Organization Science
Vol. 19, No. 5, September–October 2008, pp. 669–687
ISSN 1047-7039 | EISSN 1526-5455 | 08 | 1905 | 0669
informs®
DOI 10.1287/orsc.1070.0339

Investigating the Microstructure of Network Evolution: Alliance Formation in the Mobile Communications Industry

Lori Rosenkopf
The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104, rosenkopf@wharton.upenn.edu

Giovanna Padula
Bocconi University, Via Bocconi, 8, 20136 Milan, Italy, giovanna.padula@unibocconi.it

Theories of network evolution frequently focus on "network endogeneity," which stresses predictable, path-dependent evolution rooted in previous network structure. However, theories of technological evolution and innovation remind us that networks may undergo significant change as technological discontinuities exert pressures on existing relationships and firms engage in exploratory search. How can we incorporate sources of change into our theories of network evolution instead of focusing so squarely on sources of inertia? By using recent advances in graph theory, we develop a more flexible theory of network evolution by examining two patterns of partner selection that have the potential to change networks: "shortcut" formation between relatively unconnected partner clusters, and the entry of new firms into the "main component" of incumbent partners. Our findings suggest an important contingency for the endogeneity perspective: structural homophily predicts shortcut formation but not alliance formation within clusters. Furthermore, we demonstrate that the pattern of alliance formation between incumbents and new entrants to the alliance network is driven by a combination of endogenous and exogenous mechanisms. New entrants attach to more prominent incumbents, but they are more likely to attach with an alliance deal that comprises multiple partners. We demonstrate these findings in an industry where systemic technology encourages cooperation and where network entry is prevalent—the mobile communications industry from 1993–2002.

Key words: network evolution and change; small world; shortcuts; exploration; strategic alliances
History: Published online in *Articles in Advance* April 25, 2008.

1. Introduction

Research on the evolution of alliance networks has revealed two well-proven rules of partner selection within these networks. Specifically, pairs of firms with direct or indirect ties in existing alliance networks are more likely to form future alliances (e.g.; Gulati 1995b, Walker et al. 1997, Chung et al. 2000), as are firms with more extensive histories of alliance formation (e.g., Powell et al. 1996, Gulati and Gargiulo 1999). Taken together, these dynamics suggest that alliance networks become ever more self-reproducing and centralized, as more and more dense webs of relationships are developed among familiar and well-allied firms. Such a characterization of network evolution may be the norm, particularly in more mature industries, but does not help us address questions of how networks might change more dramatically.

Understanding substantive network change requires a theory of network evolution that extends beyond these well-accepted drivers of network evolution. Utilizing insights from graph theory and network topology, we identify two gaps in the typical studies demonstrating network endogeneity. First, we employ the small-world imagery of clusters of locally embedded firms connected by a handful of "shortcuts" (Watts and Strogatz 1998, Watts 1999). Here, although the formation of shortcuts may be motivated by very different issues than the majority of local, within-cluster ties, these drivers of shortcuts can be masked by the drivers of the more prevalent local ties. We follow the lead of Baum et al. (2003) in separating out shortcuts as a subset of network ties worthy of study in their own right. Indeed, shortcut formation is one possible route to more significant network change.

Another understudied aspect of network change is the role of entry by new firms into the network. Studies of "power-law" distributions in network topologies suggest that new entrants preferentially connect to well-connected actors in networks (Barabasi et al. 1999), but most studies of social networks limit their scope to actors that are members of the network throughout the study period. Even small-world studies in our field typically limit their scope to the "main component"—the largest group of actors that already are connected to each other by at least one tie. By considering firms that are outside the main component or not yet in the network at all, we follow the lead of small-world theorists such as Uzzi et al. (2002) and Schilling and Phelps (2007).

Most studies of alliance network evolution are unable to make substantive predictions about how firms that are not advantaged by the current network structure are able to break into these networks, because these firms do not possess the alliance ties that are known to facilitate future alliance formation. Therefore, we investigate how new entrants are attracted to partners both in and out of the network, and also how established network actors may choose to develop relationships both with new entrants and with actors in distant clusters.

Our study focuses on a domain where industry standards and network effects are prevalent, making alliance formation plentiful. We examine the dynamics of alliance networks in the cellular industry from 1993 to 2002. In established networks, we find that similar levels of prominence among firms predict alliance formation across local clusters. We also find that although firms new to the network may enter through alliances with prominent established actors, deals of this type are frequently populated by more than one new-to-the-network firm. Our results suggest that the emergence of new entrants, particularly through multiparty deals, creates new clusters that can be the source of more fundamental network change.

2. Theory

This section develops a more comprehensive theory of network evolution by acknowledging both endogenous and exogenous drivers of partner selection. We first review the two primary endogeneity mechanisms and note the gaps unexplained by this perspective. Second, we discuss how firms' exploratory search may motivate alliances with partners that would not be predicted by the endogeneity perspective. Third, we develop hypotheses about alliance formation among relatively unconnected clusters and among new entrants to fill the endogeneity gaps. Last, we consider how deals that admit unconnected firms to the alliance network may differ from deals among more familiar firms.

2.1. Network Endogeneity

Much extant research on network evolution highlights the role of previous structures in driving new alliance formation. Previous structures provide social cues about the competencies and reliability of potential partners, which reduce the search costs and risks of exposure to opportunistic behavior (Gulati 1995a, Gulati and Singh 1998). Two well-accepted rules of attachment have been emphasized as drivers of alliance formation: *cohesiveness* and *prominence*.

Cohesiveness suggests that pairs of firms with direct or indirect ties in existing alliance networks are more likely to form future alliances. Previous direct ties between two firms provide a reliable channel through which each partner can learn about the competences and the reliability of the other (Gulati 1995b). By providingunique information about partner capability and trustworthiness, a history of cooperation between two firms increases the likelihood that these firms will form new alliances with each other in the future. Furthermore, indirect ties provide a vehicle to gather information about potential partners through effective referrals (Coleman 1988). Referrals provide governance benefits that operate both ex ante, suggesting which potential partners are reliable and trustworthy (Baker 1990, Gulati 1995b); and ex post, by disseminating information on deviant behaviors (Raub and Weesie 1990). Therefore, the extent to which potential partners' networks overlap with common partners affects the likelihood of alliance formation between them (Ahuja 2000a, Chung et al. 2000).

A more structural indicator of the attractiveness of a potential partner is its *prominence* in the alliance network, because firms with more extensive histories of alliance formation are more likely to form future alliances. Differential levels of network involvement among firms introduce and reinforce systemic reputational differences among them that extend beyond their immediate circle of direct and indirect ties, affecting their visibility and attractiveness (Podolny 1993, Han 1994, Podolny and Stuart 1995). Arguing that prominence signals attractiveness, previous research argues that firms attach preferentially to other prominent firms, so that new alliances are more common between firms that occupy central positions in the overall network (Powell et al. 1996, Gulati and Gargiulo 1999). Furthermore, if prominence enhances the attractiveness of firms to future partners, not only will central firms be likely to seek other central partners, but they will also have little incentive to accept peripheral players.

The demonstration of these endogenous determinants, however, fails to address how firms that are either not prominent, or lack substantial direct and indirect ties, are able to participate in subsequent alliances. However, we know from research on technological evolution and innovation that network structures may undergo more significant changes as technological discontinuities exert pressures on existing relations (Rosenkopf and Tushman 1994, 1998) and firms engage in exploratory search to enjoy the benefits of novel recombinant processes (Rosenkopf and Almeida 2003). We argue that adjusting the focus of network evolution studies to include such "nonendogenous" ties will allow us to understand sources of more significant network change rather than focusing so strongly on how networks reproduce themselves. Therefore, we explore how the types of ties *not* predicted by the network endogeneity perspective may form. Whereas endogeneity studies tend to ignore or minimize the formation of features such as shortcuts or ties to new entrants, we make these features the focus of our analysis.

First, shortcuts, by definition, are the less common ties that span locally embedded clusters. However, our statistical methods describe aggregate tendencies for alliance formation favoring endogenous dynamics at the expense of the less common shortcut dynamics.[1] The more recent emphasis on small-world topology, however, suggests that such shortcuts need to be examined independently rather than in aggregation with other ties, because the power of shortcuts is not in their prevalence but in their scarcity and their valuable role in promoting efficiency across the overall network. Thus, for example, Baum et al. (2003) focused on shortcuts in investment banking syndicate networks and provided evidence that shortcuts can be motivated by "control" and "insurgency" rationales, which suggests that shortcuts can be formed among both core firms and peripheral firms, respectively. In this paper, we examine determinants of shortcut formation rooted in existing network structure.

Second, endogeneity studies have traditionally examined mature, stable industries with little concern for entry or exit. However, graph theorists have also emphasized how firms develop ties with even more distant, unfamiliar firms—those that have not yet entered the network (Barabasi et al. 1999). Indeed, recent studies have considered how patterns of entry may shape network structure (Powell et al. 2005, Uzzi et al. 2002). As such, although the formation of shortcuts is one way in which we might think about more radical changes to network topology, an even stronger force in fast-paced industries may be the entry of unconnected (or poorly connected) firms to established networks. However, an endogeneity perspective is unable to make substantive predictions about how firms that are not advantaged by the current network structure are able to break into these networks. Therefore, we also incorporate analyses of network entry into our study.

To fully explore the dynamics of shortcuts and new entry, we place several small-world attributes in the foreground of our study. Whereas most small-world studies limit their analyses to only the main component (the largest set of actors that are connected by any path), we emphasize the main component in both our theory and our methods, but contrast dynamics within the main component to those beyond the main component. This distinction allows us to speak of firms "embedded" within the main component forming alliances with each other separately from firms that are not embedded in the main component at a given time, but may enter the main component subsequently through an alliance with an embedded firm. We call the firms at risk of entering the main component "nonembedded firms" or "potential new entrants." Because embedded firms are able to access technological knowledge circulating in the main component (Powell et al. 1996), we theorize that different dynamics will drive alliance formation among these members than among nonembedded firms that do not yet have access to this knowledge.

At the same time, following small-world approaches, we also focus on the clustering of alliances within the main component, separating the dynamics of alliance formation within clusters from those for shortcuts across clusters. Because shortcuts serve as bridges spanning the structural holes across clusters (Burt 2005), their use suggests access to less familiar contexts compared to that of prospective partners residing within the same cluster.

