Dual Networks of Knowledge Flows:
An Empirical Test of Complementarity in Software Ecosystems

David Dreyfus
Bala Iyer
Chi-Hyon Lee
N. Venkatraman

Boston University School of Management
595 Commonwealth Ave; Room 645A
Boston, MA 02215

Email: venkat@bu.edu

Version: July 2005

Please do not quote without prior permission

Comments and suggestions welcome

Acknowledgements

We thank the Boston University Institute for Leading in a Dynamic Economy (BUILDE) for providing support for the study.

Dual Networks of Knowledge Flows:

An Empirical Test of Complementarity in Software Ecosystems

Abstract

We develop a model of complementarity of knowledge flows in software ecosystems through two knowledge-acquisition mechanisms: a formal, fine-grained, contractual governance mechanism through inter-firm alliances and a non-formal, course-grained, non-contractual mechanism of spillover capture. In contrast to studies that focus solely on knowledge-exchange in alliances, we focus on two mechanisms and test their additive and super-additive effects. We examine the effect of a software firm's position in the alliance network (formal, contractual mechanism) and patent citation network (non-formal, non-contractual mechanism). We test our model using data on a set of leading firms in the packaged software sector during the period 1995 to 1999. Our results show that software firms' sales performance is predicted by their positions within these two networks. Furthermore, these network positions are additive and complementary in their impact on sales performance. Our results are potentially generalizable to other settings that have inter-dependent information and knowledge flows across organizational boundaries within ecosystems.

Introduction

A firm's performance depends upon its internal capabilities and knowledge resources (Conner & Prahalad, 1996; Teece, Pisano, & Shuen, 1997) and its ability to access critical complementary resources from other firms within its ecosystem (Gulati & Gargiulo, 1999). Firms exploit their own, existing knowledge and explore others' knowledge to generate new knowledge (Cohen & Levin, 1989; March, 1991; Nonaka & Takeuchi, 1995) while sustaining their competitive advantage through their ability to reconfigure their knowledgebase (Henderson & Cockburn, 1994; Kogut & Zander, 1992; Teece et al., 1997).

Software is a setting that calls for knowledge interdependence between firms to achieve product interoperability (Shapiro & Varian, 1999), where a network of relationships is key for a software firm's success (Campbell-Kelly, 2003). In this study, we develop a conceptual model of a software firm's positions in two complementary networks reflecting different governance mechanisms and exploiting different knowledge flows. Firms access and leverage fine-grained knowledge through formal, contractual mechanisms (henceforth referred to as the contractual network) (Gulati et al., 1999) such as alliances. In addition, firms access and leverage course-grained (Gulati et al., 1999) knowledge through non-formal, non-contractual mechanisms (henceforth referred to as the non-contractual network) such as informal-trading by employees (Saxenian, 1991), borrowing from others (March & Simon, 1958: 209), and capturing spillover (Cohen & Levinthal, 1990). Some of the spillover capture is documented through patent-citations (Trajtenberg, 1990).

Prior research studies on networks typically focus on one focal mechanism for resource access: Ahuja (2000a) focused on how alliance networks shape innovation; Podolny & Stuart (1995) focused on patent networks to develop concepts of interconnected niches within an industry; Morgan and Hunt (1999) focused on relationship marketing; Reddy and Czepiel (1999) focused on buyer-seller relationships; and Cohen and Levinthal (1990) focused on technology R&D activities. Such narrow, piecemeal approaches to looking at knowledge flow conduits may be acceptable within specific functional domains (R&D,

marketing etc.). However, there are compelling reasons to understand how these different mechanisms co-exist within organizations because of the inherent tradeoffs across these mechanisms as managers strive to benefit from structuring their network of relationships in ways to maximize value from complementary knowledge flows. In other words, we are interested in trying to understand how a firm's position in different networks of relationships creates value.

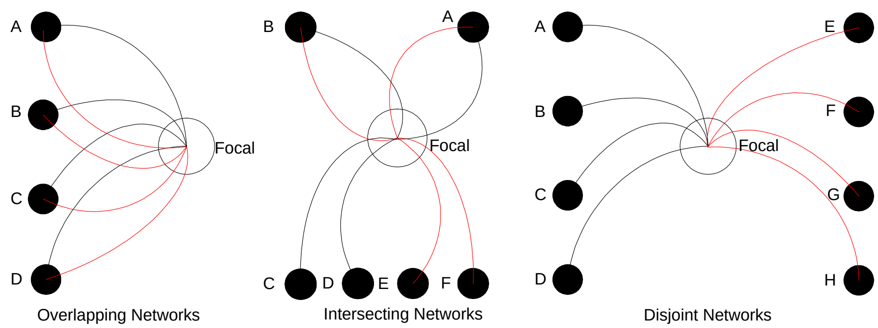

Figure 1: Three Stylized Positions for a Focal Firm in Dual Networks.

Dual networks can connect a focal firm to the same set of alters with different conduits represented by overlapping networks. Or, a focal firm can connect to a mix of same and different firms with different conduits represented by intersecting networks. Finally, it can connect to separate sets of firms represented by disjoint networks.

Different networks provide different resources and are created through different tie formation mechanisms. These networks provide firms with different tradable resources that lead to both the formation of the respective networks and a complementary effect on firms' performance. The networks may overlap to a greater or lesser extent, as diagrammed in figure 1. The degree to which the dual networks contain the same alters is an empirical question, which we explore in the software industry.

Locating and accessing these outside knowledge sources is not costless. Firms invest in joint ventures, research consortia, and R&D activities. They form alliances for distribution, marketing, and product development. Firms meet with customers, attend trade shows and analyze competitors. Both time and resources are limited; therefore, the firm must make allocation decisions that ultimately affect firm performance. When there are many sources of outside knowledge, the sources the firm selects are critical to what it learns and how it allocates its resources.

This paper is organized as follows. Section two develops the theory of complementary networks and hypotheses. Section three describes the empirical testing methodology, including the construction of the networks. Section four describes the research setting, dataset and variables. Section five describes the regression model and results. In section six we utilize network visualization techniques to provide additional insights into the phenomena. We discuss the results and directions for future research in section seven.

Theoretical Perspectives and Hypotheses

Two Mechanisms for Accessing Complementary Knowledge

It is truism that firms succeed by effectively accessing complementary knowledge resources from firms and other institutions in the broader ecosystem. In the biotechnology sector, Powell and his colleagues (Powell, Koput, & Smith-Doerr, 1996; Powell, White, Koput, & Owen-Smith, 2005) have shown that the linkages between a firm and its set of partners—formal alliances, technology licensing, links to universities etc.—are key conduits for obtaining external knowledge. An important finding from this stream of work is that there is no single linkage that governs effective knowledge flows across contexts and time, thus calling for a more comprehensive, holistic approach that recognizes multiple avenues of knowledge access.

In this vein, we focus on two mechanisms. One is inter-firm alliances and relationships that are governed by formal mechanisms of resource pooling and value appropriations (Gulati & Singh, 1998). These include license-sharing agreements, joint ventures, research consortia, joint R&D activities, and other activities governed by the formal agreements. Firms create interconnections for many reasons, such as access to financial capital, specialized knowledge, complementary assets, technical capabilities and new marketing channels (Oliver, 1990). For such reasons and others, firms form relationships with other firms and such moves create the network of relationships that act as the backdrop for competition and value delivery in this industry. We term this the *formal contractual mechanism*.

The other mechanism recognizes the non-formal interconnections that exist between companies. This may involve informal trading of know-how between employees in an industry (Saxenian, 1991), relying on innovations by lead users (von Hippel, 1988), or involve borrowing best practices through participation in different business consortia and membership in industry associations (Rosenkopf, Metiu, & George, 2001a). Other practices of non-formal accessing and using knowledge from others are reverse engineering, product examination, and sharing of common customers. These mechanisms represent the capture of spillover (Cohen et al., 1990). We term this the *non-formal, non-contractual* mechanism.

We explore knowledge flow that results from this mechanism through the patent citation network. Firms make choices as to how to allocate their scarce attention. As a result of these choices, firms learn from specific other firms and frequently create new knowledge. In industries that utilize patents to protect intellectual property, new knowledge that results in novel innovation may be patented. As we discuss later in this paper, the US Patent and Trademark Office (USPTO) requires that the antecedents of the patented innovation are documented through patent citations. As a result, we are able to trace some of the direct and indirect knowledge flows that occur between firms due to their choices in the non-contractual network.

