.S. patents are a good data source because of the rigor and procedural fairness used in granting them, the large incentives firms have to obtain patent protection in the world’s largest market for high-tech products, the high quality of services provided by the U.S. Patent and Trademark Office (USPTO), and the reputation of the United States for providing effective intellectual property protection (Pavitt, 1988; Rivette, 1993). I used the application date to assign a granted patent to a firm because this date closely captures the timing of knowledge creation (Griliches, 1990). Because patents are often assigned to subsidiaries, I carefully aggregated patents to the firm level.3

The collaboration data were obtained from multiple sources. I initially collected alliance data from the SDC Alliance Database. Although this database provided substantial content, it had many limitations. I overcame these limitations through systematic archival research using annual reports, 10K and 20F filings, Moody’s Manuals, Factiva, Lexis-Nexis, and Dialog. These last three databases index the historical full texts of hundreds of business publications from all regions of the world and include articles translated to English from their original languages, and non-English publications. I conducted broad keyword searches to identify all instances of interfirm cooperation involving the sample firms. Individuals fluent in the respective language read non-English articles and reports, identified instances of interfirm cooperation, and translated the documents into English. I recorded only collaborations that could be confirmed in multiple sources. Around 1,200 annual reports and Securities and Exchange Commission (SEC) filings and over 180,000 electronic articles were examined, and over 8,500 relevant news stories were printed out. Overall, the data set from which this study draws includes 7,904 alliances and 1,967 acquisitions initiated during 1980-96. I reviewed every record from the SDC data and corrected duplicate entries and other errors and omissions using secondary sources.

Firm attribute data were collected from Compustat, annual reports, SEC filings, the Japan Company Handbook, Worldscope, and Global Vantage.

Measurement: Dependent Variable

**Exploratory innovation.** Exploratory innovation is the creation of technological knowledge by a firm that is novel relative to its existing knowledge stock (Benner & Tushman, 2002; Rosenkopf & Nerkar, 2001). Following prior research (Benner & Tushman, 2002, Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001), I measured exploratory innovation using patent citations. I began with the list of U.S. patent classes that corresponded to the telecommunications equipment industry at the beginning of the sample period (see Table 1). I assessed the exploratory innovation of firm i in year t by classifying and tabulating all citations in the firm’s telecommunications equipment patents applied for in year t (and eventually granted). I traced each citation to determine if the firm had used the same citation or if the citation was to a patent developed by the firm during the seven years before the focal year. I used a seven-year window because organizational memory in high-tech firms is imperfect, causing the value of knowledge to depreciate rapidly over time (Argote, 1999) and creating signifi-

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3 I identified all divisions, subsidiaries, and joint ventures of each sample firm (using Who Owns Whom and the Directory of Corporate Affiliations) as of 1980. I then traced each firm’s history to account for name changes, division names, divestments, acquisitions, and joint ventures and obtained information on the timing of these events. This procedure yielded a master list of entities that I used to identify all patents belonging to sample firms for the period of study.
with SIC 366.

ment technology in this table are most frequently associated classes used in this study to represent communications equip-

exist in the late 1980s). This indicated that the 22 primary

classes listed in the baseline concor-

1988. To make this comparison, I used the USPTO’s USPC-IPC

degree to which specific international patent classes (IPCs) were

associated with U.S. SIC 366 (except for class 725, which did not

sociated with SIC 366 as the industry of manufacture as of

The primary classes listed in the baseline concor-

dance. I identified the primary patent classes common to both of

collaborative tools and services for research scientists and engi-

Community of Science Inc., an internet company that provides

in the United Kingdom, and the concordance developed by the

Technology Policy Research (SPRU), a unit of Sussex University

utilized both Silverman’s (1996) concordance method and con-

cordances provided by experts. I used the concordance for com-

munications equipment developed by scholars at Science and

constitute telecommunications equipment, I needed to develop

a concordance between primary patent classes and the three-

industrial definitions such as SIC codes (Griliches, 1990). That is,

there is not a one-to-one mapping between primary patent

classes and industries. Multiple patent classes are used in a

single industry, and a single patent class can be used in multiple

industries. Consequently, to identify the areas of technology that

constitute telecommunications equipment, I needed to develop a

cordance between primary patent classes and the three-

digit SIC code 366, “communications equipment.” To do so, I

utilized both Silverman’s (1996) concordance method and con-

cordances provided by experts. I used the concordance for com-

munications equipment developed by scholars at Science and

Technology Policy Research (SPRU), a unit of Sussex University

in the United Kingdom, and the concordance developed by the

Community of Science Inc., an internet company that provides

collaborative tools and services for research scientists and engi-

neers. I identified the primary patent classes common to both of

these expert-based concordances as a baseline and then com-

pared this list of classes with a rank-ordered list delineating the
degree to which specific international patent classes (IPCs) were

associated with SIC 366 as the industry of manufacture as of

1988. To make this comparison, I used the USPTO’s USPC-IPC

cordance. The primary classes listed in the baseline concor-
dance were associated with the highest ranked IPC classes asso-
ciated with U.S. SIC 366 (except for class 725, which did not

exist in the late 1980s). This indicated that the 22 primary

classes used in this study to represent communications equip-

tment technology in this table are most frequently associated

with SIC 366.

## TABLE 1
Primary U.S. Patent Classes Used to Represent Telecommunications Equipment*

<table>
<thead>
<tr>
<th>Class Number</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>178</td>
<td>Telegraphy</td>
</tr>
<tr>
<td>179 (discontinued)</td>
<td>Telephony</td>
</tr>
<tr>
<td>329</td>
<td>Demodulators</td>
</tr>
<tr>
<td>332</td>
<td>Modulators</td>
</tr>
<tr>
<td>333</td>
<td>Wave transmission lines and networks</td>
</tr>
<tr>
<td>334</td>
<td>Tuners</td>
</tr>
<tr>
<td>340</td>
<td>Communications: electrical</td>
</tr>
<tr>
<td>341</td>
<td>Coded data generation or conversion</td>
</tr>
<tr>
<td>342</td>
<td>Communications: directive radio wave systems &amp; devices</td>
</tr>
<tr>
<td>343</td>
<td>Communications: radio wave antennas</td>
</tr>
<tr>
<td>348</td>
<td>Television</td>
</tr>
<tr>
<td>358</td>
<td>Facsimile and static presentation processing</td>
</tr>
<tr>
<td>359</td>
<td>Optics: systems (including communication) and elements</td>
</tr>
<tr>
<td>367</td>
<td>Communications, electrical: acoustic wave systems and devices</td>
</tr>
<tr>
<td>370</td>
<td>Multiplex communications</td>
</tr>
<tr>
<td>375</td>
<td>Pulse or digital communications</td>
</tr>
<tr>
<td>379</td>
<td>Telephonic communications</td>
</tr>
<tr>
<td>381</td>
<td>Electrical audio signal processing systems and devices</td>
</tr>
<tr>
<td>382</td>
<td>Image analysis</td>
</tr>
<tr>
<td>385</td>
<td>Optical waveguides</td>
</tr>
<tr>
<td>455</td>
<td>Telecommunications</td>
</tr>
<tr>
<td>725</td>
<td>Interactive video distribution systems</td>
</tr>
</tbody>
</table>