These twin emphases on embedded versus nonembedded firms, and on shortcuts versus within-cluster alliances, are key because they allow us to distinguish what we call "semidistant" firms (already admitted to the main component but residing in different clusters of the main component) from "distant" ones (not yet admitted to the main component). This more nuanced view of distance generates the context in which firms undertake exploratory search.

2.2. Exploratory Search and Distant Partners

Although the endogeneity perspective on network evolution has traditionally emphasized the tendency of the firms to search locally among familiar prospective partners, other studies emphasize entrepreneurial behavior and exploratory search of firms reaching out for more distant partners (Burt 1992, 1998). Because shortcuts connect locally embedded regions of relationships, they can represent connections among less familiar partners, in contrast to the more familiar firms within a local cluster (Burt 2005). One rationale for distant search is that brokerage benefits derive from sparse structures and networks rich in structural holes. A structural hole indicates that the actors on either side of the hole have access to different flows of information (Hargadon and Sutton 1997). Hence, developing positions that span the bridges across different local communities enables access to new, unique information (Hansen 1999, Beckman et al. 2004). This allows firms to accomplish novel recombinant processes (Hargadon and Sutton 1997, Rosenkopf and Almeida 2003, Verona et al. 2006) and supports their strategic performance (McEvily and Zaheer 1999, Baum et al. 2000). By exposing established firms to novel, different flows of information, nonlocal search can be particularly beneficial in fast-paced, exploration investment demanding industries (Rowley et al. 2000). Thus, although within-cluster alliance formation is shaped by trust among interconnected partners, it does not provide access to more unique knowledge.[2] To access more unique and innovative knowledge, firms must go beyond local clusters, yet spanning structural holes implies collaborating with partners where no reservoir of trust has been previously built through cohesive ties.

Whereas shortcuts within the main component are one way in which distant partners may connect, a "more distant" pairing may be found between embedded firms and potential new entrants to the network. Ahuja (2000a) has shown that embedded firms may be willing to forsake the trust benefits of cooperating with embedded, closely connected firms when the new entrants possess relevant "technical capital" in the form of important inventions. In fact, systematic exploration of new sources of technical knowledge may enable embedded firms to overcome path dependence, reorienting their technological trajectories through dynamic capabilities (Teece et al. 1997). A consistent flow of new entrants may be expected to take place when industries experience disruptive technological change (Rosenkopf and Tushman 1994). When technological discontinuities emerge, new entrants possess new insights and relevant technical capital that may enable embedded firms to reposition themselves technologically and, consequently, maintain their competitive leadership (Anderson and Tushman 1990). Moreover, several case studies on high-tech industries show that by admitting new entrants, embedded firms increase the size of the community of firms adopting their technological standard (e.g., Brandenburger 1995, Chandler 1997, Collis and Pisano 2002), and are consequently more likely to influence the selection of a dominant design of an industry in their favor (Arthur 1989, Wade 1995, Schilling 1998). Thus, alliances with new entrants support firm exploration and innovation, and are particularly beneficial in technologically and competitively volatile industries. Of course, although alliances made with firms not yet embedded in the network increase the likelihood of access to unique knowledge, this benefit comes at the expense of trust built through cohesive ties, because knowledge about firms outside the network is not available through indirect network channels.

Whether distant search is accomplished through shortcuts or by admitting new entrants, these new relationships with distant partners can provide an impetus for network reform. These relationships develop new combinations of resources that can redefine the patterns of interdependence among firms in the network. As a consequence, the typical forms of network reproduction by cohesion and prominence shift, reforming extant network structure. As such, extending our current theories of network evolution to accommodate shortcuts and new entry patterns can enlarge our current understanding of network dynamics.

2.3. How and Why Do Firms Partner Across Clusters and Beyond the Main Component?

To consider selection of unfamiliar alliance partners, we combine notions of exploratory search and endogenous social cues. In other words, whereas the search for exploratory benefits explains *why* embedded firms may seek distant partners, extant structures play an important role in predicting *which* distant prospective partners collaborate. Given our distinction between semidistant embedded firms residing in different clusters in the main component and distant firms not embedded in the main component, we begin by examining shortcut generation within the main component and follow by examining alliance formation with nonembedded firms.

2.3.1. Semidistant Shortcut Generation Within the Main Component. Within the established alliance network, firms in similar structural positions in the alliance network are more likely to form subsequent partnerships (Podolny 1994). Studies of interorganizational learning (e.g., Powell et al. 1996) have suggested that exploration activity is based on developing positions that enable firms to keep pace with significant changes. To do so requires being "active participants" at the leading edge of the scientific and technological world (Cohen and Levinthal 1990), which entails some resource-sharing activities and mutual commitment that develop trustworthiness and reliability of the partners (Ahuja 2000b). In addition, the partnerships where novel scientific and technological cues are identified can provide fertile ground where these major developments may be leveraged and further knowledge built through new innovation projects (Powell et al. 1996, p. 120). As promising new developments coming from exploratory activities are more likely to be pushed further in the same partnership context from which they have emerged, collaborating on exploration with trustworthy partners is paramount. Indeed, Burt (2005) has argued that the social capital benefits accruing from brokerage require some trust-enabling coordination mechanisms across these distant partners.

In these circumstances, where the governance benefits of density are not available, the question of whether an unknown partner is trustworthy may be answered by the partner's record of prior alliance behavior. Firms with extensive alliance histories have demonstrated trustworthiness in these prior alliances, reassuring potential new allies. Thus, prominent firms in an alliance network are more likely to be selected by other firms undertaking nonlocal search. This trust-based argument leads us to hypothesize that prominent firms will tend to attach to other prominent firms for shortcuts. However, because exploration is especially important in fast-paced industries, less prominent firms are also compelled to carry out distant search. They are less able to rely on reputational benefits than are prominent firms, however, so they can be expected to attach to other less prominent network actors in their search for distant partners.

A status-based argument also predicts shortcut formation among structurally similar actors. Whereas ties with higher-status actors enhance the prestige with which a firm is viewed, ties with lower-status actors diminish it (Podolny 1993). Ceteris paribus, any firm would prefer to form an alliance with another firm of equal or higher status to maintain or increase status. Thus, whereas lower-status firms desire alliances with prominent firms to accrue some of the esteem and prestige of prominent affiliates, prominent firms will tend to attach preferentially to other prominent firms to avoid any loss of status. As a result, lower-status firms seeking to explore are typically left with opportunities to ally only with firms of equivalently low status.

In each case, a structural homophily hypothesis follows:

Hypothesis 1 (H1). *The likelihood of a new shortcut between two firms increases with the similarity in prominence between those firms.*

2.3.2. Distant Alliance Formation Between Embedded and Nonembedded Firms. Next, we consider the case when nonembedded firms can be admitted to the network through alliances with embedded firms. Here, we must consider the motivation of the embedded partner as well as that of the nonembedded partner. Clearly, the nonembedded partner seeks admission to the network and would prefer embedded partners that are advantaged by the current network structure, but only under certain circumstances would embedded firms choose to form alliances with nonembedded firms. Although nonembedded firms cannot confer status or demonstrate trustworthiness to embedded firms, they may compensate for these shortcomings by offering access to novel technology.

Just like embedded firms, nonembedded firms prefer trustworthiness and status. As we have discussed, when selecting potential partners that are distant, firms may rely on signals of trustworthiness. Lacking the governance benefits of dense cluster membership, nonembedded firms will rely on the reputation benefits signaled by network centrality and will be more likely to partner with more prominent embedded firms. Of course, reputation is likely to be correlated with other resources that are also critical to nonembedded firms, such as specialized knowledge, capital, and complementary assets.

Furthermore, a status-based argument will lead to the same prediction. As we have discussed, relationships implicitly transfer status between parties. A high-status organization increases the prestige and esteem of its affiliates (Podolny 1993, Podolny and Phillips 1996). Being a function of experience and ability to enter partnerships, status may be an indicator of the quality of a firm, so that entering into partnerships with prominent players implies a transfer of reliability and trustworthiness to the connected partners. The reputation effects provided by the connections with prominent partners are particularly critical for a new entrant, because the first connection to the network fixes an initial level of status, which is likely to shape future connections. Furthermore, partnerships with prominent incumbents can act as endorsements that influence the perception of a new entrant's competence and trustworthiness. As an example, Hsu (2004) finds that more experienced and well-connected venture capitalists acquire early-stage start-up equity at a 10%-14% discount. In other words, entrepreneurial start-ups are willing "to pay for status" while entering the financial network of VCs. Similarly, new entrants to a network may sacrifice more favorable contract terms to form alliances with high-status embedded firms (Ahuja and Polidoro 2003).

Of course, whereas new entrants search for trustworthy partners and wish to accrue status, it is less clear why more prominent and higher-status embedded firms might be willing to forsake the trust benefits of well-connected embedded actors and/or wish to risk the loss of status given by associating with an unknown firm. Here we emphasize both the opportunity for established firms to access new technology and the potential loss of status that may ensue. Henderson and Clark (1990) have argued that well-entrenched, dominant firms may have neither the ability nor the motivation to introduce architectural innovations, whereas less-entrenched firms would be expected to search actively for opportunities to introduce disruptive changes in product architecture in an industry. Madhavan et al. (1998) have suggested that peripheral actors are more likely to introduce competence-destroying change in an industry because these radical innovations may offer firms the opportunity to gain significant advantage over dominant firms. Indeed, Ahuja (2000a) has demonstrated that firms with low social capital can make attractive alliance partners when they possess "important inventions." Consequently, despite the risks of collaborating with unknown, low-status firms, embedded firms will do so to get access to relevant insights and technical capital to reposition themselves in the competitive landscape resulting from the innovation activities in the industry. Stuart (1998) finds that prestigious firms are more likely to seek "less crowded" areas of technological space for new alliances. Furthermore, Zuckerman and Phillips (2001) suggest that high-status actors are less susceptible to status loss when they do not conform, which implies that high-status actors may be able to accomplish exploration through distant partners at lower cost than middle-status actors.