Key Characteristics of the Network Structure

Networks have become an important focus of attention in recent years (Ahuja, 2000a; Baum, Shipilov, & Rowley, 2003; Burt, 1992; Freeman, Borgatti, & White, 1991; Granovetter, 1973; Powell et al., 1996; Uzzi, 1996). Researchers use a variety of constructs to conceptualize ways through which firms access resources from others. We rely on three constructs to capture network positions: *reach, redundancy, and embeddedness*. We apply reach and redundancy to the non-contractual network and reach and embeddedness to the contractual network. *Reach* reflects the direct and indirect separation of a firm from all the other firms in the network, r*edundancy* reflects the degree to which a firm maintains direct ties to firms that provide no new information, and *embeddedness* reflects the degree to which a firm's direct relational ties constrain its actions. Although we operationalize redundancy and embeddedness similarly, they reflect different concepts (see the operationalization section for more detail).

Dual Networks of Knowledge Flows

We use two mechanisms (formal, contractual and non-formal, non-contractual) and three characteristics (reach, redundancy, and embeddedness) to develop a set of hypotheses on how firms position themselves to access knowledge resources in networks for effective performance. Our rationale is as follows: We hypothesize that the role of reach for both networks is to maximize ways of accessing relevant and useful information, and critical complementary resources, from other firms. Within the contractual network, we also hypothesize about the role of embeddedness because the contractual network acts as both an information conduit and coordination mechanism between tightly connected firms. In contrast, non-contractual relationships are more about information flows and less about coordination; therefore, we limit our discussion within non-contractual relationships to the impact of redundant ties. Thus, in our focus on dual networks, we develop hypotheses on the role of these three network position constructs on organizational performance.

Reach in formal contractual network. Firms access knowledge through their direct relationships as well as indirect relationships (Ahuja, 2000a). Better performing firms have ties to more diverse knowledge sources and are better positioned to access key information and critical resources (Powell et al., 1996). We are beginning to see some consistent cumulative empirical findings that a firm's position within a network of alliances contributes to innovation (Ahuja, 2000a; Powell et al., 1996) and to its subsequent sales and financial performance (Powell, Koput, Smith-Doerr, & Owen-Smith, 2001). While most of these findings have been based on studies in industries such as chemicals (Ahuja, 2000a), steel (Rowley, Behrens, & Krackhardt, 2000), financial services (Baum, Calabrese, & Silverman, 2000) and manufacturing (McEvily & Zaheer, 1999), the role of inter-firm alliances for knowledge access in the software industry is conspicuously absent. Since this industry is characterized by the need for inter-firm coordination for product launches due to interoperability requirements and uneven rates of change in the underlying technology architecture, alliances have been growing steadily in importance (Campbell-Kelly, 2003; Cusumano, 2004). Moreover, it is an industry in which firms know more than they do and utilize alliances in order to better leverage the knowledge they generate (Brusoni, Prencipe, & Pavitt, 2001). Therefore, we expect that a firm's performance will be explained significantly by its strategic choices to enter into a set of formal relationships with firms in the extended industry network reflected by its reach.

H_1: Reach in the formal, contractual network is positively associated with performance.

Embeddedness in formal contractual network. Successful firms maximize their access to unique information and rare resources from complementary entities. They do so by coordinating their activities to make their products interoperate to increase the joint value of their products to customers. When individual firms form contractual relationships to further these coordination efforts, a network of ties is formed because focal firms' partners (also referred to as 'alters' in the network literature) may also have ties among themselves giving rise to embedded ties within networks. Such embeddedness could play both enabling and constraining roles (see for example, White (2002)) as empirical research confirms both positive and negative consequences in different contexts (Coleman, 1988; Granovetter, 1985; Uzzi, 1997; Watts, 1999).

One line of argument is that embeddedness is positive as firms involved in alliances facilitate the identification of opportunities, develop complementary products, provide access to resources and competencies they don't otherwise posses, and coordinate product development and marketing activities. The core argument is that such alliances increase the value of their joint products and services for end customers and/or lowers their joint costs of production depending on the business landscape in which firms cooperate and compete (Baum & Singh, 1994; Silverman & Baum, 2002). Embeddedness also facilitates trust and reduces the cost of monitoring network partners (Ahuja, 2000a; Coleman, 1988; Zaheer & Bell, 2005) while facilitating managerial sense-making and enhancing the collective firms' ability within the closed network to respond and adapt to fast-changing technological environments (Krackhardt & Stern, 1988; Rindfleisch & Moorman, 2001). Thus:

H_{2a}: Embeddedness in the formal, contractual network is positively associated with performance.

A competing perspective is that firms become over embedded in local networks of other firms without connecting to the broader, fast-changing market. This is akin to March's (1991) argument against excessive exploitation without adequate exploration in organizational learning. If a focal firm's alters share information, then it may not receive as much unique information as the number of its alliance partners might suggest. The firm could get the same amount of unique information with fewer alliances, since the alliances provide redundant information. Moreover, it is unable to exercise a bridging position (Burt, 1992; Zaheer et al., 2005) and has less structural autonomy (Gnyawali & Madhavan, 2001), which reduces its status, power, and freedom of action.

Firms in dense clusters (where firms have alliances with other firms in the cluster) would seem to provide a bundle of products often purchased as a unit by customers. Since consumers depend upon the joint operation of the items in the bundle, vendors form alliances to manage the interdependencies between the individual products. Under such conditions, firms may be limited in their ability to independently set prices or expand their individual piece of the market. Thus, embeddedness is a form of social constraint (Gnyawali et al., 2001; Portes & Sensenbrenner, 1993), creating perhaps a paradox of embeddedness (Uzzi, 1997). Thus, a competing hypothesis is:

H_{2b}: Embeddedness in the formal, contractual network is negatively associated with performance.

Reach in non-formal, non-contractual networks. Since von Hippel's (1988) finding on the role and prevalence of informal trading, there has been considerable interest in non-formal mechanisms for know-how exchange. Network researchers have recognized non-formal mechanisms through membership in common boards as imitative ways to understand practices (Galaskiewicz & Wasserman, 1989). Economic researchers have focused on how firms develop superior knowledge through internal R&D activities and learn from others through spillover effects (Cohen et al., 1990), where the value of spillover is due to the absorptive capacity created by internal R&D. Firms seek access to coarse-grained knowledge from spillovers through a variety of mechanisms—participation in conferences, tradeshows, and professional organizations; reading each other's publications; studying each other's patents, products, and related innovations; and hiring each other's employees.

Reach in non-formal networks reflects breadth of direct and in-direct knowledge sources accessed as organizations strive to balance exploration of new domains with the exploitation of current domains (March, 1991). In general, lower reach in non-formal networks reflects a conservative posture to limit knowledge to familiar domains while a higher level of reach signals a company's desire to seek, access and internalize knowledge from newer domains. Using patent-citations as an operationalization of non-formal access to knowledge, Rosenkopf and Nerkar (2001b) found that in their study of the optical disk industry, the impact of exploration on technological development beyond the optical disk domain was the greatest when exploration spanned organizational and technological boundaries, providing support for our hypothesis.

H_3: Reach in the non-formal, non-contractual network is positively associated with performance.

Redundancy in non-formal, non-contractual networks. If the focal firm is gathering information from two other firms, A and B, which are gathering information from each other, there is some inevitable overlap. Some of the information that the focal firm gets from firm A is indirect knowledge from firm B, which the focal firm is also getting directly. Thus, the focal firm has redundant ties.

Redundant ties reduce the firm's access to non-overlapping information flows (Burt, 1992). Given two firms with the same reach, the firm with fewer redundant ties has access to more unique information. Moreover, firms with fewer redundant ties are more likely to be less constrained in their ability to enter into new markets. Although redundant ties can foster trust (Ahuja, 2000a; Coleman, 1988), the role of trust is minimal (if not irrelevant) in appropriating spilt knowledge in non-contractual networks. There is no exchange relationship in which either party in an inadvertent knowledge sharing relationship has an expectation of performance on the other party. Therefore, we predict:

H_4: Redundancy in the non-formal, non-contractual network is negatively associated with performance.