*Because patents are classified by technological and functional principles, they do not map easily to product-based industrial definitions such as SIC codes (Griliches, 1990). That is, there is not a one-to-one mapping between primary patent classes and industries. Multiple patent classes are used in a single industry, and a single patent class can be used in multiple industries. Consequently, to identify the areas of technology that constitute telecommunications equipment, I needed to develop a concordance between primary patent classes and the three-digit SIC code 366, “communications equipment.” To do so, I utilized both Silverman’s (1996) concordance method and concordances provided by experts. I used the concordance for communications equipment developed by scholars at Science and Technology Policy Research (SPRU), a unit of Sussex University in the United Kingdom, and the concordance developed by the Community of Science Inc., an internet company that provides collaborative tools and services for research scientists and engineers. I identified the primary patent classes common to both of these expert-based concordances as a baseline and then compared this list of classes with a rank-ordered list delineating the degree to which specific international patent classes (IPCs) were associated with SIC 366 as the industry of manufacture as of 1988. To make this comparison, I used the USPTO’s USPC-IPC concordance. The primary classes listed in the baseline concordance were associated with the highest ranked IPC classes associated with U.S. SIC 366 (except for class 725, which did not exist in the late 1980s). This indicated that the 22 primary classes used in this study to represent communications equipment technology in this table are most frequently associated with SIC 366.

The extent to which a firm draws on elements of knowledge (e.g., patent citations) it has previously used reflects its practice of local search and exploitation of its extant knowledge stock. The extent to which it uses citations with which it has no experience is indicative of distant search and exploratory innovation (Benner & Tushman, 2002). This measure ranges from pure exploitation (no exploration) at the low end to pure exploration (no exploitation) at the high end. It is consistent with research that has conceptualized and measured exploitation and exploration, or local and distant search, as the ends of a continuum (Benner &

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4 Two aspects of the patent data used to construct this measure merit discussion. First, during the period of study, the USPTO did not publish patent applications. A patent application date was only observable when a patent was granted. Because I observed patents using their date of application and because there is a delay between the date of application for a patent and its eventual granting, I may not have observed all patents applied for in a particular year and eventually granted, because the USPTO had not rendered a decision by the time I collected my patent data. The influence of such a right-censoring bias, caused by the delay between patent application and issuance, is likely to be negligible in this study. Around 99 percent of all applications are reviewed within five years of application (Hall et al., 2001), which is the period between the end of the sample (1997) and the last year of patent data collection (2002). Second, patent examiners often add citations to patent applications (Alcacer & Gittelman, 2006), which suggests applicant firms are not necessarily aware of all cited patents. Third-party citations often manifest as noise in the measurement of patent-based variables (Jaffe, Trajtenberg, & Fogarty, 2002). Noise in the measurement of a dependent variable increases standard errors and reduces the likelihood of finding statistically significant effects (Gujarati, 1995).

5 Though I focus on one domain of search (i.e., technological knowledge), firms search multiple domains, such as customer and geographic space (Gupta, Smith, & Shalley, 2006; Sidhu et al., 2007). Portraying exploitation
As a robustness check, I applied an alternative measure of exploratory innovation from prior research (e.g., Ahuja & Lampert, 2001; McGrath & Nerkar, 2004). I computed this measure as the number of new three-digit technology classes in which firm \( i \) patented in year \( t \), classifying a technology class as new if the firm had not patented in that class in the past seven years. The USPTO assigns patents to about 450 technology classes, with each class demarcating an area of technology. The extent to which a firm enters new technological domains is indicative of exploration (Ahuja & Lampert, 2001; McGrath & Nerkar, 2004). This measure was broader than the citation-based measure since it took into account all technology classes in which a firm might patent.

**Measurement: Explanatory Variables**

Following prior research (e.g., Ahuja, 2000; Stuart, 2000), I sampled alliances involving technology development or exchange because my phenomenon of interest and theory concerned the transfer and creation of technological knowledge. I excluded unilateral licensing deals and alliances formed for the sole purpose of marketing, distribution, or manufacturing.

**Network technological diversity.** To measure network technological diversity, I employed Rodan and Galunic’s (2004) measure of knowledge heterogeneity. This measure incorporates information about the knowledge distance between a focal actor and each of its partners and the distances among the partners. I began at the dyad level and measured the technological distance between pairs of firms using Jaffe’s (1986) index. For each firm-year, I measured the distribution of a firm’s patents across primary patent classes. Following Sampson (2007), I used a moving four-year window to establish a firm’s patenting profile. This distribution located a firm in a multidimensional technology space, captured by a K-dimensional vector \( f_i = [f_{i1}, \ldots, f_{ik}] \), where \( f_{ik} \) represents the fraction of firm \( i \)’s patents that are in patent class \( k \). This approach rests on an assumption that the distribution of a firm’s patents across classes reflects the distribution of its technical knowledge and exploration as ends of a continuum in one domain of search does not preclude the possibility that firms can simultaneously achieve high levels of both exploitation and exploration in multiple domains (Gupta et al., 2006). A universal argument about the mutual exclusivity or independence of exploitation and exploration may be impossible (Gupta et al., 2006).