Thus, whereas network actors can be expected to accomplish distant search by forming alliances to peripheral firms—because they are more likely to possess the relevant technical capital to face the competitive challenges brought by the innovation efforts—peripheral firms in turn can be expected to attach preferentially to more prominent network actors to take advantage of status transfer and reputation benefits. Hence, this line of reasoning would suggest that the attachment bias underlying distant partner selection processes would tend toward a social asymmetry hypothesis (Ahuja and Polidoro 2003), so that, ceteris paribus, distant shortcuts will occur that link nonembedded firms to prominent ones.[3, 4]

Hypothesis 2 (H2). *The likelihood that a new entrant attaches to an incumbent firm increases with the prominence of the latter.*

2.4. Power of Numbers? Exploratory Alliances Among Multiple Parties

In addition to investigating partner selection among distant and semidistant firms, we can also focus on a characteristic of these alliances themselves. Little attention has focused on the number of parties contracting in an alliance, which we will term "deal size." In fact, although many alliances contain more than two parties, most extant research treats these multiparty deals solely as multiple, discrete, dyadic relationships.[5] Multiparty deals may be expected to be particularly relevant in alliance formation for exploration purposes, because exploration-type activities may encompass high-risk innovations and large investments (Teece et al. 1997).

Exploration activity is likely to be associated with more disruptive change, which will require coordination of complementary assets (Tripsas 1997) among a wider array of actors. Cooperation to share the risks and costs of innovation as well as cooperation based on knowledge widespread across various different actors may be accomplished more effectively by multiparty deals. The role of larger deals is further heightened in systemic industries. Because systemic technologies are based on complex knowledge that cuts across firm boundaries (Tushman and Rosenkopf 1992; Rosenkopf and Nerkar 1999, 2001), new alliance formation in these contexts is likely to take account of the widespread nature of complex knowledge and therefore is manifested in larger deals.

In addition, large deals convey a surrogate for governance benefits. Because ties across distant partners lack the benefits of embeddedness in cohesive structures (Walker et al. 1997, Rowley et al. 2000, Baum et al. 2003), their formation through larger deals creates densely linked clusters around their members. In this case, several participants mutually control their behavior and contributions to the alliance, thereby providing a relational context where trust and cooperation can be effectively promoted. Even if this mechanism cannot supplement ex ante referrals about potential partners' qualities, it can provide ex post referrals and governance benefits close to those experienced by firms embedded in a dense structure.

Taken together, these arguments prompt us to predict that, ceteris paribus, exploration-type alliances should be more commonly developed through multiparty deals than through dyadic ones. Furthermore, because exploration-type search is a matter of degree (Vicari et al. 1996), the size of a deal may be positively associated with the degree to which the search may be characterized as distant. Because we have argued above that exploration may motivate alliances across clusters to semidistant firms and outside the main component to distant firms, we would expect that the number of partners in alliances would increase as these alliances span cluster boundaries, and even more as these alliances reach outside the main component:

Hypothesis 3 (H3). *Among embedded firms, alliances that generate shortcuts will have more partners than alliances limited to within a single cluster.*

Hypothesis 4 (H4). *Alliances that attach nonembedded firms to the main component will have more partners than alliances limited to within the main component.*

3. Method

We tested our hypotheses by examining U.S.-based alliance formation in the cellular industry from 1993 to 2002. The transition from analog to digital platforms in mobile communications technology was followed by the development of a mass market that stimulated industry growth. The early 1990s were characterized by technological ferment, with many variants of digital technologies competing to become the industry standard. Concurrent with the establishment of code division multiple access (CDMA) technology in the United States was the effort to develop protocols for the suite of personal communications services (PCS) enabling the operation of hand-held devices. Thus, the cellular industry is a fertile ground for examining our questions during this time frame because it exploits a particularly dynamic context: Industry standards and network effects are prevalent; technology is systemic; and entry and exit are also plentiful.

3.1. Sample and Data

We tested our hypotheses using longitudinal data on strategic alliances formed in the U.S. cellular communication business from 1993 to 2002. The firms in our sample include both service providers (primary four-digit SIC code 4812) and manufacturers of cellular equipment (primary four-digit SIC code 3663). We employed two rules to guide our construction of the industry network. First, each alliance included at least one participant that was a member of the target industry (indicated by its primary four-digit SIC). Second, to be included in the target industry network, each alliance had to operate in that industry, as indicated by its primary SIC of activity. As per the first rule, we also included alliance partners from beyond the target industry because excluding them would eliminate our ability to observe many of the indirect relationships between industry members, thus biasing our measures of industry connectivity. Coupling the first and second rules insures that the industry network consists of alliance activities focused on the designated industry.[6]

We collected alliance data from the Securities Data Corporation (SDC) database, which includes all contractual arrangements in which two or more entities have combined resources to form a new, mutually advantageous business arrangement to achieve predetermined objectives. This information comes from SEC filings and their international counterparts, trade publications, wires, and new sources. SDC provides information aboutboth alliance announcements and their realization and termination. Only alliances with realization dates were recorded. Furthermore, when available, we used information on alliance termination to remove that alliance from subsequent calculations. However, because data on alliance terminations are not as well documented as formations, we also employed a five-year moving window in the analysis of our network data, so that the alliances in our database are limited to a five-year life span.[7]

We also used the SDC database to track corporate-level changes such as mergers and acquisitions and corrected our data accordingly. All firms that had divested 100% of their shares at the ultimate parent level were removed from the data set after that event. In these circumstances we also assumed that the alliances were transferred from the seller to the acquirer, and the latter was added to the database if it was not already included. Consequently, our network analyses have been carried out, for any point in time, on working alliances. Alliance formation data provided at the subsidiary level were matched and recorded in our database at the parent level. Data on firm size were collected from Compustat, Worldscope, and Amadeus.

Basic characteristics of the yearly alliance networks are displayed in Table 1. Both the number of firms active in any alliance and the total number of ties among these firms steadily increase over the study period. We identified the main component of the alliance network in each year as the largest group of firms connected over any path of alliance ties. Although the number of firms in the main component grows correspondingly until 2000, its population stabilizes at this time. Nonetheless, the total number of ties within the main component continues to increase. The main component ratios suggest that by 1994, almost 80% of all firms with active alliances are members of the main component, and approximately 90% of all alliances reside within this component. To further suggest the dominance of the main component, we also computed the ratio between the number of firms in the main component and the number of firms in the second-biggest component. By 1994, the main component represents approximately 20 times more firms than the second-largest component, reinforcing the sense that there is little isolated clustering. All these percentages appear to be reasonably stable and suggest that we capture most of the dynamics of alliance evolution by focusing on new alliances within the main component as well as on the pattern of entry into the main component.

The remaining rows summarize the small-world characteristics of our network from 1991–2002.[8] Consistent with prior studies (Uzzi et al. 2002, Baum et al. 2003, Davis et al. 2003), the small world emerges rapidly (seen by the dramatic rise in the small-world coefficient between 1993 and 1995) and demonstrates an enduring structure. This emergence is driven by movement in the clustering coefficient ratio, because the average path length remains relatively consistent.

Figure 1 displays Pajek-generated visualizations of four different years of alliance networks. In each graph, the triangles represent the firms that entered the network

Table 1 Evolution of Network Connectivity and Small-World Characteristics of the Cellular Alliance Network

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
No. of active firms	16	31	40	72	88	95	101	112	118	118	118	120
No. of ties	14	28	38	104	126	139	146	153	163	169	171	173
No. of firms in MC[1] (n)	9	12	25	56	71	74	82	89	93	94	94	94
No. of ties MC	10	16	29	94	115	123	132	140	145	153	155	156
No. of ties in MC per firm (k)	2.22	2.67	2.32	3.36	3.30	3.35	3.34	3.26	3.27	3.40	3.45	3.47
Percent of active firms in MC	0.56	0.39	0.63	0.78	0.81	0.78	0.81	0.80	0.79	0.80	0.80	0.78
Percent of ties in MC	0.71	0.57	0.76	0.90	0.91	0.89	0.90	0.91	0.89	0.91	0.91	0.90
No. of firms in MC/no. of firms in second-biggest component	3	3	5	18.67	17.75	18.5	20.5	22.25	23.25	23.5	23.5	23.5
C_a[2]	0.410	0.487	0.351	0.596	0.623	0.625	0.649	0.669	0.662	0.596	0.593	0.601
L_a[2]	2.194	2.197	3.575	3.714	3.761	3.730	3.807	3.840	3.901	3.779	3.745	3.736
C_r[3]	0.247	0.222	0.093	0.060	0.046	0.045	0.041	0.037	0.035	0.036	0.037	0.037
L_r[3]	2.752	2.533	3.825	3.324	3.574	3.559	3.653	3.800	3.827	3.709	3.672	3.653
C_a/C_r[4]	1.661	2.192	3.782	9.942	13.421	13.800	13.927	18.273	18.834	16.457	16.172	16.290
L_a/L_r[4]	0.797	0.867	0.982	1.117	1.052	1.048	1.042	1.011	1.019	1.019	1.020	1.023
SW[5]	2.083	2.527	3.851	8.897	12.754	13.168	15.281	18.082	18.476	16.151	15.855	15.929

(1) MC = main component.