Complementarity in Dual Networks: Additivity and Super-Additivity

Additivity arguments. What are the benefits to a firm for locating within multiple networks for access to critical knowledge resources? Following transaction cost economics (Williamson, 1975), we argue that to the extent a firm is located within multiple networks, these networks provide distinct benefits to the firm. If a firm could get the *same* benefit from two different networks, it would choose the one that provides maximal benefits at the lowest cost. Firms seek to develop a portfolio of relationships with different governance mechanisms such that the governance modes maximize value while minimizing transaction and coordination costs (Gulati et al., 1998). So, we expect firms to select their knowledge sources to maximize knowledge creation with optimal transaction and coordination costs. The knowledge that flows from one firm to another may be technical, managerial, or market oriented, and industry differences influence the type and amount of knowledge that flows between firms. The mechanisms that firms use to protect valuable intellectual property (Levin, Klevorick, Nelson, & Winter, 1987) within different industries may also influence the type of information available in each network and the types of networks that exist within an industry. The selection of different network links may also be influenced by a firm's capacity to absorb the external knowledge due to the degree of difficulty associated with locating, accessing, and internalizing the requisite knowledge (Cohen et al., 1990).

Powell, White, Koput, & Owen-Smith (2005) argue that firms are multivocal: they gain access to different resources through relationships with distinct set of firms that evolve over time. In this paper, we have sought to distinguish between contractual and non-contractual relationships that together provide access to valuable knowledge resources. Our belief is that these are mutually interdependent since relationships governed by one governance mechanism (e.g., contractual) do not provide access to resources that are governed by the other (e.g., non-contractual).

For example, Microsoft may participate in every major industry associations to learn about different emerging technology trends (non-contractually) and form different sets of formal relationships to access complementary knowledge, which may be more immediately relevant for product enhancements. The firm may investigate new technologies based upon the innovator's customers' acceptance and independently decide to acquire the firm, license the technology, or complete with the innovator. The decision as to whether or not to forge a fine-grained, formal relationship with an innovator can be largely independent of the decision to form a non-contractual relationship with them. One mode of knowledge access is not a substitute for another. Firms need different antenna to search for different signals.

Thus, we assert that the formal alliance mechanisms do not provide a superior form of knowledge access to non-contractual mechanisms. Nor are non-contractual relationships a substitute for contractual relationships—they provide distinct and complementary access to knowledge resources, thus creating an image of a firm meshed in a complex and dynamic set of relationships. Based on the logic that formally contracted relationships confer access to distinctly different type of knowledge than non-formal, non-contractual relationships, we assert that these relationships are additive. Thus:

H_5: Reach in the contractual and non-contractual networks are additively associated with performance.

Super-additivity arguments. Next, we are interested in the question of whether the distinct resources are merely additive or are they super-additive, namely do they mutually reinforce one another? Some set of resources are complementary or super-additive when returns to one type of resource are increased by having more of the other (Milgrom and Roberts, (1990). In other words: returns to both are greater than the returns to each in isolation. Since network linkages are important resources (Gulati et al., 1999), a potentially important research question is whether different types of relationships are complementary, thereby conferring super-additive returns. Prior research focused on dyadic linkages have not examined this question, which lies at the core of understanding how firms navigate in multiple ecosystems spanning different constituencies and distinct types of organizational processes.

Our assertion is that a firm's position, and its subsequent access to knowledge, in its contractual network increases the returns to the firm's position in the non-contractual network, and vice versa. Organizations create new knowledge by applying its absorptive (Cohen et al., 1990) and combinative capabilities (Kogut et al., 1992) to externally sourced knowledge. Because firms enter into contractual relationships to gain access to this new knowledge, or are the targets of spillover search because they have this new knowledge, the generation of new knowledge makes the organization more attractive as a potential partner in both the contractual and non-contractual networks (Ahuja, 2000b; Podolny, 2001; Rosenkopf et al., 2001a). However, the type of knowledge created as a result of access to the fine-grained knowledge of the contractual network and the course-grained knowledge of the non-contractual network are different. In addition, the mechanisms by which a firm improves its position in each network, and the mechanisms through which a firm's position in one network increases its ability to position itself in the other network, are similar but not identical.

To continue with our earlier example of Microsoft and unnamed innovators – by attending industry conferences and exploring the new technologies of innovative companies, Microsoft can identify new partner opportunities. Its position in the non-contractual network can help it improve its position in the contractual network. By investing in access in the contractual network (partnerships), Microsoft is able to coordinate the release of products that had their genesis in the innovations of the non-contractual targets of Microsoft's investigations. In this case, Microsoft's position in the contractual network increases the returns to the knowledge gained in the non-contractual network.

The firm's position in the contractual network is enhanced both by its previous position in that network (Gulati et al., 1999) and by its position in the non-contractual (Ahuja, 2000b; Rosenkopf et al.). The firm's position in the alliance network can be enhanced through its internal knowledge generation efforts, its knowledge generation efforts facilitated by fine-grained knowledge exchange, its knowledge generation efforts facilitated by spillover from the non-contractual network, and through endogenous improvement as the firm uses its existing network connections in both networks to learn about new partnership opportunities (Ahuja, 2000b; Gulati et al., 1999; Rosenkopf et al., 2001a).

A firm's moves in the alliance network enables it to create new products (Kotabe & Swan, 1995; Rothaermel, 2001; Rothaermel & Deeds, 2004) and enter new markets, inducing the firm into examining new products and technologies and, thereby, improving its position in the non-contractual network. By creating new venues for innovation, such new product and market entry generates demand for additional information from the non-contractual network, including information related to products, innovations, and market strategies. As the firm seeks additional spillover knowledge, it expands the list of firms from which it could potentially learn. Thus, the firm's position in the non-contractual network is also the result of exogenous and endogenous tie formation as the firm develops ties based upon learning through the alliance network and its existing position within the non-contractual network.

In addition to the direct effect of position in one network improving the firm's ability to position itself in the other, network tie formation confers status to the well-positioned firm, which improves the firm's relative position in the network. Firms face uncertainty in selecting which potential partners are trustworthy, knowledgeable, or otherwise worth studying. Firms learn about each other's products by studying them, and they can learn about each other's customers and markets through conversations, industry events, and observation, but such data are incomplete. In order to reduce uncertainty, firms also utilize the position of potential alters in their respective networks as status indicators (Podolny, 2001). The status of a firm in one network increases its attractiveness to firms in the other network. Status in the contractual network makes a firm more likely to be viewed as a source of spillover, as well as a more attractive employer. New employees, in turn, can convey and help internalize spillover (Almeida & Kogut, 1999). Status in the non-contractual network – as a nexus of different technologies and markets – increases the firm's attractiveness to potential contractual partners.

We have previously characterized the complementary returns to network position in terms of network position and its associated access to knowledge. We now assert that the information available from the two networks has different characteristics (Haunschild & Beckman, 1998) and is also complementary (Tanriverdi & Venkatraman, 2005). Information gathered from contractual relationships has the potential for being far more tacit or process oriented than the information gathered through spillover because contractual relationships allow for finer-grained information exchange. Contractual partners expend the effort and resources to gain access to resources that complement their own (Powell et al., 1996). Since network position is complementary to both network formation and information access, and the information accessed in both networks is also complementary, we formally hypothesize:

H_6: Dual networks (contractual and non-contractual) are super-additively associated with performance.

Research Setting: The Software Industry

Software is an example of systems-based competition (Shapiro et al., 1999) in a knowledge-intensive industry that calls for high levels of interoperability (Baldwin & Clark, 1997) between suppliers of complementary products. Firms form alliances to develop new products, align product features, and coordinate release cycles and obtain industry knowledge such as product features, software development processes, market information, customer data, release cycles, and hidden algorithms. This is also a setting in which the importance of patents is growing: over 15% of all patents granted today are for software, which accounts for over 25% of the total growth in the number of patents between 1976 and 2001 (Bessen & Hunt, 2003). Thus, the patterns of contractual and non-contractual knowledge flow in a knowledge intensive industry, and the availability of data representing these flows, makes software an ideal setting in which to test the theory of additivity and super-additivity.