(Jaffe, 1986). The technological distance, \( d \), between firms \( i \) and \( j \) in year \( t \) was calculated as:

\[
d_{ijt} = 1 - \left[ \frac{1}{\sqrt{K}} \sum_{k=1}^{K} f_{ik} f_{jk} \left( \frac{1}{\left( \sum_{k=1}^{K} f_{ik}^2 \right)^{1/2}} \left( \sum_{k=1}^{K} f_{jk}^2 \right)^{1/2} \right) \right].
\]

This measure was bounded between 0 (complete similarity) and 1 (maximum diversity) and symmetric for the two firms. I used these pairwise distance values to construct annual distance matrices, \( D_t \), which reflected the technological distances between all possible pairs of sample firms.

Next, I computed the uniqueness of the knowledge of each partner \( j \) in firm \( i \)’s alliance network in year \( t \). The uniqueness of firm \( j \) is a function of the uniqueness of its partners, \( k \), and firm \( j \)’s distance from them. Following Rodan and Galunic (2004), I defined the uniqueness of firm \( j \), \( u_p \), as:

\[
\lambda u_j = \sum_k d_{jk} \times u_k.
\]

The uniqueness of each firm is found in the solution of the eigen equation \((\lambda U = DU)\), where \( U \) is an eigenvector of \( D \) and \( \lambda \) is its associated eigenvalue. The elements of \( U \) are the uniqueness values for each firm, and \( D \) is the matrix of pairwise technological distances. I measured the technological diversity available to firm \( i \) in its (ego) network of alliance partners in year \( t \) as:

\[
\text{Network technological diversity}_{it} = \frac{1}{N} \sum_{j=1}^{N} d_{ij} \lambda u_j,
\]

where \( d_{ij} \) is partner \( j \)’s distance from \( i \) and \( \lambda u_j \) is \( j \)’s uniqueness score computed for \( i \)’s \( N \) partners. The \( 1/N \) term compensates for the fact that lambda increases linearly with network size. This measure increases linearly with the distances among \( i \) and its partners (Rodan & Galunic, 2004).

**Network density.** To measure ego network density, I constructed annual adjacency matrices for the period 1987–96 that indicated the presence of a technology alliance, in existence at the end of a focal year, between all possible undirected pairwise combinations of sample firms. An alliance with more than 2 firms entered the adjacency matrix as separate dyadic combinations of all firms in the alliance. Of all sample alliances, 89 percent involved only 2 firms, and the average alliance had 2.38 firms. Because alliances often endure longer than one year, constructing adjacency matrices using only alliances formed in a focal year would have understated the true connectivity of the network. Consequently, I collected alliance data for each firm beginning in 1980 and researched each
alliance to identify its date of dissolution or continuance through the last sample year.⁶

Ego network density was the percentage of all possible ties among an ego’s alters that had been formed (Scott, 1991). Ego networks in which a firm’s alliance partners are themselves allied imply higher values of density. To test the robustness of the effect of density, I substituted Burt’s (1992) measures of efficiency and then constraint into alternative specifications. The Appendix presents these specifications. Both efficiency and constraint are measures of triadic closure (see Borgatti [1997] for a comparison). Figure 1 presents an example of a sample firm’s ego network, specifically, Motorola’s network of technology alliances at the end of 1992, and lists the values for the density, efficiency, and constraint of this network. Algebraic explanations of each measure are also shown.

Control Variables

To minimize alternative explanations and isolate the marginal effects of the explanatory variables, I controlled for several firm- and alliance-level variables whose influence on exploratory innovation might be confounded with the explanatory variables. Given the firm-level analysis used in this study, I aggregated alliance-level observations to the firm level. I used multiple-year moving windows of differing lengths to compute five control variables. These window lengths ranged from four to seven years and differed by control variable. I based the choice of window length for each control variable on prior research. Using alternative window lengths (±1 year) for these control variables did not substantively change the results of the explanatory variables presented in Table 2.

Network size. More alliance partners may provide a firm with access to greater technical diversity. Moreover, measures of ego network density are sensitive to network size, making network size an important control variable (Friedkin, 1981). I computed network size as the natural logarithm of the number of telecom technology alliance partners maintained by firm i in year t.

Alliance duration. Alliance longevity can lead to greater interfirm trust (Gulati, 1995), stronger reciprocity norms (Larson, 1992) and relation-specific routines (Levinthal & Fichman, 1988), increasing interfirm learning (Simontin, 1999). I measured alliance duration as the average number of years firm i had participated in its existing telecom technology alliances at the end of year t (see footnote 6).

Repeated ties. Prior ties between firms can increase interfirm trust (Gulati, 1995), the development of relation-specific learning heuristics, and interfirm learning (Lane & Lubatkin, 1998). Following Gulati and Gargiulo (1999), I calculated repeated ties as the average number of alliances firm i had formed with its current group of alliance partners in the five years prior to year t.

Joint venture. Research has suggested equity joint ventures are superior governance mechanisms for interfirm learning and knowledge transfer (Kogut, 1988; Mowery et al., 1996). I computed the variable as the proportion of firm i’s telecom technology alliances governed by equity joint ventures in year t.

International alliance. International alliances provide access to diverse knowledge (Rosenkopf & Almeida, 2003), but they experience greater coordination and communication problems and cultural conflicts than domestic alliances, and this experience diminishes interfirm learning (Lyles & Salk, 1996). I measured this variable as the fraction of firm i’s telecom technology alliances in year t involving foreign firms.

Partners’ market overlap. Because partners tend to protect their knowledge when they are product-market competitors, overlaps in partners’ markets can impede interfirm knowledge transfer (Dutta & Weiss, 1997). I computed market overlap as the proportion of firm i’s portfolio of telecom technology alliances in year t having partners with the same primary four-digit SIC code as firm i.

Firm sales. Firm size can have both negative and positive effects on firm innovation (Teece, 1992). I controlled for firm size using the natural log of sales (in millions of U.S. dollars) for firm i in year t.