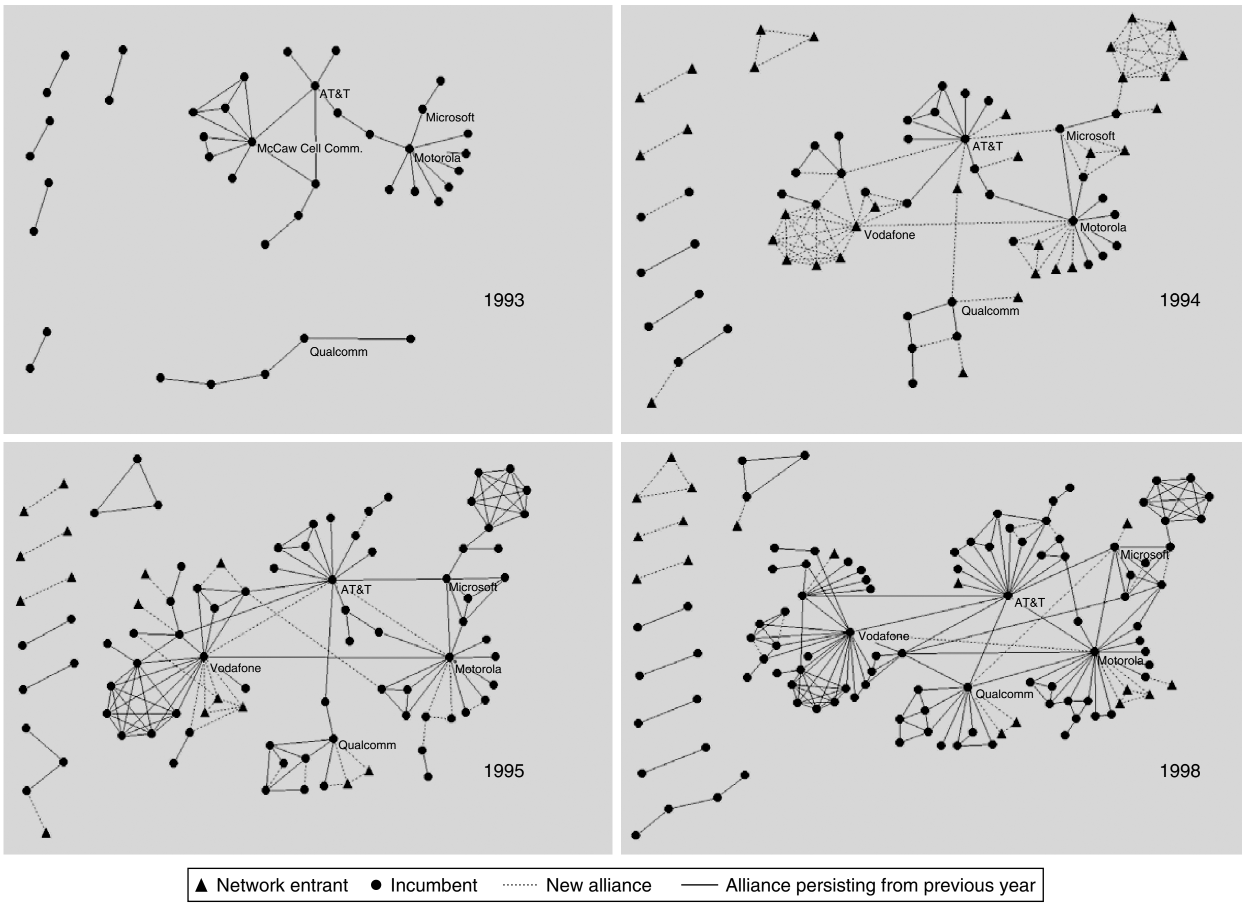
(2) Actual network cluster coefficient (C_a) and path length (L_a).

(3) Random network cluster coefficient ($C_r = k/n$) and path length ($L_r = \ln(n)/\ln(k)$), i.e., cluster coefficient and path length of a randomly connected network of the same size/density as actual.

(4) Actual-to-random ratios: Cluster coefficient ratio (C_a/C_r) and path length ratio (L_a/L_r).

(5) Small-world connectivity index: $(C_a/C_r)/(L_a/L_r)$.

Figure 1 The Evolution of Network Topology



that year and the circles represent the firms that were members of the network before the year began ("incumbents"). Similarly, the distinction between alliances formed that year and alliances previously formed is shown by dotted lines versus solid lines.

Several characteristics of these networks and their evolution are obvious in these figures. First, by examining the yearly patterns of linkages among actors, a main component hosting the majority of alliances and actors is immediately apparent. Outside the main component, numerous dyadic and triadic deals among the minority of firms that have not been admitted to the main component can also be observed, where none of these nonembedded firms appear to be involved in more than two alliances. Second, by examining the actors and distinguishing new entrants from incumbents, we can observe that firms new to the alliance network may enter in either the main component or outside of the main component. Third, we can also see that multiparty deals (fully connected clusters) tend to draw many new entrants directly into the main component.[9]

We can also observe network evolution across these figures. We can observe the small world emerge by comparing the 1993 and 1994 networks. The 1994 network grows by an influx of new entrants, and the alliances among the new and established actors in the main component are suggestive of clusters anchored around five key firms: AT&T, Vodafone, Microsoft, Motorola, and Qualcomm. Note also that these key firms tend to demonstrate some shortcuts with each other, creating the links across clusters. Examining the 1995 and 1998 networks, it is clear that the network topology established in 1994 remains consistent throughout the remainder of the study period. Subsequent structures maintain the clusters and shortcuts around these key firms, where new entrants and new alliances tend to increase the size of clusters and the number of links between actors in a given cluster. As an example, consider the Qualcomm cluster: In 1993, Qualcomm has not yet been admitted to the main component. Upon its admission in 1994, a small cluster has emerged, where Qualcomm appears to be the hub linking the others in its cluster to the main component. In both 1995 and 1998, an increase in actors in the Qualcomm cluster is evident. Although Qualcomm is clearly the central actor in the cluster with the majority of linkages among cluster members (which include both telecommunications (e.g., US Wireless) and consumer electronics (e.g., Sony)), additional alliances are forming among other actors in this cluster as well. By 1998, a clear series of shortcuts between Qualcomm and other prominent hubs (AT&T, Microsoft, Motorola) has emerged.

Analyzing alliance formation within the main component required that we identify clusters in order to discriminate the alliances embedded within the local cohesive regions of relationships from the shortcuts. We used CONCOR, a hierarchical clustering algorithm that successively splits the firms into groups of firms based on their structural equivalence (Breiger et al. 1975). Numerous researchers (Nohria and Garcia-Pont 1991, Walker et al. 1997) have used CONCOR or a variant of this procedure to identify clusters. Because CONCOR groups structurally equivalent firms, we insured that the intracluster densities were greater that the intercluster densities by merging clusters that violated this relationship. Full detail on our procedure for cluster identification is provided in Appendix 1. Once clusters were determined, shortcuts were defined as the alliances between firms belonging to different clusters.

3.2. Measures

To test our hypotheses, we constructed variables at two different levels of analysis. For our hypotheses on alliance formation (H1 and H2), we developed variables using the dyad-year as the unit of analysis, whereas for our hypotheses on deal size (H3 and H4), we developed variables using the deal as the unit of analysis.

3.2.1. Dependent Variables. We constructed an event history for each dyad spanning the years 1993 to 2002.[10] For each dyad-year record, we coded a dichotomous dependent variable, *Alliance formation*, indicating whether the pair of firms formed an alliance in the given year. Alliances reported among more than two firms are represented as alliance formation dyads among each of the firms included in the alliance. To avoid double counting, we discarded reverse-ordered dyads.

We identified four different risk sets on which we run these dyadic regressions. Three focus on alliance ties formed among members of the main component in any given year: ties between clusters (shortcuts), ties within clusters, and all ties. We examine each of these three sets to demonstrate the differences between the predictors of shortcuts and within-cluster ties, and also to demonstrate which of these effects are observable on the aggregate set of ties in the main component. Our fourth risk set examines alliance ties formed by firms that are not members of the main component: These firms have the potential to break into the main component by forming alliances both with firms embedded in the main component and with each other.[11, 12]

The variable *Deal size* indicates the number of partners represented in each alliance formed. Using the deal as the level of analysis, we examine the determinants of both the full risk set of deals as well as the subset of embedded deals formed solely within the main component.

3.2.2. Independent Variables. All of our dyadic independent variables are derived from the alliance network structure. To compute these network measures, we constructed year-by-year adjacency matrices representing the relationships between the firms involved in each of our risk sets. As per our choice to use a five-year moving window, each year included the cumulative alliances that had been formed among industry panel members for the previous five years.

In constructing these matrices, we also made some choices about the treatment of different types of alliances, the accumulation of multiple ties by the same pairs of partners, and the past alliances that should be included. Because our study is concerned with the structural pattern of interaction between firms, and the resulting topology of the overall network, we constructed binary adjacency matrices for each year. In other words, our indication of ties between firms is not sensitive to the number of ties between the firms if multiple alliances are active, and it is not sensitive to the "strength" of the alliance as denoted by governance form. This is consistent with a strict definition of topology as provided by the small-world theoretical formulation.[13] We computed all the network measures using UCINET 6.0 (Borgatti et al. 2002).

Structural Homophily. For embedded firm dyads, we assessed the similarity of the two firms' network positions. *Structural homophily* was constructed by calculating the ratio of each firm's Bonacich (1987) eigenvector measure of network centrality. Use of the Bonacich measure is consistent with prior efforts to capture the position of an organization in a network (Mizruchi 1993; Podolny 1993, 1994; Gulati and Gargiulo 1999). The eigenvector measure accounts for both direct and indirect firms' ties, so that, using this index, the most central organizations are those linked to many firms, which are in turn linked to several other firms.[14] We computed the eigenvector measure of the network centrality of each firm for each year and normalized them so that the eigenvector score of the most central firm for any year would equal one. To ascertain the similarity in the centrality position of any pair of firms, we computed the ratio of the smaller to the larger centrality score of the two members of the dyad. This variable ranges from zero to one, with higher scores representing higher similarity in network position between the firms.

Incumbent Prominence. For dyads where at least one member is not in the main component, we needed to assess the network position of the embedded firm only. *Incumbent prominence* represents the normalized Bonacich (1987) eigenvector measure of network centrality, as above, for the firm embedded in the main component. If neither firm of the dyad is a member of the main component, this score is set to zero.

Cross-Cluster and Nonembedded Deals. For deal-level analyses, *Cross-cluster deal* is a binary variablethat is set to one for alliances among embedded firms that have been formed with members of more than one cluster as indicated by CONCOR. The variable is set to zero if all the members of the embedded deal are members of the same CONCOR cluster. Similarly, for the full set of alliance deals, *Nonembedded deal* is a binary variable that is set to one for alliances that include nonembedded firms. The variable is set to zero if all the members of the deal are already members of the main component.

3.2.3. Control Variables.

Time. To control for unobserved temporal factors such as progressive legitimization or economic conditions that may influence alliance formation or deal size, we constructed dummy variables for each year. We then compared these results with those coming from using a single variable *Time*, which ranges from zero to eight (with the default year being 1993), thereby assuming linearity in the effects of time. Because we observed no differences in the results based on the alternative controls for time, we chose to use the time trend for simplicity of presentation.