We assembled a research database of firms in the prepackaged software industry (SIC code 7372) during 1995-1999 by combining data from multiple sources. Space limitations prevent a detailed discussion, but an appendix is available on request. Our sample frame consists of the 77 firms that were in the top 50 firms (by sales) in at least one year of our sample timeframe. For the 77 firms we have 254 firm/year observations. These firms cite 3,843 other non-focal firms (also included in our dataset). Our 77 focal firms applied for 3,891 patents during 1995—1999 that were subsequently granted. The non-focal firms applied for 314,026 patents during this same time period that were subsequently granted. We also collected alliance data on the focal firms and their alliance partners from the SDC Corporation database. For every alliance and its participants (i.e., ultimate parent), we extracted the type and year of the alliance. Our 77 focal firms announced 1,669 alliances between 1995 and 1999 with 1,127 non-focal alliance partners. We selected only those arrangements that involved significant knowledge transfer.

Construction of Alliance network

Our approach to construct alliance networks follows the conventional logic (Ahuja, 2000a; Powell et al., 1996) but we include firms in the alliance network that are outside the focal firms' industry because we are interested in all the firms that contribute to the focal firm's knowledge. We define the software alliance network as a dynamic, undirected, dichotomous (binary) graph with node and edge sets N_t and E_t respectively. The firms that can enter N are one of our 77 focal firms or one of the 1,127 non-focal alliance partners. The average number of ties across focal firms and years is 15. A firm is in N_t if it is a participant in an alliance announcement during time [t-2, t]. We assume alliances last three (3) years because they are generally multi-year and alliance terminations are rarely reported. An edge is added to E_t connecting two nodes in N_t if the two nodes were in the same alliance during time [t-2, t]. The network contains alliances between focal firms, between focal and non-focal firms, and between non-focal firms.

Year	Node Count	Edge Count	Density	Average Path Length	Cluster Coefficient
1995	869	6,132	0.008	3.393	0.390
1996	869	5,396	0.007	3.428	0.369
1997	898	4,828	0.006	3.480	0.364
1998	894	4,586	0.006	3.479	0.346
1999	1,008	4,538	0.004	3.548	0.363

Table 1: Alliance network characteristics

Table 1 is a summary of our alliance network. An interesting characteristic in our dataset is the low density of edges, low average path lengths, and high clustering of nodes. A network that is both highly locally clustered and has a short average path length is described as a 'small world' (Watts, 1999), which allows members to quickly share novel information.

Patent citation network

Patent citations have reflected technological significance as well as for viewing innovation as a continuous process (Jaffe & Trajtenberg, 2002; Trajtenberg, 1990). Patent citation networks have been created to measure technological niches using patents as nodes and the citations between patents as links (Podolny et al., 1995). Prior research has also used the citations to a firm's patent portfolio as the basis for their firm-status measure (Stuart, Hoang, & Hybels, 1999). We utilize a similar approach in creating our patent citation network where firms are nodes and the links between nodes are the citations between one firm's patent portfolio and another firm's patent portfolio. Following Podolny and Stuart's (1995) argument that patent citations represent the building of new innovations on existing ones, we argue that this represents learning by the firm that is granted the patent.

Each patent contains information about the invention, inventor, the company to which the patent is assigned, the technological antecedents of the invention (the citations), and the technological class (of which there are over 400) to which the expert patent examiner (from the US Patent Office) has assigned the patent. Thus, the patent acts as a document-based, fossilized knowledge trace of new knowledge development. Because the citations limit the value of the new patent, the firm applying for a patent attempts to minimize the number of citations. However, the patent examiner's job is to identify all relevant antecedents. The larger community of individuals and firms from whom the inventor is seeking protection also seeks to limit the scope of the patent by making sure that all prior art is identified. Therefore, we make the assumption that the citations represent the sources from whom the inventor learned even though these sources may be broader than those the inventor explicitly explored.

Patent production by software companies is a recent phenomenon, and represents a small portion of the total number of software patents (Bessen et al., 2003). However, we are using patents to identify learning by software firms: we are not investigating software patents per se. The firm's motivation for patenting (which are central to other streams of research using patents, see for example: Bessen & Hunt (2003)) is not relevant here. We are using the patent citation network primarily to understand the pattern of non-contractual learning by a set of focal firms in SIC 7372 as they all confront the same appropriability regime.

We define the patent citation network as a dynamic, directed, dichotomous (binary) graph with node and arc sets N_t and A_t respectively. The firms that can enter N are one of our 77 focal firms or one of the 3,843 non-focal firms assigned a patent that one of our 77 focal firm's patent's cite. The average number of alters for our focal firms in any given year is 37. A firm is in N_t if it applies for a patent in time t that is subsequently granted or if it is assigned a patent that is cited in time *t* by a node in N_t. An arc is added to

A_t connecting two nodes A and B in N_t if firm A applies for a patent in time t that cites a patent assigned to firm B. The network contains arcs between focal firms, between focal and non-focal firms, and between non-focal firms.

Year	Node Count	Arc Count	Density	Average Path Length*	Cluster Coefficient
1995	2,986	62,548	0.007	2.51	0.427
1996	3,235	66,922	0.006	2.51	0.436
1997	3,459	74,213	0.006	2.47	0.456
1998	3,438	67,838	0.006	2.49	0.468
1999	3,206	53,571	0.005	2.57	0.453

Table 2: Patent citation network characteristics. *Reachable pairs only.

An interesting characteristic of the patent-citation network in our dataset is the low density of edges, low average path lengths, and high clustering of nodes. Thus, it is similar to the alliance network in terms of the topological structure.

Operationalization of Constructs

Our dependent variable is software firm's performance operationalized by firm sales. Our sample firms are all primary SIC code 7372 (prepackaged software). Sales as a proxy for firm performance have been used in some recent studies—see particularly Powell, Koput, Smith-Doerr, and Owen-Smith (2001). We measured a software firm's sales as company *i*'s total revenues (in millions) in year *t*. The range for t for this study is 1995 to 2000. Due to the skewed nature of revenues (even among the top 50 firms), we used the logarithm of revenue.

Alliance network reach$^{i}_{t-1}$. We measure a company's reach by calculating its closeness centrality. The alliance closeness centrality (Wasserman & Faust, 1994) of company *i* in year *t-1* measures the number of direct ties to other companies in the network in year *t-1* plus the number of indirect ties to all other firms in the network, weighted by the reciprocal of their distance to the focal firm. Alliance closeness centrality is calculated using undirected edges between nodes. Due to the range of closeness centrality measures in our network we used the logarithm of the raw measure.

Patent network reach$^{i}_{t}$. We measure patent network reach through the firm's closeness centrality in the patent citation network. The patent closeness centrality (Wasserman et al., 1994) of company *i* in year *t* measures the number of direct ties to other companies in the network in year *t* plus the number of indirect ties to all other firms in the network, weighted by the reciprocal of their distance to the focal firm. We calculate the closeness centrality by counting the number of arcs originating at company *i* in time *t.* We assume that the knowledge borrowing that resulted in the patent application in time *t* occurred in time *t-1*. Due to the range of closeness centrality measures in our network we used the logarithm of the raw measure.

Alliance network embeddedness$^{i}_{t-1}$. Alliance embeddedness is measured by the clustering coefficient of the firm's ego network within the alliance network using undirected ties. The alliance clustering coefficient of company *i* in year *t-1* measures the degree to which a company's alliance partners are also partners with each other (Watts, 1999). We calculate the clustering coefficient by dividing the total number of edges between company *i*'s partners in time *t-1* by the total number of possible edges between those partners (Wasserman et al., 1994).

Patent network redundancy$^{i}_{t}$. We measure patent network redundancy through the clustering coefficient of the firm's ego network within the patent citation network using directed ties. The patent clustering coefficient of company *i* in year *t* measures the degree to which a company's alters are also alters of each other (Watts, 1999). We calculate the clustering coefficient by dividing the total number of arcs between company *i*'s alters in time *t* by the total number of possible arcs between those nodes (Wasserman et al., 1994). We assume that the knowledge borrowing that resulted in the patent application in time *t* occurred in time *t-1*.

Patent and alliance network reach super-additivity$^{i}_{t-1}$. We create a variable to measure complementarity between position in the alliance network and position in the patent citation network by calculating an interaction term for our regression model. The interaction variable is calculated by multiplying *Alliance closeness reach*$^{i}_{t-1}$ and *Patent closeness reach*$^{i}_{t}$.