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⁶I researched each alliance using the sources described previously. I also contacted company personnel to identify dissolution dates, which proved very useful in identifying the termination or ongoing status of joint ventures (JVs). For nearly all JVs, I was able to identify the months they were ended or their ongoing status at the end of the sample period. For each remaining JV, I assumed it existed until the end of the last year in which it was documented or until the end of the year after the year it was founded, whichever was later. For non-JV alliances, I recorded termination on the basis of specified tenure, if mentioned in the archival sources, or announcement of dissolution (either from archival sources or company contact). In cases in which I could not establish precise dissolution, I followed Ahuja (2000) and presumed an alliance to exist until the end of the last year in which it was documented or until the end of the year after the year it was founded, whichever was later. I performed a t-test of the difference in mean duration between alliances with formal dissolution announcements and those with assumed dissolution dates and found no significant difference.
FIGURE 1
Motorola’s 1992 Ego Network Structure of Technology Alliances

In the figure, Motorola is the focal actor, or ego. Below are the values of ego network density, efficiency and constraint for Motorola’s 1992 technology alliance network and an explanation of each measure. Burt (1992) provides a detailed explanation of the measures of efficiency and constraint and Borgatti (1997) provides a comparison of the three measures.

The values for the density, efficiency, and constraint of this network and their algebraic computation are as follows:

**Density** = 26.67%

\[
\text{Ego network density} = \left( \frac{\left( \sum_j \sum_q x_{jq} \right)}{\left( N(N-1)/2 \right)} \right) \times 100, \quad j \neq q.
\]

where \(x_{jq}\) represents the relative strength of the tie between alter \(j\) and alter \(q\), and \(N\) represents the number of alters to which ego \(i\) is connected. Because I treated alliances as either present or absent (i.e., they do not vary in terms of strength), all values of \(x_{jq}\) were set to 1 if a relationship existed and 0 otherwise. The term \([NN - 1]\) was divided by 2 to reflect that alliances are undirected ties. Variable range, 0–100%.

**Efficiency** = 0.75

\[
\text{Ego network efficiency} = \left( \sum_i \left( 1 - \sum_j p_{ij}m_{ij} \right) \right) / N, \quad j \neq q,
\]

where \(p_{ij}\) is the proportion of \(i\)'s ties invested in the relationship with \(j\), \(m_{ij}\) is the marginal strength of the relationship between alter \(j\) and alter \(q\) (as I used binary data, all values of \(m_{ij}\) were set to 1 if a tie existed and 0 otherwise), and \(N\) represented the number of alliance partners to which focal firm was connected. This measure could vary from 0 to 1, with higher values indicative of greater efficiency (i.e., structural holes).

**Constraint** = 0.15

\[
\text{Ego network constraint} = \sum_i \left[ p_{ij} + \sum_q p_{ij}p_{qj} \right], \quad q \neq i, j,
\]

where \(p_{ij}\) is the proportion of \(i\)'s ties invested in the relationship with \(j\), \(p_{ij}\) is the proportion of \(i\)'s ties invested in the relationship with \(q\), and \(p_{qj}\) is the proportional strength of alter \(q\)'s relationship with alter \(j\). This measure can vary from 0 to 1, with higher values indicative of greater constraint (i.e., fewer structural holes).
## TABLE 2
Descriptive Statistics and Correlationsa

| Variables                        | Mean  | s.d.  | Min. | Max. | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   | 17   | 18   |
|----------------------------------|-------|-------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1. Exploratory innovation        | 0.72  | 0.19  | 0    | 1    | 4    |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2. Network technological diversity| 0.22  | 0.33  | 0    | 1.71 | 0.19 |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 3. Network density               | 33.88 | 32.99 | 0    | 100  | 0.18 | -0.27|      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 4. Network sizeb                  | 1.33  | 0.99  | 0    | 3.56 | -0.25| 0.79 | -0.38|      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 5. Alliance duration             | 3.10  | 1.87  | 0    | 14   | 0.08 | 0.14 | -0.14| 0.20 |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 6. Repeated ties                 | 0.38  | 0.46  | 0    | 4    | 0.19 | 0.49 | -0.17| 0.43 | 0.13 |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 7. Joint venture                 | 0.18  | 0.19  | 0    | 1    | 0.02 | 0.39 | -0.18| 0.38 | 0.26 | 0.20 |      |      |      |      |      |      |      |      |      |      |      |      |
| 8. International alliance        | 0.30  | 0.25  | 0    | 1    | -0.06| 0.16 | -0.14| 0.18 | 0.02 | 0.08 | -0.28 |      |      |      |      |      |      |      |      |      |      |      |
| 9. Partners’ market overlap       | 0.33  | 0.24  | 0    | 1    | 0.02 | 0.04 | 0.08 | -0.07| -0.02| -0.09| -0.12| 0.14 |      |      |      |      |      |      |      |      |      |      |
| 10. Salesb                        | 6.47  | 2.66  | -2.99| 11.34| -1.17| 0.64 | -0.20| 0.61 | 0.39 | 0.55 | 0.40 | 0.17 | -0.05|      |      |      |      |      |      |      |      |      |
| 11. Firm current ratio            | 2.32  | 1.58  | 0.003| 23.46| -0.13| 0.09 | -0.22 | 0.19 | -0.26| -0.29 | 0.17 | 0.06 | -0.37|      |      |      |      |      |      |      |      |
| 12. Firm R&D intensity            | 0.13  | 0.76  | 0    | 20.25| 0.03 | 0.07 | -0.01 | -0.27| -0.03| -0.18 | -0.08 | -0.02 | -0.20 | 0.09 |      |      |      |      |      |      |      |
| 13. Firm patent stock             | 582.06| 1,267.74| 1 | 6,875| -0.14| -0.50 | -0.21 | 0.44 | -0.21 | 0.67 | 0.29 | 0.15 | -0.11 | 0.63 | -0.25 | 0.04 |      |      |      |      |      |      |
| 14. Firm age                      | 45.39 | 36.03 | 2    | 150  | 0.13 | 0.58 | -0.18 | 0.52 | 0.38 | 0.37 | 0.50 | 0.25 | -0.04 | 0.74 | -0.30 | -0.09 | 0.11 |      |      |      |      |      |
| 15. Firm alliance experience      | 0.14  | 0.75  | 0.001| 19.25| -0.02 | 0.09 | 0.14 | -0.18 | -0.08 | 0.03 | -0.15 | 0.07 | -0.08 | -0.09 | -0.29 | 0.05 | 0.36 | 0.52 | -0.16|      |      |
| 16. Firm technological diversity  | 0.76  | 0.31  | 0    | 1    | -0.11| 0.34 | -0.19 | 0.32 | 0.32 | 0.25 | 0.40 | 0.11 | -0.09 | 0.59 | -0.38 | -0.02 | -0.07 | 0.53 | -0.18|      |      |
| 17. Firm acquisitions             | 0.96  | 1.71  | 0    | 16   | -0.06| 0.34 | -0.08 | 0.32 | 0.03 | 0.07 | 0.24 | 0.06 | 0.34 | -0.11 | -0.04 | -0.06 | 0.38 | -0.09 | 0.20 |      |
| 18. U.S.-Canada                   | 0.65  | 0.48  | 0    | 1    | -0.1 | -0.50 | 0.14 | -0.31 | -0.30 | -0.39 | -0.52 | -0.29 | -0.11 | -0.65 | 0.29 | 0.06 | 0.09 | -0.61 | 0.13 | -0.43 | -0.19 |      |
| 19. Europe                        | 0.19  | 0.39  | 0    | 1    | 0.04 | 0.51 | -0.10 | 0.39 | 0.14 | 0.06 | 0.50 | 0.21 | 0.12 | 0.18 | -0.18 | -0.03 | -0.06 | 0.55 | -0.08 | 0.30 | 0.40 | -0.66|