Cluster Density. We also controlled for the density of the cluster in which each embedded firm resides, because Rowley et al. (2000) suggest that dense clusters strengthen the tendency to explore with distant partners. For each cluster, cluster density represents the actual number of alliances formed within the cluster divided by the number of all possible ties that can be formed within the cluster—that is, $[N(N-1)]/2$, where N is the number of firms belonging to the cluster. Normalizing the within-cluster alliance count by dividing by the number of possible alliances controls for the fact that the within-cluster alliance count will vary greatly with the size of the cluster.[15] For embedded firm pairs, we constructed a dyadic measure of *Cluster density* for each pair of firms as the arithmetic mean of the cluster density score of each member of the dyads. For nonembedded pairs, we used the density of the embedded firm's cluster. For deal-based analyses, we average the cluster densities of each embedded firm involved in the deal. If a dyad or a deal included only nonembedded firms, cluster density was set to zero.

Firm Size. Because alliance formation is positively associated with firm size (Stuart 1998), we controlled for the number of employees in each firm. We constructed a dyadic measure for the *Firm size* variable as the arithmetic mean of the firm's size score for each member of the dyad or the deal, depending on the unit of analysis. This variable is logged due to high skew.

Horizontal Relationships. The propensity to form alliances and their distribution across clusters and shortcuts can also be influenced by industry-related technological features. To control for these effects, we coded the firms according to their main SIC code, so that we could discriminate service providers from equipment manufacturers from other firms whose main activity does not fall in the target industry. We then created a dummy variable called *Horizontal dyad* and coded 1 if both firms in the dyad were in the same industry as shown by their main SIC code (identifying the dyads at risk of forming horizontal ties) and 0 if they were not (identifying the cross-industry dyads). For deal-based analyses, *Horizontal deal* was coded 1 if all firms in the deal were in the same industry, and 0 otherwise.

Network Endogeneity. We also controlled for three well-established measures of relational and structural embeddedness associated with alliance formation in the network endogeneity literature. First, *Repeated ties* represents the number of previous alliances formed between the two firms in the previous five years. Because the marginal value of any subsequent alliance for the formation of new alliances between any two firms is expected to decrease as additional alliances are developed over time between these firms, we also include the square of this term. Second, to capture indirect ties in addition to direct ties, we computed the number of partners shared by the two members of a dyad as a result of their alliances in the previous five years. Following Gulati (1995b), to capture the effect of indirect ties in the absence of direct ties, we only allow the variable *Common ties* to take this count as its value when the members of the dyad have no prior direct ties with each other during the previous five years. In other words, when *Repeated ties* is greater than zero, *Common ties* is set to zero. Third, another common measure in the endogeneity literature is *joint prominence*. It is similar to the structural homophily variable, but represents the mean of the two normalized Bonacich centrality scores rather than the ratio.

Cross-Cluster Dyad. Based on the results of network partition provided by CONCOR, we constructed a dummy variable to indicate when a pair of firms belonged to the same cluster or different clusters within the main component. *Cross-cluster dyad* (*CC*) is valued 1 when each member of the dyad belongs to a different cluster, and 0 when both members of the dyad are members of the same cluster. We also included an interaction term between cross-cluster dyad and structural homophily (*CC* × *Structural homophily*) to assess whether the effects of structural homophily differ with the extent to which new alliances form within, rather than across, clusters.

Main Component and New Entrant Prominence. We included the count of the number of firms in the main component during the year. *Main component* controls for the extent of opportunities for new entrants to attach to the main component. We also controlled for the prominence of new entrants, because firms not embedded in the main component may still have formed alliances. *New entrant prominence* measures the degree centrality (count of active alliances) for potential new entrants to the main component.

Average Previous Deal Size. For deal-based analyses, we controlled for the aggregate experience that partners would have in multiparty deals. To do so, we calculated the average deal size for each partner's active alliances. For analyses limited to embedded firms, *Average deal size* represents the average across all partners in the deal. For analyses that span embedded firms and new entrants, we separated the expertise across each group. Here, *Average incumbent deal size* represents the average across all incumbents, while *Average new entrant deal size* represents the average across all firms that are not in the main component. If no firm has any deal experience, we set this variable to zero.

Descriptive statistics and correlations for dyads and deals are displayed in Tables 2 and 3.

3.3. Analyses

To explore the determinants of dyad-level alliance formation, we regressed alliance formation in a given year (1994–2002) on all network structure-based independent variables and control variables for the previous year (1993–2001). To estimate the effects of a covariate vector on the likelihood of a new alliance formation, we used a population-averaged logistic regression model (Stata 8.1) that accounts for unobserved heterogeneity, allowing for correlations across observations over time.[16]

We ran several models over several risk sets to explore the patterns of alliance formation among embeddedfirms. These models demonstrate the changing

Table 2 Descriptive Statistics and Correlations for Dyads

Variable	Mean	S. D.	Min.	Max.	1	2	3	4	5	6	7	8	9
A. Among firms embedded in different clusters in the main component ($N = 13{,}794$)													
1. Alliance formation	0.002	0.04	0	1	—	—	—	—	—	—	—	—	—
2. Time	5	2.2	0	8	−0.04	—	—	—	—	—	—	—	—
3. Cluster density	0.40	0.15	0.19	0.72	−0.01	0.36	—	—	—	—	—	—	—
4. Firm size	9.46	1.82	1.65	13.06	0.03	−0.06	0.02	—	—	—	—	—	—
5. Horizontal dyad	0.8	0.4	0	1	−0.01	0.00	−0.03	0.06	—	—	—	—	—
6. Repeated ties	0.02	0.17	0	3	0.12	−0.01	0.02	0.07	−0.1	—	—	—	—
7. (Repeated ties)^2	0.03	0.29	0	9	0.09	−0.02	0.01	0.07	−0.09	0.9	—	—	—
8. Common ties	0.11	0.34	0	5	0.05	0.03	0.23	0.35	−0.14	0.28	0.21	—	—
9. Joint prominence	0.23	0.21	0.01	0.97	0.07	−0.13	0.2	0.29	−0.03	0.20	0.15	0.49	—
10. Structural homophily	0.19	0.19	0.001	0.99	0.08	−0.16	0.16	0.1	−0.03	0.08	0.06	0.2	0.69
B. Among firms embedded within the same cluster in the main component ($N = 3{,}319$)													
1. Alliance formation	0.005	0.07	0	1	—	—	—	—	—	—	—	—	—
2. Time	5.20	2.17	0	8	−0.06	—	—	—	—	—	—	—	—
3. Cluster density	0.32	0.19	0.15	1	−0.06	0.47	—	—	—	—	—	—	—
4. Firm size	9.78	1.82	2.41	13.07	−0.02	0.01	0.18	—	—	—	—	—	—
5. Horizontal dyad	0.75	0.44	0	1	−0.00	0.02	0.08	0.14	—	—	—	—	—
6. Repeated ties	0.19	0.42	0	3	0.15	−0.11	−0.14	−0.04	0.03	—	—	—	—
7. (Repeated ties)^2	0.21	0.55	0	9	0.16	−0.09	−0.10	−0.004	0.001	0.92	—	—	—
8. Common ties	2.23	0.92	0	4	−0.05	0.06	0.16	0.04	0.04	−0.42	−0.34	—	—
9. Joint prominence	0.27	0.26	0.001	0.93	0.00	0.09	0.42	0.31	0.03	0.29	0.29	0.12	—
10. Structural homophily	0.16	0.19	0.001	0.99	−0.02	0.11	0.31	0.25	−0.07	0.2	0.19	−0.09	0.65
C. Among all firms where at least one member of the dyad is not in the main component ($N = 6{,}669$)													
1. Alliance formation	0.02	0.14	0	1	—	—	—	—	—	—	—		
2. Time	2.31	2.07	0	8	−0.09	—	—	—	—	—	—		
3. Cluster density	0.24	0.18	0	0.5	−0.06	0.55	—	—	—	—	—		
4. Firm size	9.04	1.85	2.90	12.97	−0.02	−0.14	−0.04	—	—	—	—		
5. Horizontal dyad	0.77	0.42	0	1	−0.01	−0.05	−0.05	0.06	—	—	—		
6. Main component	54.59	20.27	25	82	−0.11	0.92	0.56	−0.12	−0.05	—	—		
7. New Entrant prominence	0.03	0.19	0	2	0.01	0.07	−0.01	0.09	0.07	0.06	—		
8. Incumbent Prominence	0.18	0.2	0	1	0.04	0.12	0.26	0.18	−0.11	0.14	−0.01		

Notes. Due to space limitations, we do not include the descriptive statistics and correlations over the overall risk set of embedded dyads, including both within- and between-cluster dyads. Note that the descriptive statistics and the correlation structure for this larger risk set are comparable to those resulting from the more restrictive risk sets A and B. Also note that in this omitted risk set, *Cross-cluster dyad* obtains a high correlation rate only against *Repeated ties* (−0.27) and *Common ties* (−0.41), demonstrating that the traditional endogenous drivers of alliance formation are negatively related to the distance across prospective partners. The interaction term *CC* × *Structural homophily* is highly correlated with its terms (*Cross-cluster dyad* 0.37; *Structural homophily* 0.84) as well as with *Joint prominence* (0.49) because of the high correlation of *Structural homophily* with *Joint prominence*.