Controls. We calculated the total revenue of all firms in SIC 7372 for year *t* to control for general industry growth and price changes. We measured company age in year *t* as the difference between the year *t* and the firm's incorporation date. To control for differences in patenting opportunity due to firm specific research interests, we controlled for technical opportunity. We calculate technical opportunity by creating an industry vector of patenting activity, the focal firm's vector of patenting productivity, and then calculate the Pearson correlation coefficient between the two vectors. This measures the distance between the firm and the industry average in time *t*. In each year *t* we create a vector with one dimension for each patent class. For each class we count the number of patents applied for in year *t* subsequently assigned to that class. To create the industry vector we utilize all patents in our dataset. To create each firm's vector we utilize the firm's patents. We assume that the resulting technical opportunity measure reflects the opportunity in time *t-1* because of the lag between performing research and applying for the patent.

To control for the possibility that different patterns of alliance activity were more valuable than others, we controlled for alliance diversity. We calculate alliance diversity by creating an industry vector of alliance activity, the focal firm's vector of alliance activity, and then calculate the Pearson correlation coefficient between the two vectors. This measures the distance between the firm and the industry average in time *t-1*. In each year *t-1* we create a vector with one dimension for each alliance type. For each type we count the number of alliances coded in year *t* to that type.

Analysis

We test our hypotheses using estimates from a cross-sectional, time-series regressions using generalized least squares in the presence of heteroskedasticity across panels (Green, 2003). We have more firms than years in our sample, thus calling for a cross-sectional approach; however, since we have multiple years, we strengthen the validity of our results through the use of a panel design. We build our model additively in five stages to examine the specific performance effects of a firm's set of network characteristics. The independent variables are lagged by one year under the assumption that there is a lag between access to knowledge and the development of capabilities and firm performance. In model 1 we consider industry and firm controls. In model 2 we add variables that represent the firm's position in the alliance network. In model 3 we replace the alliance network measures with patent citation network measures in order to consider the importance of each network independently. In model 4 we combine the network measures from both the alliance and patent citation networks in order to consider their additive qualities. In model 5 we test for an interaction effect between the alliance and patent citation networks.

We use a cross-sectional time series feasible generalized regression, with heteroskedastic correction, of the form:

$$Sales_t^i = V_t\alpha + W_{t-1}^i\beta + X_{t-1}^i\gamma + \varepsilon_t^i$$

The vector V_t contains industry controls (i.e., Industry size). The vector W^i_{t-1} contains focal company controls (i.e., Technical opportunity and Alliance diversity). The vector X^i_{t-1} contains the network covariates (i.e., Alliance cluster coefficient, Alliance closeness centrality, Patent cluster coefficient, Patent closeness centrality).

Results

As shown in Table 3, the continuous improvement in model fitness as variables are added provides support for the general hypothesis that the networks have individual, additive, and super-additive explanatory power. Controlling for the firm's position in the alliance network, its position in the patent citation network adds to the explanatory power. Similarly, controlling for the firm's position in the patent citation network, adding the firm's position in the alliance network adds explanatory power. Finally, the addition of an interaction variable, testing for super-additivity, improves the model. The hypotheses tests and general observations regarding the regression coefficients are performed with the full, final model (#5).

We use the coefficient of alliance closeness centrality to test H1. The coefficient is 0.336 ($p < 0.01$) and supports H1. The corresponding coefficient for patent network reach is also positive (coefficient: 0.297, $p < 0.01$) supporting H3. Both types of network reach seen through closeness centrality (direct and indirect ties together) have positive effects.

For the alliance embeddedness hypothesis (H2), we had two competing expectations that differ in terms of the directionality. The coefficient for alliance embeddedness has a negative effect on performance (coefficient: -0.076, $p < 0.01$). Thus, the arguments for the negative effect of embeddedness are supported. Examining the coefficient of patent-citation cluster coefficient tests hypotheses H4. As predicted, its tie redundancy has a negative effect on performance (coefficient: 0.139, $p < 0.01$).

We test our additivity hypothesis (H5) by looking at the change in model fitness when going from one network to two. A firm's position in the contractual and non-contractual networks additively enhances performance ($p < 0.001$). Examining the coefficient of the closeness centrality interaction term tests hypothesis H6. We find that a firm's position in the contractual and non-contractual networks is super-additively associated with performance (coefficient: 0.082, $p < 0.01$).

[Table 3 goes about here]

Network Visualization

Why network visualization? Network visualization creates a capacity for building intuition and theorizing about a phenomena that is unsurpassed by statistical analysis (Moody, McFarland, & Bender-deMoll, 2005). Wide-ranging distributional shapes, nonlinear relations, and spatial proximity are particularly well suited to visual summarization. We utilize network visualization to both help identify the phenomena — firms existing in dual networks — and changes to the topology of the networks themselves (Powell et al., 2005). Through the use of visualization we have a much richer, intuitive understanding of the distinctness of the dual networks and the firm's joint position within them. Such visualizations complement our statistical inferences, which we use for hypothesis testing.

How we depict the network? Appendix A contains a series of Pajek (de Nooy, Mrvar, & Batagelj, 2005) visualizations. The images show the networks we constructed for 1995 and 1999[1]. For each year, we show the entire network and the ego networks (the network consisting of a focal firm and its adjacent alters) for Microsoft Corporation and Adobe Systems Incorporated. We selected Microsoft because it is the largest firm within our focal set and we selected Adobe as a typical modal firm with a moderate number of patents and alliances. For each network, we show three views: the alliance network, the patent network, and the joint alliance and patent network. The focal firms are highlighted in red boxes, sized proportional to the logarithm of their sales. The edges (lines) between nodes are colored according to relationship type. Alliance relationships are shown in blue, patent-citation relationships are shown in green, and relationships involving both alliances and patent-citations are shown in red.

Each of the three views is constructed similarly. The alliances or patent citations of the focal firm(s) are used to identify the alters. The focal firm(s) and their alters constitute the set of nodes in the network. We then draw all the edges that exist between and among the focal firm(s) and their alters and color them according to the logic described above.

What do the visualization tell us? Two striking observations become apparent after examining figures 2 and 3. Note that there are very few red lines—implying that firms that a focal firm has an alliance with are not the same as the firms that the firm cites in its patents. That is, the firms have mutually exclusive relationships with these two types of firms. Visually, this provided additional corroboration for the additivity hypothesis, which was empirically confirmed through statistical analysis. However, the visualization provides an additional insight that goes beyond the statistical analysis: the focal firms are not the most *central* in their own networks. This is somewhat surprising since we specifically included only those firms that had an alliance or patent citation relationship with the focal firms when we created the networks. As shown in figures 2 and 3, the focal firms are in the periphery of their alliance network both in 1995 and 1999. The patent citation network visualizations indicate similar profiles. The packaged software companies are learning from many other firms, which are also learning from each other. Although the visualizations suggest the networks are quite dense, the statistics (network

[1] Yearly rendering is not done due to space limitations. A full set of “movies” that show the full network and company-specific ego networks for Microsoft Corporation and Adobe Systems Incorporated for each year in the sample frame are available from the authors.

density across networks and years varies from 0.4% to 0.8%) suggest that the networks are actually quite sparse. The core-periphery structure we observe in the visualizations is consistent with high small-world measures (the ratio of the network's cluster coefficient to average path length compared to a random network's with the same number of nodes and density varies across network and years from 45.5 to 114.7) (Watts, 1999). The small-worldiness enables information to travel quickly between otherwise unconnected nodes. Whether the value of high-closeness centrality predicts performance because of more distinct information or because high-closeness centrality increases the probability of receiving valuable information, requires further investigation. What we can say is that the firms with high closeness centrality seem to be better positioned to receive valuable information.

Going beyond the overall network to the visualizations of Adobe's and Microsoft's networks, we find similar patterns. First, in both cases we see that some of the firms' alters are redundant – the partners are linked to each other – and some are distinct. Second, there are very few linkages that show *both* alliance and patent citation relationships — implying that these firms are accessing distinct networks to gain access to distinct, valuable information. Thus, the visualizations, while serving to corroborate the statistical tests, also provide useful insights to further examine patterns of interconnected networks across domains.