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*a* n(firms) = 77; n(observations) = 707. All correlations greater than |.07| are significant at *p* < .05.

*b* Logarithm.
Firm current ratio. The availability of slack resources can increase exploratory search (Singh, 1986) and lead to greater innovative performance (Nohria & Gulati, 1996). I controlled for the unabsorbed slack resources of firm $i$ in year $t$ using its current ratio (current assets/current liabilities) (Singh, 1986).

Firm R&D intensity. A firm’s R&D expenditures are investments in knowledge creation (Griliches, 1990) and contribute to its ability to absorb extramural knowledge (Cohen & Levinthal, 1990). I measured R&D intensity by dividing firm $i$’s R&D expenses by its sales in year $t$.

Firm patent stock. The more patents a firm has, the more patents and references it can cite; a large patent stock could thus negatively affect the price of its technology class $j$ in year $t$. Telecom equipment firms often use both acquisitions and alliances to source knowledge (Amesse et al., 2004). I controlled for the number of telecom equipment acquisitions (i.e., those in which the target company’s primary SIC code was 366) made by firm $i$ during the four years prior to and including year $t$.

U.S.-Canada/Europe/Asia. I used dummies denoting the regional origin of a firm to control for regional effects. “U.S.-Canada” was coded 1 if a firm was headquartered in the United States or Canada. “Europe” was coded 1 if the firm was headquartered in Europe. Asia was the omitted category.

Model Specification and Estimation

The dependent variable was a proportion and presented several challenges to linear regression (Gujarati, 1995). Thus, I used three alternative modeling approaches. First, I estimated the models with exploratory innovation as the dependent variable using panel linear regression and robust standard errors. Following common econometric practice (Greene, 1997), I also estimated models with a log-odds transformation of exploratory innovation. Finally, I estimated models using a generalized estimating equation (GEE) approach in which I specified a probit link function and an exchangeable correlation matrix and computed robust errors (Papke & Wooldridge, 2005). As a robustness check, I compared the results from these alternative specifications. I included year dummies to control for period effects, such as differences in macroeconomic conditions or industry technological opportunity. Either firm-specific fixed or random effects can be used to control for unobserved firm heterogeneity (Greene, 1997), such as differences in motivations to pursue, and abilities to develop, exploratory innovations. Because the use of random effects relies on an assumption that errors and regressors are uncorrelated, I used a Hausman (1978) test to choose between fixed and random effects. I also checked for first-order serial autocorrelation in the errors. I lagged all independent variables one year, which reduced concerns of reverse causality and avoided simultaneity.

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7 The transformed variable is as follows: $\ln(\text{exploratory innovation})/1 - \text{exploratory innovation}$. Because the transformation is undefined when exploratory innovation is equal to 0 or 1, I recoded these values as follows: $0 = 0.0001$ and $1 = 0.9999$. 

---

Technological diversity $t_i = \left[ 1 - \sum_{j=1}^{J} \left( \frac{N_{ij}}{N_{it}} \right)^{2} \right] \times \frac{N_{it}}{N_{it} - 1},$

where $N_{it}$ is the number of patents obtained by firm $i$ in the past four years. $N_{ijt}$ is the number of patents in technology class $j$ in firm $i$’s four-year patent stock. This variable could range from 0 to 1 (maximum diversity).