Table 3 Descriptive Statistics and Correlations for Deals

Variable	Mean	S. D.	Min.	Max.	1	2	3	4	5	6	7	8
D. Among firms embedded in the main component ($N = 47$)												
1. Deal size	2.07	0.33	2	4	—	—	—	—	—	—	—	
2. Time	3.90	2.18	1	8	0.12	—	—	—	—	—	—	
3. Cluster density	0.37	0.20	0.15	1	0.03	0.05	—	—	—	—	—	
4. Firm size	9.93	1.98	1.65	13.45	0.47	−0.02	−0.13	—	—	—	—	
5. Horizontal deal	0.38	0.49	0	1	−0.15	−0.31	−0.23	0.10	—	—	—	
6. Average deal size	1.01	0.37	1	2.75	0.67	0.17	−0.04	0.50	−0.17	—	—	
7. Cross-cluster deal	0.58	0.50	0	1	0.16	0.37	0.37	−0.04	−0.48	0.20	—	
E. Among all firms ($N = 111$)												
1. Deal size	2.24	0.78	2	7	—	—	—	—	—	—	—	—
2. Time	3.49	2.24	1	8	−0.02	—	—	—	—	—	—	—
3. Cluster density	0.33	0.22	0.05	1	0.07	0.04	—	—	—	—	—	—
4. Firm size	9.18	2.05	1.05	13.45	0.31	−0.15	−0.12	—	—	—	—	—
5. Horizontal deal	0.43	0.50	0	1	0.10	−0.33	−0.18	0.09	—	—	—	—
6. Main component	62.43	25.42	25	82	0.06	0.91	0.03	−0.17	−0.27	—	—	—
7. Average incumbent deal size	0.90	0.48	1	6	0.01	0.41	−0.04	0.01	−0.26	0.43	—	—
8. Average new entrant deal size	0.04	0.20	0	1	−0.09	−0.25	−0.05	0.31	−0.09	−0.34	−0.43	—
9. Nonembedded deal	0.16	0.36	0	1	0.41	−0.40	0.20	0.33	0.21	−0.69	0.55	−0.45

effects of our independent variables when we examine only shortcuts, only within-cluster ties, or all ties. Subsequently, we examine alliance formation among dyads where one or both of the members of the dyad is not embedded in the main component.

To explore how structural considerations might predict deal size, we regressed deal size in a given year (1994–2002) on all network structure-based independent variables and control variables for the previous year (1993–2001).[17] Hence, we used a Poisson model (Stata 8.1) that is consistent with the count nature of our dependent variable.[18]

3.4. Results

Table 4 displays logistic estimates of the probability that a dyad of firms will form an alliance in a given year. Models 1A–3A examine shortcut formation among firms embedded in the main component. Examining the control variables (1A), we observe that most of the drivers of alliance formation traditionally emphasized by the endogeneity perspective have a role in predicting shortcut formation as well. For example, *Repeated ties* demonstrates a significant curvilinear relation with shortcut formation. Likewise, the positive and significant coefficient of *Joint prominence* demonstrates that shortcuts tend to be more common among central firms. In contrast to extant studies, however, our results show that *Common ties* has no significant effect on new alliance formation among firms residing in different clusters. *Firm size* is positively and significantly related to alliance formation, revealing that the propensity to form shortcuts increases with the average size of the firms. *Time* is negatively and significantly related to alliance formation, suggesting that shortcut formation decreases over time in the time span examined by the study. All other control variables have no significant effect on our dependent variable. These results are consistent throughout the other two models (2A and 3A), with one exception. Given the high correlation between *Joint prominence* and *Structural homophily*, we substitute *Structural homophily* for *Joint prominence* in Model 2A, and *Structural homophily* generates a significant positive effect. When we include both variables simultaneously in Model 3A, *Structural homophily* is significant, whereas *Joint prominence* is not. Furthermore, the chi-squared values indicate that the Model 2A, only including *Structural homophily*, is the preferred fit. This demonstrates that shortcuts tend to be more common among firms with similar levels of centrality in the network,[19] confirming Hypothesis 1.

In contrast, Models 1B–3B explore how the same independent variables affect alliance formation among firms that reside within the same cluster, rather than across clusters. Here, *Repeated ties* obtains a positive effect on alliance formation within clusters, but the second-order term is not significant. As before, *Common ties* have no effect on alliance formation. Importantly, neither *Joint prominence* nor *Structural homophily* affects alliance formation within clusters. Because clusters host closer partners by definition, we can expect that there would be less variation across these observations with respect to the limited set of within-cluster pairs. Indeed, Models 1C and 2C aggregate the information from the prior two sets of regressions (A and B) by demonstrating that the effect of *Structural homophily* obtains across clusters only.

Models 1D–2D examine alliance formation among new entrants and are therefore run on a risk set made up of dyads between two new entrants or one embedded firm and one new entrant, excluding dyads between

Table 4 Logistic Estimates of Dyad-Level Alliance Formation

	A. Among firms embedded in *different clusters* in the main component ($N = 13{,}794$)			B. Among firms embedded within the *same cluster* in the main component ($N = 3{,}319$)		
Independent variable	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B
Structural homophily		2.94**	2.46**		−2.29	−2.96
Time	−0.39**	−0.40**	−0.40**	−0.19	−0.19	−0.18
Cluster density	−0.01	−0.01	−0.01	−0.03	−0.03	−0.02
Firm size	0.29*	0.41*	0.41*	−0.08	−0.06	−0.09
Horizontal dyad	−0.14	0.04	0.01	−0.09	−0.21	−0.21
Repeated ties	3.49**	3.57**	3.52**	4.47**	4.81*	4.81**
(Repeated ties)^2	−1.22*	−1.20*	−1.19*	−0.81	−0.87	−0.88
Common ties	0.25	0.43	0.39	0.21	0.24	0.27
Joint prominence	2.48*		0.60	−0.09		0.71
Chi-square	100.85**	106.49**	104.91**	32.75**	34.48**	33.97**

	C. Among all firms embedded in the main component, both within the same cluster and in different clusters ($N = 17{,}113$)		D. Among dyads where at least one firm is not embedded in the main component ($N = 6{,}669$)	
	Model 1C	Model 2C	Model 1D	Model 2D
Structural homophily	1.66**			
Incumbent prominence				1.24*
Time	−0.28**	−0.29**	0.17	−0.24
Cluster density	−0.03	−0.02	0.06*	0.06*
Firm size	0.03	0.12	−0.03	−0.04
Horizontal dyad	0.09	0.02	−0.57*	−0.51*
Repeated ties	2.97**	3.19**	−0.03	−0.03
(Repeated ties)^2	−0.72*	−0.76*		
Common ties	0.51*	0.41		
Cross-cluster (CC) dyad	0.38	−0.69		
CC dyad × Structural homophily		4.93**		
Main component			−0.05	−0.05
New entrant prominence			0.19	0.23
Chi-square	153.74**	160.46**	39.07**	43.49**

$^*p < 0.05$; $^{**}p < 0.01$.

two embedded firms. Our baseline Model 1D shows that *Cluster density* obtains a positive, significant effect, suggesting that incumbents embedded in more densely connected clusters show a higher propensity to attach to new entrants compared to those embedded in less densely connected clusters. Moreover, *Horizontal dyad* has a negative, significant effect, demonstrating that distant search in the form of attaching to new entrants is more likely to occur amongst firms at different stages of the value chain. All other control variables are insignificant throughout. Turning to Model 2D, *Incumbent prominence* obtains a significant and positive effect on the probability of alliance formation, supporting Hypothesis 2.

Table 5 displays the Poisson estimates of deal size. Models 1E–2E examine alliances formed among firms embedded in the main component only. Neither of the models has much explanatory power. Only *Average deal size* has a significant effect on current deal size, and *Cross-cluster deals* do not exhibit greater size. Thus, we are unable to support Hypothesis 3: Among embedded firms, there is no difference in the number of partners among alliances within clusters and across clusters.

In Models 1F–2F we examine all alliances formed. Again, the control variables are not particularly informative: Only *Firm size* obtains a significant effect. However, with the inclusion of the *Nonembedded deal* indicator, Model 2F demonstrates a significant fit, and a significant positive effect of this indicator. Thus, nonembedded deals are associated with a greater number of partners than deals limited to within the main component, supporting Hypothesis 4.

4. Discussion and Conclusions

Our study shifts the focus in studies of network evolution from how networks stay the same to how networks might change more significantly. To do so, we utilized several factors that have been underemphasized in extant studies focusing on network endogeneity. Each of these factors—the small-world topology, the entry of new firms into preexisting networks, and the existence of multiparty alliances—generates avenues by which

Table 5 Poisson Estimates of Deal Size

E. Among firms embedded in the main component ($N = 47$)

Independent variable	Model 1E	Model 2E
Cross-cluster deal		−0.13
Time	0.05	0.04
Cluster density	0.18	0.19
Firm size	0.01	0.01
Horizontal deal	0.03	0.02
Average deal size	0.37*	0.37*
Pseudo R^2	0.03	0.03

F. Among all firms, both among firms embedded in the main component and among nonembedded firms ($N = 111$)

Independent variable	Model 1F	Model 2F
Nonembedded deal		1.48**
Time	−0.12	−0.13
Cluster density	0.31	0.24
Firm size	0.06*	0.01
Horizontal deal	0.04	0.03
Main component	0.01	0.01
Average incumbent deal size	0.07	0.09*
Average new entrant deal size	−0.27	−0.48
Pseudo R^2	0.20	0.07*

*$p < 0.05$; **$p < 0.01$.

researchers and practitioners alike can observe differences in network structure and suggest several future research directions.

Our findings underscore the well-accepted role of endogenous determinants in network evolution. However, our twin emphases on the less prevalent shortcut formation and on network entry highlight the reality that incumbent firms occasionally seek to form alliances with less familiar firms to access more unique knowledge, and these alliances are the ones more likely to generate substantial changes in network structure. Our use of small-world constructs like main components and clusters allowed us to hypothesize and find determinants of exploratory activity with these distant firms. Indeed, our results, taken together, suggest that the notion of distance in this topology is nuanced, where firms within clusters are considered local, firms in different clusters but still within the main component are considered semidistant, and firms outside the main component are more distant. Such a consideration of distance highlights the trade-offs of increasing distance, where access to more unique knowledge is available at the expense of decreasing familiarity and the governance benefits generated by trust.

More specifically, the small-world topology allowed us to explore how alliance formation dynamics within clusters might differ from those across clusters. Indeed, our results focusing on the main component clearly showed that a typical driver of endogeneity—structural homophily—predicts shortcut formation, but not within-cluster alliance formation. Thus, focusing on clusters allows us to consider the motivation for alliance formation within clusters' embedded subnetworks separately from the motivation for alliance formation among less-known partners that span separate clusters. Much more research is needed that exploits this network structure.