Discussions

Most studies on organizational networks focus on single networks — more specifically: alliances and partnerships formed by a set of firms within an industry or set of industries. In this research we have extended the conceptualization of a firm embedded in a single network to one in which a firm is embedded in multiple, possibly overlapping, networks to access complementary knowledge resources that underlie success in software networks. We developed a simple, parsimonious typology of networks. A network is either fine-grained, formal, and contractual, or it is course-grained, non-formal, and non-contractual. We theorized, and empirically observed that software firms embed themselves in these dual networks governed by different mechanisms in order to gain access to different, complementary knowledge resources. Our main empirical contribution is that within the set of leading software firms that we studied, firms' positions within these networks, and the knowledge resources that firms access in these different networks, are both additive and super-additive in terms of firm performance measured by sales.

Networks of relationships are important resources as they allow firms to access different types of knowledge — they may involve market intelligence, product information, and technical knowledge. Some types of knowledge may be product oriented (impacting the design and deployment of new software products) while others could be process focused (to coordinate the delivery of interdependent software products). Some types of knowledge are codified while others are more tacit. Such complexities require firms to construe the best set of mechanisms to access these different types of knowledge. We found that the knowledge accessed by a firm's position in the different networks is distinct and complementary. A particularly important finding is that the value of each type of knowledge is increased as the firm has more of the other type. The firm's position in each network is also complementary to the firm's efforts to improve its position in the other network. An enhanced position in the contractual network improves the firm's ability to position itself in the non-contractual, and vice versa. These preliminary results in one setting raise the need for further theorizing about how different types of resources can be accessed through different types of mechanisms, and further examination of whether they are additive and super-additive or not. This will go towards developing a richer and more micro-level understanding of networks as critical resources (Gulati et al., 1999) under different conditions.

This research overcomes two limitations in prior research on network formation and value appropriation. First, most studies focus on a single type of business relationship – technology alliances, marketing relationships, vendor relationships, or joint R&D activities – or different types of non-contractual relationships – employee mobility, interlocking directorates, or social ties. This research creates an initial typology in which business relationships can be characterized as contractual or non-contractual. Each type has a distinctive governance mechanism and knowledge type. This study suggests that, for example, alliance relationships are an instance of a more general classification – contractual relationships – that may share many affordances and be subject to many of the same challenges.

Second, because most studies lacked a clear distinction between network types, they did not explore the ramifications of the multiple networks in which firms are embedded. In characterizing a firm as belonging to two classes of networks, we are able to explore their additive and complementary qualities. We anticipate that as the typology of relationship types is expanded, the additional categories will share the qualities of being additive and complementary. Promising candidate frames include interlocked boards of directors[2], participation in open source projects, and inter-firm equity linkages.

This study makes three methodological contributions. First, we measure a firm's position in its non-contractual network through the creation of a patent-citation network. We showed through Pajek visualizations and summary statistics that knowledge flows across multiple networks and provided a method for documenting non-contractual approaches to knowledge access. Second, we measure and test dual network position by collecting data on two networks. Specifically, we followed a consistent protocol to create these two networks and then used them in a single statistical model. Future refinements may explore methods of assessing how firms position in multiple networks more holistically. Third, we combine statistics with visualizations to understand dual networks, as they appear to provide complementary insights. Future refinements may enhance more systematic ways to create interplays between statistics and visualizations as ways to both develop and test theoretical assertions.

Our findings also have important implications to practice — especially designers of organization structure, processes and systems. How should a firm coordinate the different knowledge conduits embedded within different knowledge networks? Does the firm require new structural roles, new processes for alliance formation, and new mechanisms for managing non-contractual relationships? How can knowledge management systems be designed to reflect the multi-faceted nature of knowledge and its absorption (Kale, Dyer, & Singh, 2001)? Some researchers have called for specific structural roles for coordinating the value from alliances (Kale, Singh, & Perlmutter, 2000). Our findings raise the need for

[2] We performed preliminary tests which suggests that network position in the directorate interlock network is additive in our regression model. However, we have insufficient data to construct a network of all the interlocks

new structural roles, different process for absorbing different types of knowledge, as well as systems that allow for combining multiple types of knowledge for maximal performance. Each network in which a firm is positioned has its own governance mechanism and offers access to unique and possibly complementary set of resources. The time is ripe for the systematic consideration of organizational architecture that goes beyond a single firm's boundaries and incorporates an extended set of alliances and partnerships that may be governed through multiple types of mechanisms.

Limitations and Extensions

We enumerate a set of limitations underlying this study as avenues of future extensions. First, our research limited to the top firms in the prepackaged software industry (SIC 7372) should be replicated and extended to establish the robustness of findings—especially the additive and super-additive properties. Second, our study relied exclusively on secondary data. The research design should benefit greatly from primary assessments of how information and knowledge is absorbed from multiple networks. What information flows from the different networks? Is the information distinct? What information from which networks is most valuable to the firm? How do firms actively leverage their position in one network in the other? How do firms combine the different types of knowledge? Third, one of the limits in any network study is the definition of the network. At some level, all firms are connected to all other firms. However, the attenuation of information across arcs being what it is, and the impracticality of identifying all links, requires that we define the network narrowly. Broadening the scope of knowledge access may enhance the confidence in the findings. Similarly, our results based on the software industry—with implicit need for interfirm cooperation for complementary knowledge—are worthy of tests in other industries that may rely less on interfirm knowledge flows to develop more insights on the contingency nature of dual or multi networks.

---

using the node selection methods we chose for the alliance and knowledge-spilling networks. Our preliminary directorate-interlock tests were based upon a network consisting only of our focal 77 firms.

The networks in our study were all scale-free small-worlds in which the number of edges touching a specific node follows a power-law distribution. That is, the networks are characterized by a few nodes having a great many links, and many nodes having very few links. In order to generalize our findings, future research should explore the results of this research in network topologies with different characteristics. For example, these results may not hold if the network is not a small-world or is not also scale-free.

Network-based research has added to our understanding of the firm as both consisting of internal networks (i.e., formal, informal, advice, friendship, etc.) and existing within a networked ecosystem. No doubt, the internal networks influence the firm's behavior in the external ecosystem. However, the networked ecosystem is, itself, a network of networks. From a social network analysis perspective, firms exist simultaneously in multiple networks, and these networks are interdependent. Analyzing a firm in one network without taking into account the interrelated others leaves much of the story untold. The networks may overlap to varying degrees, provide complementary resources, or jointly constrain the firm. This paper has made the first step towards examining a firm's role in creating and exploiting these interlocked networks, but much work remains.

References

Ahuja, G. 2000a. Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. ***Administrative Science Quarterly***, 45: 425-455.

Ahuja, G. 2000b. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. ***Strategic Management Journal***, 21(3): 317.

Almeida, P., & Kogut, B. 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks. ***Management Science***, 45(7): 905.

Baldwin, C., & Clark, K. 1997. Managing in an age of modularity. ***Harvard Business Review***, 75(5): 84-93.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. ***Strategic Management Journal***, 21(3): 267-294.

Baum, J. A. C., Shipilov, A. V., & Rowley, T. J. 2003. Where do small worlds come from? ***Industrial and Corporate Change***, 12(4): 697-725.

Baum, J. A. C., & Singh, J. V. 1994. Organizational Niches and the Dynamics of Organizational Mortality. ***American Journal of Sociology***, 100(2): 346-380.

Bessen, J., & Hunt, R. M. 2003. An Empirical Look at Software Patents. ***Working Paper No. 03-17/R***.

Brusoni, S., Prencipe, A., & Pavitt, K. 2001. Knowledge specialization, organizational coupling, and the boundaries of the firm: Why do firms know more than they make? ***Administrative Science Quarterly***, 46(4): 597-621.

Burt, R. 1992. ***Structural Holes: The Social Structure of Competition***. Cambridge, MA: Harvard University Press.

Campbell-Kelly, M. 2003. ***From airline reservations to Sonic the Hedgehog : a history of the software industry***. Cambridge, Mass.: MIT Press.

Cohen, W. M., & Levin, R. C. 1989. Empirical Studies of Innovation and Market Structure. In R. D. Willig (Ed.), ***Handbook of Industrial Innovation***, Vol. 2. Holland: Elsevier Science Publishers.