**Firm acquisitions.** Acquisitions can enhance acquirer innovation (Ahuja & Katila, 2001). Telecom
TABLE 3
Results of Random-Effects Panel Linear Regression Analysis Predicting Firm Exploratory Innovation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.85** (0.06)</td>
<td>0.89** (0.07)</td>
<td>0.89** (0.07)</td>
<td>0.89** (0.07)</td>
<td>0.86** (0.07)</td>
<td>0.85** (0.07)</td>
</tr>
<tr>
<td>Network size$^b$</td>
<td>−0.03 (0.01)</td>
<td>−0.05 (0.01)</td>
<td>−0.05 (0.01)</td>
<td>−0.04 (0.01)</td>
<td>−0.04 (0.01)</td>
<td>−0.04 (0.01)</td>
</tr>
<tr>
<td>Alliance duration</td>
<td>−0.01 (0.01)</td>
<td>−0.01 (0.01)</td>
<td>−0.01 (0.01)</td>
<td>−0.01 (0.01)</td>
<td>−0.01 (0.01)</td>
<td>−0.01 (0.01)</td>
</tr>
<tr>
<td>Repeated ties</td>
<td>0.01 (0.02)</td>
<td>0.01 (0.02)</td>
<td>0.02 (0.02)</td>
<td>0.01 (0.02)</td>
<td>0.02 (0.02)</td>
<td>0.01 (0.02)</td>
</tr>
<tr>
<td>Joint venture</td>
<td>0.08 (0.06)</td>
<td>0.08 (0.06)</td>
<td>0.08 (0.06)</td>
<td>0.07 (0.06)</td>
<td>0.05 (0.06)</td>
<td>0.05 (0.06)</td>
</tr>
<tr>
<td>International alliance</td>
<td>−0.09 (0.04)</td>
<td>−0.08 (0.04)</td>
<td>−0.08 (0.04)</td>
<td>−0.08 (0.04)</td>
<td>−0.07 (0.04)</td>
<td>−0.08 (0.04)</td>
</tr>
<tr>
<td>Partners’ market overlap</td>
<td>−0.04 (0.04)</td>
<td>−0.03 (0.04)</td>
<td>−0.03 (0.04)</td>
<td>−0.02 (0.04)</td>
<td>−0.02 (0.04)</td>
<td>−0.01 (0.04)</td>
</tr>
<tr>
<td>Firm sales$^b$</td>
<td>−0.02 (0.01)</td>
<td>−0.03 (0.01)</td>
<td>−0.03 (0.01)</td>
<td>−0.02 (0.01)</td>
<td>−0.02 (0.01)</td>
<td>0.00 (0.01)</td>
</tr>
<tr>
<td>Firm current ratio</td>
<td>0.00 (0.01)</td>
<td>0.00 (0.01)</td>
<td>0.00 (0.01)</td>
<td>0.00 (0.01)</td>
<td>0.00 (0.01)</td>
<td>0.00 (0.01)</td>
</tr>
<tr>
<td>Firm R&amp;D intensity</td>
<td>−0.08 (0.08)</td>
<td>−0.08 (0.08)</td>
<td>−0.08 (0.08)</td>
<td>−0.08 (0.08)</td>
<td>−0.07 (0.08)</td>
<td>−0.06 (0.08)</td>
</tr>
<tr>
<td>Firm patent stock/1,000</td>
<td>−0.004 (0.00)</td>
<td>−0.002 (0.00)</td>
<td>−0.002 (0.00)</td>
<td>−0.002 (0.00)</td>
<td>−0.003 (0.00)</td>
<td>−0.003 (0.00)</td>
</tr>
<tr>
<td>Firm age</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Firm alliance</td>
<td>−0.01 (0.03)</td>
<td>−0.02 (0.03)</td>
<td>−0.02 (0.03)</td>
<td>−0.02 (0.03)</td>
<td>−0.02 (0.03)</td>
<td>−0.02 (0.03)</td>
</tr>
<tr>
<td>Network technological diversity</td>
<td>0.06 (0.03)</td>
<td>0.06 (0.03)</td>
<td>0.06 (0.03)</td>
<td>0.06 (0.03)</td>
<td>0.07 (0.04)</td>
<td>0.08 (0.04)</td>
</tr>
<tr>
<td>Network technological diversity squared</td>
<td>0.00 (0.04)</td>
<td>0.00 (0.04)</td>
<td>0.00 (0.04)</td>
<td>0.00 (0.04)</td>
<td>0.06 (0.03)</td>
<td>0.07 (0.04)</td>
</tr>
<tr>
<td>Network density</td>
<td>0.05 (0.02)</td>
<td>0.10 (0.04)</td>
<td>0.046 (0.13)</td>
<td>0.53** (0.14)</td>
<td>0.48 (0.36)</td>
<td></td>
</tr>
<tr>
<td>Network technological diversity × density</td>
<td>0.05* (0.02)</td>
<td>0.10* (0.04)</td>
<td>0.046** (0.13)</td>
<td>0.53** (0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year dummies included</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
| $^a$ n(firms) = 77; n(observations) = 707. Huber-White robust standard errors are in parentheses.  
$^b$ Logarithm.  
$^†$ p < .10  
$^*$ p < .05  
$^{**}$ p < .01  
Two-tailed tests.

RESULTS

Table 2 reports descriptive statistics and correlations. The panel was unbalanced and consisted of 77 firms and 707 firm-year observations. Table 3 presents the results of the panel regression analysis used to test the hypotheses. I report the results for untransformed exploratory innovation for ease of interpretation. The results using a logit transformation and those from GEE estimation are consistent with those reported in Table 3. I estimated models 1–7 using firm random effects for three reasons: (1) significant unobserved heterogeneity was present, (2) Hausman specification tests were not significant, supporting the use of random effects, and (3) significant serial correlation was not present. Huber-White (or “sandwich”) robust standard errors are reported, and all significance levels are for two-tailed tests. Multicollinearity does not seem to have unduly influenced the regression results because the average variance inflation factor (VIF) for each model and the VIFs for all variables were below the rule-of-thumb value of ten (Gujarati, 1995).

Hypothesis 1 predicts an inverted U-shaped effect of network technological diversity on firm exploratory innovation. Models 2–6 in Table 3 provide partial support for this hypothesis. In each of these models, network technological diversity exhibited a positive and significant effect on exploratory innovation. However, the squared term was not significant in any model in which it was entered. Thus, although I found evidence of a positive linear effect of network diversity, I did not...
find evidence of a curvilinear effect. Hypothesis 2 predicts network density strengthens the effect of network technological diversity on exploratory innovation. Models 5–6 show the interaction had a significant, positive effect on exploratory innovation, supporting Hypothesis 2. The interaction of network diversity squared and network density was not significant (model 6). Although not predicted, network density had a positive and significant effect on exploratory innovation, independent of diversity (models 4–5). The Wald statistics at the bottom of Table 3 indicate models 2–6 provide significant improvement in fit relative to model 1. I constructed each test for incremental improvement in fit relative to the baseline model, because making it relative to the previous model would have provided the same information as the significance level of the newly entered variable, since each explanatory variable was entered alone (Gujarati, 1995). The Appendix contains an assessment of the robustness of the results and alternative explanations.

**DISCUSSION**

This study was motivated by important limitations of research on alliance networks and firm innovation. This literature has largely ignored the potential influence of network composition, particularly the technological diversity of a firm’s partners. This research also draws on seemingly incompatible theoretical arguments and has produced conflicting empirical results regarding the influence of network structure. These conflicts stem from an assumption that a firm’s access to diverse information and the innovation benefits of network closure are mutually exclusive. In part because of this assumption, potential complementarities between network structure and composition have been largely unexamined. Finally, research on alliance networks and firm innovation has focused on the volume of firm innovation, with little consideration of its exploratory content.

This study addressed these limitations by examining the influence of the composition and structure of a firm’s network of horizontal technology alliances on its degree of exploratory innovation. The theoretical framework suggested network composition and structure play different, yet complementary, roles in exploratory innovation. Regarding network composition, I drew on research on recombinatory search to predict that the technological diversity in a firm’s alliance network has an inverted U-shaped relationship with its exploratory innovation. Although increasing diversity increases the number, variety, and novelty of potential innovative combinations, excessive diversity impairs a firm’s ability to recognize and utilize knowledge components in its network, reducing its ability to produce exploratory innovations. Regarding network structure, I built on research on interfirm networks and interfirm learning and argued that the density of a firm’s horizontal alliance network increases its ability to access, mobilize, and integrate its partners’ knowledge, thus increasing its ability to benefit from technologically diverse partners. In so doing, this study moved beyond the dyadic perspective typically used in interfirm learning research (cf. Tiwana, 2008).