A corollary benefit of the main component emphasis is the opportunity to discriminate between alliance formation within the main component and alliance formation that admits new firms into the main component. Because many of the endogeneity-focused studies limit their analyses to more mature industries and the set of firms that operate in the industry for the entire span of the study, the opportunity to explore more significant change in networks is reduced. Indeed, 73% of the firms in the network at the end of our study period joined the network after our study period began. Thus, entry seems to be a stronger source of network change than shortcut formation. Further, our results suggest that prominence plays a major role in the creation of relationships between new entrants and incumbents, and more research is required that explores the mutuality of these relationships, along the lines of Ahuja and Polidoro (2003).

In addition, by analyzing the main component entry dynamics, we demonstrated that although prominence of incumbents does suggest attractiveness for new entrants, the deals that admit new entrants into the network are frequently populated by more than two firms. Future research must examine the motivation for these deals that bring together multiple nonembedded firms with an embedded partner. Is it that established firms are collecting a set of capabilities to pursue future technology/market combinations, or is it that the peripheral, nonembedded firms define the opportunity and then go in search of a partner with deep pockets? Furthermore, are such deals a natural outcome in many industries, or far more common in systemic industries like wireless?

Beyond these conceptual issues, the analysis of the multiparty alliances highlights the opportunity to improve methodology for examining their implications. Although we have learned much about network structure from studies that utilize the dyad or the firm as the level of analysis, our ability to integrate information at the deal level or the cluster level in these sorts of analyses is still quite limited. Studies that examine the antecedents of multiparty alliances and distinguish them from those of single-partner alliances can contribute a great deal to research that has typically assumed that multiparty alliances are simply collections of dyadic alliances.

Our work also highlights how research streams focused on social capital and on small worlds usefully intersect. Burt's (2005) discussion of the interdependence between learning and trust benefits is clearly related to our effort to couple instrumental search goals with reliance on social cues in alliance formation. Our finding that different dynamics describe alliance formation within, between, and beyond local clusters supports his increasing emphasis on the complementarity of brokerage and closure in studies of social capital. Thus, the inclusion of small-world topology in theories of network evolution can help us discern more beneficial network structures. Although some initial studies have demonstrated the value of small worlds (Schilling and Phelps 2007, Uzzi and Spiro 2005), studies that share our focus on the microstructure of networks can contribute much more to our understanding of the interdependence between brokerage and closure.

Finally, significant opportunities arise to connect studies of network evolution to both the technological trajectories that provide context for alliance formation and also to the movement of key individuals between firms. As technological discontinuities provide the impetus for network reformation, our approach allows researchers to uncover the major sources of this network reformation. Do networks reform because of the entry of new firms? The development of new clusters? Increased search for partners outside of established clusters? Or, at the extreme, by the emergence and growth of a new component that proves the undoing of the established network? At the same time, to what extent can the network-building activities of new entrants be facilitated or constrained by the prior experiences of their executive teams? Future research must provide insight into these areas, which can help researchers and practitioners understand both endogenous and exogenous sources of network change.

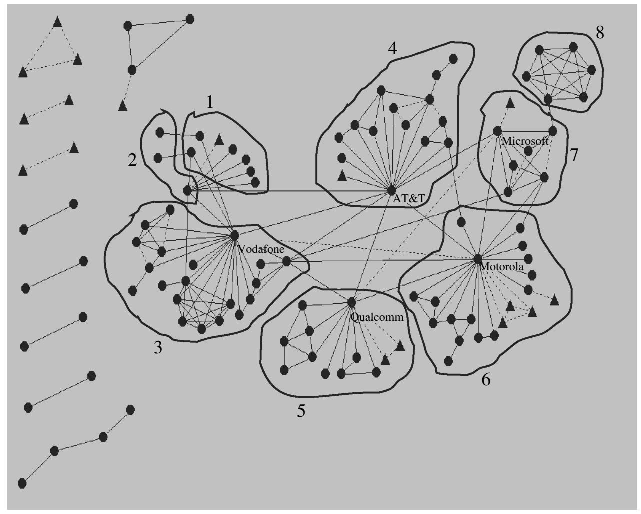
Acknowledgments

The authors acknowledge financial support from the Mack Center for Technological Innovation at The Wharton School of the University of Pennsylvania, Bocconi University, and SDA Bocconi School of Management. They are also grateful to Gautam Ahuja and their three anonymous reviewers for thoughtful comments throughout the review process.

Appendix

Because the determination of clusters is as much art as science, here we set out the procedure we used to make this determination as systematic as possible. For our research purposes, we needed to partition the actors within the main component into more densely connected clusters of relationships. To do so, we used CONCOR, a procedure that successively partitions the firms into blocks of powers of 2 (2 blocks, 4 blocks, 8 blocks, 16 blocks, etc.) based on their structural equivalence. Of course, because structural equivalence does not require cohesion (Burt 1987), this procedure alone would not guarantee that members within a block actually obtain the cohesiveness that we would expect from clusters. Therefore, to determine the ultimate clusters for our analysis, we adhered to the following procedure.

Figure A.1 **Potential Network Clusters for 1998 Suggested by a Three-Partition CONCOR Procedure**



To assess whether a given partition of firms into clusters effectively separates more cohesive blocks from each other, we determined that any set of clusters admitted into our analyses would demonstrate a higher density within each cluster than between any two clusters. If this assumption was violated by a suggested clustering via CONCOR, we merged the clusters where between-cluster density exceeded within cluster density until we met this criterion.

In CONCOR, there is no standard stopping rule about the number of successive partitions to permit. Because our network visualizations (for example, Figures 1(a)–(d)) appeared to suggest three to six clusters, depending on the year, we chose to allow three partitions for our analyses, which enabled

Figure A.2 **Final 1998 Network Clusters, After Merging Potential Clusters 1 and 2**

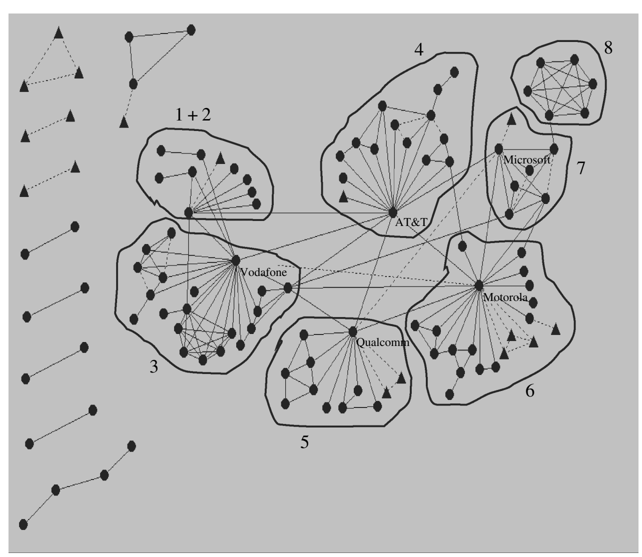


Table A.1 Density Matrix of the 1998 Potential Network Clusters

Cluster	1	2	3	4	5	6	7	8
1	0.00	0.38	0.01	0.00	0.00	0.00	0.00	0.00
2	0.38	0.00	0.03	0.02	0.00	0.00	0.00	0.00
3	0.01	0.03	0.24	0.01	0.00	0.00	0.01	0.00
4	0.00	0.02	0.01	0.24	0.01	0.01	0.01	0.00
5	0.00	0.00	0.00	0.01	0.29	0.00	0.01	0.00
6	0.00	0.00	0.00	0.01	0.00	0.15	0.02	0.00
7	0.00	0.00	0.01	0.01	0.01	0.02	0.62	0.02
8	0.00	0.00	0.00	0.00	0.00	0.00	0.02	1.00

the identification of eight ($2 \times 2 \times 2$) potential clusters. Note that alternative design choices for the number of partitions were less suitable. Specifically, four partitions (yielding 16 cluster candidates) required many more merges, ultimately revealing results essentially comparable to the three-partition solution. More importantly, two partitions (yielding four cluster candidates), although satisfying the criterion of greater within-cluster density than across-cluster density, tended to have less difference between the within-cluster and across-cluster densities due to the aggregation of distinct subclusters into this small set of potential clusters. Therefore, the three-partition approach was used, ultimately resulting in five clusters in 1993; eight clusters in 1994, and seven clusters in all other years.

Figures A.1 and A.2 and Tables A.1 and A.2 depict our cluster generation procedure, using 1998 data as an example. Figure A.1 displays the results of a three-partition CONCOR[20] analysis and Table A.1 displays the inter- and intracluster densities. To satisfy the criterion above, the intracluster densities (on the diagonal) must exceed the intercluster (off-diagonal) densities. Although this is true for Clusters 3 through 8, Clusters 1 and 2 each have zero density on the diagonal, suggesting that the clusters represent structural equivalents that are not cohesive with each other. Further examination of the rows surrounding these zero diagonals suggest that these two clusters should be merged together, because there are significant linkages spanning these clusters, which would create cohesiveness within a merged cluster. Figure A.2 and Table A.2 depict the revised clusters after this merge is completed. Now, all diagonal (intracluster) densities exceed all off-diagonal (intercluster) densities, so this is the seven-cluster solution we use to discern shortcuts formed between clusters in the subsequent year.

Table A.2 Density Matrix of the Final 1998 Network Clusters, After Merging Clusters 1 and 2

Cluster	1+2	3	4	5	6	7	8
1+2	0.18	0.02	0.01	0.00	0.00	0.00	0.00
3	0.02	0.24	0.01	0.00	0.00	0.01	0.00
4	0.01	0.01	0.24	0.01	0.01	0.01	0.00
5	0.00	0.00	0.01	0.29	0.00	0.01	0.00
6	0.00	0.00	0.01	0.00	0.15	0.02	0.00
7	0.00	0.01	0.01	0.01	0.02	0.62	0.02
8	0.00	0.00	0.00	0.00	0.00	0.02	1.00

Endnotes

[1]Indeed, before the recent surge of small-world studies, Walker et al. (1997) proposed that a firm's motivation to generate structural holes might lead to the formation of alliances with unfamiliar partners. Despite this insight, their empirical results did not demonstrate support for this hypothesis because the majority of relationships were formed with familiar partners.

[2]Of course, Burt (2000) argues that the trust benefits of closure may be overrated, in that dense clusters may reinforce the tendency of actors to echo "socially desirable" information. Because alliance clusters in some cases represent a division of labor, the threat of hold-up may exist, lessening trust and increasing "echo." Although this perspective generates a slightly different slant on the full range of information shared within clusters, it is still consistent with our larger view that more unique information is available beyond local clusters.