Cohen, W. M., & Levinthal, D. A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. ***Administrative Science Quarterly***, 35: 128-152.

Coleman, J. S. 1988. Social capital in the creation of human capital. ***American Journal of Sociology***, 94: S95-S120.

Conner, K., & Prahalad, C. K. 1996. A Resource-based Theory of the Firm: Knowledge Versus Opportunism. ***Organization Science***, 7(5): 477-501.

Cusumano, M. A. 2004. ***The business of software : what every manager, programmer, and entrepreneur must know to thrive and survive in good times and bad***. New York: Free Press.

de Nooy, W., Mrvar, A., & Batagelj, V. 2005. ***Exploratory Social Network Analysis with Pajek***. New York: Cambridge University Press.

Freeman, L. C., Borgatti, S. P., & White, D. R. 1991. Centrality in Valued Graphs - a Measure of Betweenness Based on Network Flow. ***Social Networks***, 13(2): 141-154.

Galaskiewicz, J., & Wasserman, S. 1989. Mimetic Processes Within An Interorganizational Field: An Empirical Test. ***Administrative Science Quarterly***, 34(3): 454.

Gnyawali, D. R., & Madhavan, R. 2001. Cooperative networks and competitive dynamics: A structural embeddedness perspective. ***Academy of Management Review***, 26(3): 431-445.

Granovetter, M. S. 1973. The Strength of Weak Ties. ***American Journal of Sociology***, 78(6): 1360-1380.

Granovetter, M. S. 1985. Economic action and social structure: The problem of embeddedness. ***American Journal of Sociology***, 91: 481-510.

Green, W. H. 2003. ***Econometric Analysis*** (Fifth ed.). New Jersey: Prentice Hall.

Gulati, R., & Gargiulo, M. 1999. Where do interorganizational networks come from? ***The American Journal of Sociology***, 104(5): 1439.

Gulati, R., & Singh, H. 1998. The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. ***Administrative Science Quarterly***, 43(4): 781.

Haunschild, P. R., & Beckman, C. M. 1998. When do interlocks matter?: Alternate sources of information and interlock influence. ***Administrative Science Quarterly***, 43(4): 815.

Henderson, R., & Cockburn, I. 1994. Measuring Competence? Exploring Firm Effects in Pharmaceutical Research. ***Strategic Management Journal***, 15(Special Issue; winter): 63-84.

Jaffe, A. B., & Trajtenberg, M. 2002. ***Patents, Citations, and Innovations: A Window on the Knowledge Economy***. Cambridge: The MIT Press.

Kale, P., Dyer, J., & Singh, H. 2001. Value creation and success in strategic alliances: Alliancing skills and the role of alliance structure and systems. ***European Management Journal***, 19(5): 463.

Kale, P., Singh, H., & Perlmutter, H. 2000. Learning and protection of proprietary assets in strategic alliances: Building relational capital. ***Strategic Management Journal***, 21(3): 217.

Kogut, B., & Zander, U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. ***Organization Science***, 3(3): 383-397.

Kotabe, M., & Swan, K. S. 1995. The role of strategic alliances in high-technology new product development. ***Strategic Management Journal***, 16(8): 621.

Krackhardt, D., & Stern, R. N. 1988. Informal Networks and Organizational Crises - an Experimental Simulation. ***Social Psychology Quarterly***, 51(2): 123-140.

Levin, R. C., Klevorick, A. K., Nelson, R., & Winter, S. G. 1987. Appropriating the Returns from Industrial Research and Development. ***Brookings Papers on Economic Activity***, 3: 783-831.

March, J. G. 1991. Exploration and Exploitation in Organizational Learning. ***Organization Science***, 2(1): 71.

March, J. G., & Simon, H. A. 1958. ***Organizations***. New York: Wiley.

McEvily, B., & Zaheer, A. 1999. Bridging ties: A source of firm heterogeneity in competitive capabilities. ***Strategic Management Journal***, 20(12): 1133-1156.

Milgrom, P., & Roberts, J. 1990. The Economics of Modern Manufacturing: Technology, Strategy, and Organization. ***American Economic Review***, 80(3): 511-528.

Moody, J., McFarland, D., & Bender-deMoll, S. 2005. Dynamic Network Visualization. ***The American Journal of Sociology***, 110(4): 1206.

Morgan, R. M., & Hunt, S. 1999. Relationship-based competitive advantage: The role of relationship marketing in marketing strategy. ***Journal of Business Research***, 46(3): 281-290.

Nonaka, I., & Takeuchi, H. 1995. ***The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation***. New York: Oxford University Press.

Oliver, C. 1990. Determinants of Interorganizational Relationships - Integration and Future-Directions. ***Academy of Management Review***, 15(2): 241-265.

Podolny, J. M. 2001. Networks as the pipes and prisms of the market. ***American Journal of Sociology***, 107(1): 33-60.

Podolny, J. M., & Stuart, T. E. 1995. A role-based ecology of technological change. ***The American Journal of Sociology***, 100(5): 1224.

Portes, A., & Sensenbrenner, J. 1993. Embeddedness and Immigration: Notes on the Social Determinants of Economic Action., ***American Journal of Sociology***, Vol. 98: 1320: University of Chicago Press.

Powell, W., Koput, K. W., & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. ***Administrative Science Quarterly***, 42(1): 116-145.

Powell, W. W., Koput, K. W., Smith-Doerr, L., & Owen-Smith, J. 2001. Network Position and Firm Performance: Organizational Returns to Collaboration in the Biotechnology Industry. In S. Andrews, & D. Knoke (Eds.). Greenwich, CT: JAI Press.

Powell, W. W., White, D. R., Koput, K. W., & Owen-Smith, J. 2005. Network Dynamics and Field Evolution: The Growth of Interorganizational Collaboration in the Life Sciences. ***American Journal of Sociology***, 110(4): 1132.

Reddy, S. K., & Czepiel, J. A. 1999. Measuring and Modeling the Effects of Long-Term Buyer-Seller Relationships in Corporate Financial Services Markets. ***Journal of Business Research***, 46(3): 235-244.

Rindfleisch, A., & Moorman, C. 2001. The acquisition and utilization of information in new product alliances: A strength-of-ties perspective. ***Journal of Marketing***, 65(2): 1.

Rosenkopf, L., Metiu, A., & George, V. P. 2001a. From the bottom up? Technical committee activity and alliance formation. ***Administrative Science Quarterly***, 46(4): 748-772.

Rosenkopf, L., & Nerkar, A. 2001b. Beyond Local Search: Boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, 22(4): 287.

Rothaermel, F. T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. ***Strategic Management Journal***, 22(6/7): 687.

Rothaermel, F. T., & Deeds, D. L. 2004. Exploration and Exploitation Alliances in Biotechnology: A System of new Product Development. ***Strategic Management Journal***, 25(3): 201-221.

Rowley, T., Behrens, D., & Krackhardt, D. 2000. Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries. ***Strategic Management Journal***, 21(3): 369-386.

Saxenian, A. 1991. The Origins and Dynamics of Production Networks in Silicon Valley. ***Research Policy***, 20(5): 423-437.

Shapiro, C., & Varian, H. R. 1999. ***Information Rules: a strategic guide to the network economy*** (1 ed.). Boston: Harvard Business School Press.

Silverman, B. S., & Baum, J. A. C. 2002. Alliance-based competitive dynamics. ***Academy of Management Journal***, 45(4): 791.

Sorenson, O., & Stuart, T. E. 2001. Syndication Networks and the Spatial Distribution of Venture Capital Investments. ***The American Journal of Sociology***, 106(6): 1546.

Stuart, T. E., Hoang, H., & Hybels, R. C. 1999. Interorganizational Endorsements and the Performance of Entrepreneurial Ventures., ***Administrative Science Quarterly***, Vol. 44: 315-349: Administrative Science Quarterly.

Tanriverdi, H., & Venkatraman, N. 2005. Knowledge Relatedness and the performance of multibusiness firms. ***Strategic Management Journal***, 26(2): 97-120.

Teece, D. J., Pisano, G., & Shuen, A. 1997. Dynamic capabilities and strategic management. ***Strategic Management Journal***, 18(7): 509-533.

Trajtenberg, M. 1990. A Penny for Your Quotes: Patent Citations and the Value of. ***The Rand Journal of Economics***, 21(1): 172.