The results are mostly consistent with the predictions of the theoretical framework. I predicted a curvilinear effect of network diversity, yet I found evidence of a positive linear effect on exploratory innovation. I speculate on this result below. I also found the density of a firm’s network of horizontal technology alliances strengthened the effect of diversity. These results do not seem to be biased by endogeneity and are robust to the use of many firm- and alliance-level controls, alternative specifications and estimation routines, firm fixed and random effects, and the use of alternative measures.

Although I predicted an inverted U-shaped effect of network technological diversity, I found a positive, linear effect. There are at least three possible explanations for this result. First, sample firms may have avoided alliances with excessively diverse partners. Indeed, Mowery et al. (1998) found that firms typically avoid forming alliances with highly dissimilar partners. Without a sufficient number of excessively diverse networks, only a linear relationship can be observed. Although this argument suggests the parameter estimates for network diversity and its square might be biased by sample self-selection, I tested for such endogeneity and found none (see the Appendix). Second, Rosenkopf and Almeida (2003) found that once a firm had formed an alliance, it was just as likely to learn from technologically dissimilar firms as from similar firms. They theorized firms typically make the necessary investments in interfirm learning mechanisms to learn effectively from highly diverse partners. If sample firms typically made such investments, then they would have been able to mitigate, to some extent, the absorptive capacity problems associated with increasingly diverse partners. Finally, increasing technological distance among a firm’s partners may have increased their willingness to share knowledge with the focal firm because they were less concerned their knowledge would leak to rivals via a common partner. When a firm’s network consists of partners with similar and thus substitutable knowledge stocks, competitive concerns
can lead them to withhold information and knowledge from a common partner to prevent its leakage to rivals via this common intermediary (Khanna, Gulati, & Nohria, 1998).

This study has important implications for research and practice. First, this study contributes to a debate in the literature concerning the network structure of social capital by suggesting that research has overemphasized the informational benefits of structural holes for firm innovation. The prior research assumption has been that structural holes increase an actor’s timely access to diverse information. Because structural holes and network closure are inversely related, this argument implies the informational benefits of structural holes must come at the expense of the benefits of network closure, and vice versa. Prior conflicting findings about the effect of structural holes on firm innovation may be influenced by a confounding of the structural holes effect with an unobserved compositional effect of partner knowledge diversity. This study suggests the extent to which an actor’s network is composed of alters with diverse knowledge bases will provide it access to informational diversity, independent of network structure. The benefits of network closure and access to diverse information and know-how can coexist in a firm’s alliance network, and the combination of the two enhances its exploratory innovation. This finding coincides with the results of a recent longitudinal qualitative study of interfirm networks. In their examination of six biotechnology firms, Maurer and Ebers (2006) found firms with dense networks of partners with diverse resources experienced greater growth and development.

Second, this study contributes to the innovation search literature. Much of this literature stresses the proclivity of firms to practice local search. Little research explores how firms are able to overcome the inertial tendencies of local search. The results of this study suggest having access to diverse knowledge is important. This finding reinforces and complements the results of recent alliance-level research, which shows partner technological diversity affects the rate of firm innovation (Sampson, 2007). While Sampson (2007) also found that the use of equity joint venture, a formal alliance governance mechanism, positively moderated the influence of partner dissimilarity on firm innovation, my results suggest informal governance provided by network closure positively moderated the influence of network-level diversity on firm exploratory innovation performance. Research has shown alliances enhance firm innovation performance, but it is difficult to establish from these past studies whether firms expanded their technical competencies in the process. The findings of this study suggest alliances can spur exploratory innovation when they provide access to technologically diverse partners that are densely connected to one another.

Finally, the results of this study have managerial implications. The findings confirm alliances can improve a firm’s development of exploratory innovations. The theory and results point to the benefits of forming alliances with technologically diverse partners in densely connected networks. Thus, managers should attend to the structure of the alliance networks in which their firms are embedded, because these structures have implications for firm performance. Although technology alliance partners are often selected based on their technological capabilities (Stuart, 1998), the results of this study suggest a firm’s ability to learn from technologically diverse partners depends on the degree of network closure around these relationships. Managers should evaluate how their choices about forming new alliances and ending existing relationships will affect the structure of their networks. Moving from the dyad level of analysis to the network level can sensitize managers to the importance of understanding how social structure influences firm performance (Gulati, 1998).

The results and contributions of this study should be considered in light of its limitations. First, although I emphasized the benefits of dense and diverse alliance networks for firm innovation, I did not consider their long-term costs. Research suggests network density reduces the diversity of information available in a network over time (Lazer & Friedman, 2007). Dense links provide redundant paths to the same information sources. Soon everyone in the network comes to have the same information (Burt, 1992). Over time, this homogeneity would harm innovation. This argument implies that the diversity of information in a network is fixed and results from the diversity of information possessed by actors when the network was formed. Thus, the only way to inject novel information into a network is to add connections to new actors who, as a function of their ties to others outside the focal network, can provide such novelty (Burt, 1992; Granovetter, 1973). Access to diverse information is determined solely by the connective structure of ties among actors (Obstfeld, 2005).

These are unrealistic assumptions. Not only does this argument assume actors are equally and easily able to absorb or imitate the information they do not initially possess, it also rules out the possibility of recombinant innovation. Given some degree of heterogeneity among actors in the information and knowledge they possess, the sharing and diffusion of these resources provides the potential for their
novel recombination into new knowledge that did not previously exist (Fleming, 2001). If innovation is a process of the recombination of existing knowledge, then innovations actually increase the potential for subsequent innovations. In short, recombinations beget more recombinations (Fleming, 2001). From this perspective, a network established with some degree of diversity in the information and knowledge actors possess will facilitate the development of even more diverse information and knowledge. Thus, diversity begets diversity (Kauffman, 1995: 291). Moreover, as the results of this study suggest, network density can facilitate this process. Rather than driving out diversity, dense networks that begin with specialized and therefore diverse actors may generate more, rather than less, diversity. Although a detailed investigation of this issue was beyond the scope of this study, it represents an important topic for future research.