Uzzi, B. 1996. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. ***American Sociological Review***, 61(4): 674-698.

Uzzi, B. 1997. Social structure and competition in interfirm networks: The paradox of embeddedness. ***Administrative Science Quarterly***, 42(1): 37-69.

von Hippel, E. 1988. ***The Sources of Innovation***. New York: Oxford University Press.

Wasserman, S., & Faust, K. 1994. ***Social Network Analysis: Methods and Applications***. Cambridge: Cambridge University Press.

Watts, D. J. 1999. Networks, dynamics, and the small-world phenomenon. ***American Journal of Sociology***, 105(2): 493-527.

White, H. C. 2002. ***Markets from networks : socioeconomic models of production***. Princeton, N.J.: Princeton University Press.

Williamson, O. E. 1975. ***Markets and Hierarchies: Analysis and Antitrust Implications***. New York: The Free Press.

Zaheer, A., & Bell, G. 2005. Benefiting From Network Position: Firm Capabilities, Structural Holes, and Performance. ***Strategic Management Journal (forthcoming)***.

Table 3: Results

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Industry size	0.162	0.130	0.216	0.179	0.181
	(6.89)**	(8.19)**	(7.02)**	(6.51)**	(6.63)**
Age	0.303	0.297	0.302	0.347	0.335
	(16.54)**	(19.30)**	(10.33)**	(13.33)**	(12.01)**
Alliance diversity		0.024		0.103	0.094
		(9.78)**		(2.74)**	(2.54)*
(H1) Alliance network reach		0.299		0.366	0.336
		(8.62)**		(9.51)**	(8.76)**
(H2) Alliance network embeddedness		-0.073		-0.083	-0.076
		(3.27)**		(3.19)**	(2.87)**
Technical opportunity			0.247	0.131	0.137
			(5.43)**	(3.43)**	(3.62)**
(H3) Patent network reach			0.275	0.307	0.297
			(4.30)**	(6.17)**	(5.99)**
(H4) Patent network redundancy			-0.142	-0.143	-0.139
			(2.79)**	(3.43)**	(3.43)**
(H6) Reach interaction					0.082
					(2.89)**
Constant	-0.009	0.003	-0.020	-0.016	-0.016
	(0.39)	(0.18)	(0.65)	(0.60)	(0.60)
Observations	253	253	253	253	253
Number of panels	68	68	68	68	68
Chi-Squared	284.11	601.11	283.83	707.10	568.97
Log Likelihood	-237.61	-203.90	-229.04	-196.29	-193.23
Degrees Of Freedom (DF)	2	5	5	8	9
Model fitness (-2LL)	475.22	407.80	458.08	392.58	386.47
Model comparison logic		**(2) – (1)**	**(3) – (1)**	**(4) – (2)**	**(5) – (4)**
Δ(-2LL)		112.74	17.14	23.34	7.36
Δ(DF)		3	3	3	1
P-Value Chi-squared difference test (Δ(-2LL), Δ(DF))		0***	0***	0.00003***	0.00667**

Absolute value of z statistics in parentheses

Table 3: Regression model results

Appendix A – Visualizations

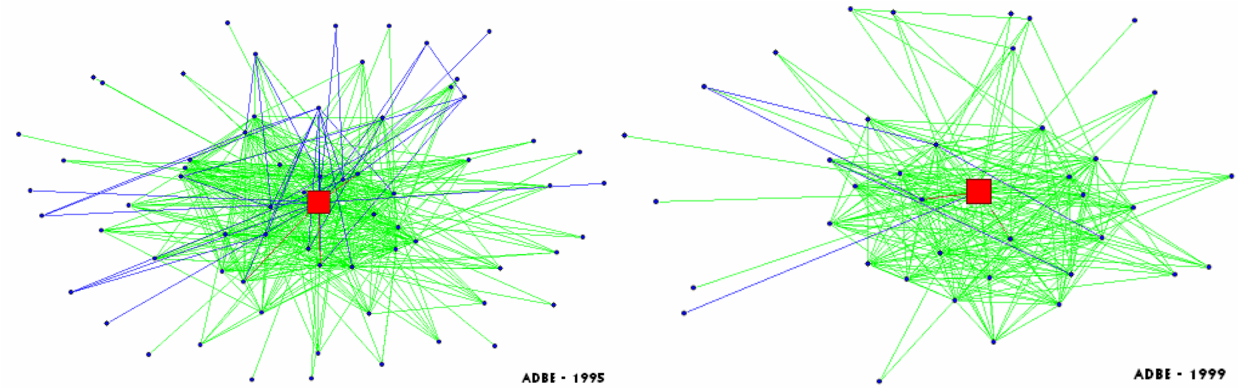

Figure 2. Adobe's ego network drawn from dual networks – 1995 and 1999. Adobe is the red square, its alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.

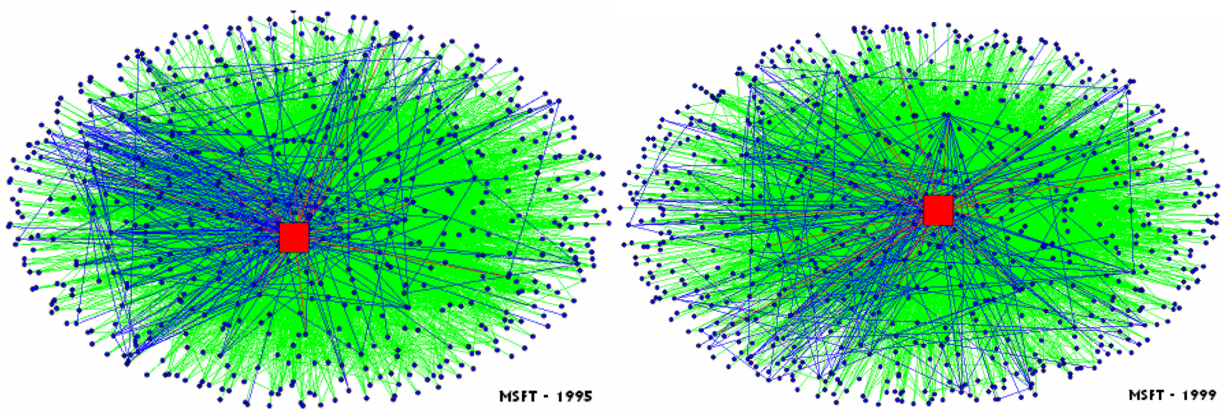

Figure 3. Microsoft's ego network drawn from dual networks – 1995 and 1999. Microsoft is the red square, its alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.

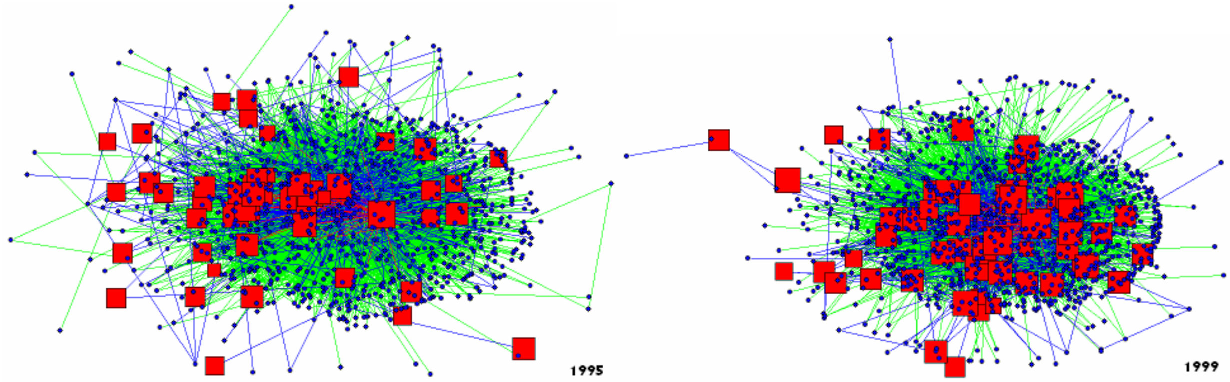

Figure 4. Software industry dual networks – 1995 and 1999. The top 77 firms in SIC 7372 are the red squares (sized by the logarithm of reported sales), their alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.