Next, because I used patents to assess exploratory innovation, the measure may not capture all of a firm’s exploratory innovations. If firms systematize patent exploratory knowledge for unobserved reasons, parameter estimates may be biased. I attempted to control for this potential source of bias using control variables and firm effects. Additionally, firms may patent knowledge in anticipation of entering alliances because of concerns about future leakage of this knowledge to partners (Brouwer & Kleinknecht, 1999). Exploratory inventions tend to have a greater impact on subsequent technological development (Rosenkopf & Nerkar, 2001) and may therefore be of greater economic value (Narin, Noma, & Perry, 1987). Thus, firms may patent exploratory inventions before entering alliances to appropriate their greater economic value. The use of a one-year lag between collaboration and patenting and the use of firm effects reduces the likelihood of such a bias.

Another possible limitation is that an alliance survivor bias may have influenced the results. If sample firms formed alliances with the intent of exploratory learning and if successful alliances survived, then observed alliances will be those that yielded the greatest exploratory benefit. Such a self-selection bias is unlikely in this study. First, because I have time-varying data on alliances and I observe alliance formation and dissolution, my data include both successful and unsuccessful alliances. Second, research shows firms often exit alliances before they yield knowledge transfer benefits (Deeds & Rothaermel, 2003) and often maintain alliances that negatively affect interfirm knowledge transfer (Gomes-Casseres, Hagedoorn, & Jaffe, 2006). Third, firms enter technology alliances for reasons other than technological exploration (Hagedoorn, 1993). Finally, if alliances that are beneficial for exploration tend to survive, I would expect a positive effect of the number of alliances maintained by a firm on its exploratory innovation. I do not observe such an effect.

Finally, the archival data used in this study cannot provide direct evidence of the causal processes and mechanisms that I hypothesized. Although my hypothesis concerning network density relied on an established and empirically validated argument that density promotes trust and reciprocity, my data did not allow me to observe trust and reciprocity among personnel involved in the sample alliances. The results are consistent with theoretical expectations, yet a better understanding of the microsociological foundations that underlie the observed effects of alliance network structure and composition is needed to validate the causal inferences of this study. In particular, longitudinal qualitative research should explore how interorganizational and interpersonal networks interact to produce social capital and how this social capital influences knowledge transfer and innovation.

Conclusion

Because firms have strong incentives to pursue exploitation at the expense of exploration, the question of how and when firms are able to explore effectively is fundamental to understanding how organizations adapt, thrive, and survive. As Moran and Ghoshal concluded, “An organization that is not adequately enabling and motivating new possibilities is more likely to witness its own decline” (1999: 410). The results of this study reinforce the “relational view” of firm resource creation and advantage (Dyer & Singh, 1998) by helping to identify the conditions under which alliances enable a firm to create exploratory technological innovations that can provide it with the technological foundations for new commercial possibilities. The results suggest the benefits of network closure and access to diverse information can coexist in a firm’s alliance network and the combination of the two increases exploratory innovation.

REFERENCES


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### APPENDIX

**Alternative Explanations and Robustness Checks**

I considered several alternative explanations and assessed the robustness of the results. First, I removed the time-invariant variables and used firm fixed-effects. The results were similar to those obtained using random effects, which is consistent with the insignificant Hausman tests (1978) mentioned in the main text. Next, I considered the potential endogeneity of network structure and network diversity. The formation and dissolution of alliances reflect choices made by firms. These choices may be based on expectations of the exploration-enhancing benefits of alliances. This introduces the possibility of an unobserved sample self-selection process causing an endogeneity bias. Network structure may, however, be exogenous for a few reasons. Firms form technology alliances for reasons other than exploratory innovation (Hagedoorn, 1993) and do not easily or quickly alter their alliances to optimize their networks for particular objectives (Maurer & Ebers, 2006). Thus, at any point in time, alliance networks are not necessarily structured to maximize exploratory innovation and are, at least weakly, exogenous. Last, the structure of a firm’s alliance network is beyond the sole control and influence of any one firm in the network and is therefore not a firm choice variable. Although network diversity may change slowly because of inertia in a firm’s alliance relationships and thus may not be optimized for exploratory innovation at a given point in time, the level of diversity in a firm’s ego network is largely under its control.

Because endogeneity is an empirical question, I tested for the presence of deleterious endogeneity related to both network density and network diversity. I used Davidson and MacKinnon’s test (1993), as implemented by the “dmeoxgxt” procedure in Stata 10. This test compares the estimated coefficient for the assumed endogenous regressor (e.g., density or network diversity) obtained from ordinary least square (OLS) fixed-effects regression with the estimate obtained from a two-stage instrumental variables fixed-effects regression. The null hypothesis is that OLS fixed effects yields a consistent parameter estimate. This procedure requires a valid instrumental variable for the two-stage estimator so that the second-stage estimates can be identified. I used firm technological diversity to instrument for network density and network diversity in separate regressions because it was not significantly correlated with exploratory innova-
tion but was correlated with density and network diversity. Neither the endogeneity test associated with network density nor that associated with network diversity was significant. Thus, the parameter estimates for these variables in Table 3 do not appear to be unduly influenced by endogeneity.

I performed additional unreported analyses to assess the robustness of my findings. First, I experimented with alternative specifications by removing insignificant variables and then removing all control variables. The results related to the three explanatory variables were robust to these alternative specifications. Second, I estimated the full model using a GEE approach in which I specified a probit link function and an exchangeable working correlation matrix and computed robust standard errors (Papke & Wooldridge, 2005). Results from this analysis for the three explanatory variables were consistent with those reported in Table 3. Third, I substituted Burt’s (1992) measures of network efficiency and constraint for the density measure discussed above. The results obtained using these alternative measures of ego network closure were statistically stronger but otherwise consistent with those reported in Table 3. Finally, I used the alternative measure of exploratory innovation discussed in the main text. Because this variable was a count and took on only nonnegative integer values, I estimated the full model with negative binomial panel regression, using year dummies and firm random effects (Greene, 1997). The results were consistent with those reported in Table 3. Overall, the results of the various robustness analyses converged and provided added support for both hypotheses.

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