[3]Another application of the social asymmetry hypothesis could suggest that alliances between core and peripheral firms might be more likely within the main component. We do not believe that this is a likely phenomenon with regard to shortcuts in the main component, as given by our arguments developing Hypothesis 1. However, this does not preclude core-peripheral alliances within clusters, which are not the focus of our analysis, and would likely be predicted by cohesiveness within clusters. Our argument for prominent embedded firms finding (peripheral) nonembedded firms attractive partners is spawned by the cases where these nonembedded firms bring new-to-the-network technology, consistent with the Ahuja and Polidoro (2003) argument. Peripheral embedded firms are unlikely to bring new-to-the-network technology.

[4]In an interesting analogy, Sorenson and Stuart (2001) find that prominent venture capital firms are more likely to fund spatially distant targets.

[5]Specifically, an alliance between one incumbent and two new entrants is treated as three dyads: one each between the incumbent and the two new entrants, and another between the two new entrants.

[6]Whereas our networks are generated via a focus on industry-specific alliances, other authors have chosen to generate networks via a focus on firms participating in that industry (e.g., Gulati and Gargiulo 1999; Ahuja 2000a, b). Given our need to understand the broader network topology and to identify new entrants, firm-generated networks were less likely to reveal these phenomena. A similar approach has been used by Schilling and Phelps (2007).

[7]The choice of a five-year window is consistent with extant alliance studies (e.g., Gulati and Gargiulo 1999, Stuart 2000) and conforms to Kogut's (1988) finding that the normal life span of most alliances is no more than five years. Schilling and Phelps (2007), in contrast, use a three-year window for their alliance network study. In our data, for the alliances with terminations reported in SDC Platinum (14 of 111), the mean length of the terminated deal is 2.5 years, with a standard deviation of three years. We ran our analyses with three-year windows and found that our results are robust to the selection of either time frame.

[8]Following Watts and Strogatz (1998) and Watts (1999), we look for the presence or absence of a small world by comparing the actual network's clustering coefficient (C_a) and path length (L_a) to the clustering coefficient (C_r) and path length (L_r) of a randomly connected network of the same size and

density. Formally, a small world is said to exist if C_a is at least twice as large as C_r while L_a is approximately the same as L_r (Newman et al. 2001). For a random network the clustering coefficient is calculated as k/n and average path length can be computed as $\ln(n)/\ln(k)$, where k is the average number of degrees per node and n is the number of nodes. Thus, the small world diverges from a random network by exhibiting high clustering while still maintaining short path lengths.

[9]Several multiparty deals are pictured in our figures. First, Unitel was formed in 1994 as a joint venture between network incumbent BellSouth and six network entrants (ENI, Fiat, Fininvest, Premafin, Millicom, and Vodafone) to bid for a mobile telephone network license. This deal is represented by the cluster of seven firms in the lower-left quadrant. Second, also in 1994 (seen in the upper-right quadrant), the Wireless Cable Digital Alliance is a consortium of six new entrants (American Telecasting, Andrew, California Amplifier, EMCEE Broadcast Product, Microwave Filter, and Zenith Electronics) to jointly develop digital technologies for delivery of digital video programming and other services. Third, in 1995, RPG Cellular Services was formed as a joint venture between Vodafone and three new network entrants (Itochu, RPG, and AirTouch Communications) to provide cellular telephone services in India (seen in the lower-left quadrant). Finally, in 1998, an alliance was formed between Motorola and three new entrants (Netscape, Nextel, and Unwired Planet) to provide a wireless telephone package combining voice, data, and Internet services in the United States (seen in the lower-right quadrant).

[10]Because the determination of our variables relies on the identification of the main component, we begin our statistical analyses during the first year in which a main component is evident.

[11]In analyses not reported here, we also split this risk set into the subset of dyads with one firm already embedded in the main component and the subset of dyads with neither firm embedded. Results were comparable, so we only report the results for the combined set of dyads.

[12]Ties among nonembedded dyads may arise as a function of multiparty deals that include more than one nonembedded firm as well as deals limited to nonembedded firms.

[13]The use of binary (rather than valued) adjacency matrices may raise the concern that we overemphasize structural considerations at the expense of relational ones. Our methodological choice is motivated by our desire to incorporate the small-world methodological assumptions, which are primarily structural (Watts and Strogatz 1998, Watts 1999). However, to incorporate relational considerations, we include count measures for cohesiveness controls, which are discussed later in this section.

[14]To compute the Bonacich (1987) index, we tested multiple values of the weighting factor *Beta*, which denotes the extent to which indirect ties should affect the focal firm's centrality. We report results for the *Beta* parameter set at the three-quarter of the inverse of absolute value (or modulus) of the largest eigenvalue, which is consistent with previous research (e.g., Podolny 1993). However, our results are robust to a range of positive values of *Beta*. They are also robust when *Beta* is set to zero, which essentially reduces the Bonacich measure to one of degree centrality.

It is worth noting that two firms with equivalent Bonacich centrality with *Beta* set to 0.75 may not experience the exact same structure, because one could have a smaller number of higher-status partners whereas the other could have a larger number of lower-status partners. Fortunately, the convergence of the results with *Beta* set to both 0.75 and 0 strengthens our claim of structural homophily. We thank an anonymous reviewer for pointing this out.

[15]We considered using a variable representing cluster size (the number of firms in the cluster) as well. Clearly, cluster density is a function of cluster size N, and the two variables are correlated at -0.34. Accordingly, alternative specifications of our model with cluster size in place of cluster density, as well as both cluster size and cluster density together, did not add any explanatory power to our models; cluster density alone is the preferred predictor. Another specification with cluster size and number of ties in the cluster (instead of cluster density) again did not exceed the predictive power of cluster density alone.

[16]Our decision to employ a population-averaged model rather than a random or fixed-effects model is based on the following considerations. Recent studies of alliance formation within dyads (Gulati 1995b, Stuart 1998, Rosenkopf et al. 2001) have used random effects rather than fixed effects because of the biases inherent in fixed effects over short time horizons and because of the presence of time-invariant predictors for which fixed effects do not provide any coefficient estimates. However, random-effects models are based on the assumption that the random components are independent from the time-varying predictors, a restrictive condition that seems incorrect in our research design and that would consequently lead to biased estimates if employed to our case. Because the population-averaged approach makes no explicit assumption about the random component in the regression model, it relaxes the random-effects models restrictions by allowing for any possible correlations between random component and time-varying predictors. At the same time, it can accommodate short time frames and time-invariant predictors. Consequently, in our case the population-averaged approach is the preferred way to obtain estimates adjusted to account for the correlation across observations through time.

[17]Although firm fixed effects might be desirable, our limited number of observations for the deal-based analyses preclude their inclusion.

[18]Although the dependent variable does not suffer from overdispersion, we tested negative binomial models to insure there was no improvement in fit over our Poisson models.

[19]The *Joint prominence* result suggests that the alliance formation among firms with similar levels of centrality is generated by more prominent firms forming alliances with each other than by more peripheral firms forming alliances with each other.

[20]Visual representations of our 1998 network clusters were obtained using Pajek 1.19 (de Nooy et al. 2005).

References

Ahuja, G. 2000a. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management J.* **21**(3) 317–343.

Ahuja, G. 2000b. Collaboration networks, structural holes and innovation: A longitudinal study. *Admin. Sci. Quart.* **45**(3) 425–455.

Ahuja, G., F. Polidoro, Jr. 2003. Structural homophily or social asymmetry? The formation of alliances by poorly-embedded firms. Working paper, University of Michigan, Ann Arbor.

Anderson, P., L. M. Tushman. 1990. Technological discontinuities and dominant designs: A cyclical model of technological change. *Admin. Sci. Quart.* **35**(4) 604–633.

Arthur, B. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Econom. J.* **99** 116–131.

Baker, W. E. 1990. Market networks and corporate behavior. *Amer. J. Sociol.* **96**(3) 589–625.

Barabasi, A. L., R. Albert, H. Jeong. 1999. Mean-field theory for scale-free random networks. *Physica Part A* **272** 173–187.

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

Baum, J. A. C., A. V. Shipilov, T. J. Rowley. 2003. Where do small worlds come from? *Indust. Corporate Change* **12**(4) 697–725.

Beckman, C. M., D. Phillips, P. Haunschild. 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. *Organ. Sci.* **15**(3) 259–275.

Bonacich, P. 1987. Power and centrality: A family of measures. *Amer. J. Sociol.* **92**(5) 1170–1182.

Borgatti, S. P., M. G. Everett, L. C. Freeman. 2002. *Ucinet for Windows: Software for Social Network Analysis*. Analytic Technologies, Harvard, Cambridge, MA.

Brandenburger, A. M. 1995. Power play (A): Nintendo in 8-bit video games. Harvard Business School Case 9-795-102.

Breiger, R. L., S. A. Boorman, P. Arabie. 1975. An algorithm for clustering relational data, with applications to social network analysis and comparison with multidimensional scaling. *J. Math. Psych.* **12** 326–383.

Burt, R. L. 1987. Social contagion and innovation, cohesion versus structural equivalence. *Amer. J. Sociol.* **92**(6) 1287–1335.

Burt, R. L. 1992. *Structural Holes*. Harvard University Press, Cambridge, MA.

Burt, R. L. 1998. The network structure of social capital. Paper presented at the Social Network and Social Capital Conference, Duke University, Durham, NC.

Burt, R. 2000. The network structure of social capital. R. I. Sutton, B. M. Staw, eds. *Research in Organizational Behavior*. JAI Press, Greenwich, CT, 345–423.

Burt, R. L. 2005. *Brokerage and Closure. An Introduction to Social Capital*. Oxford University Press, New York.

Chandler, A. D., Jr. 1997. The computer industry. The first half-century. D. B. Yoffie, ed. *Competing in the Age of Digital Convergence*. Harvard Business School Press, Boston, 37–122.

Chung, S., H. Singh, K. Lee. 2000. Complementarity, status similarity and social capital as drivers of alliance formation. *Strategic Management J.* **21**(1) 1–22.

Cohen, W. L., D. A. Levinthal. 1990. Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* **35**(1) 128–152.

Coleman, J. S. 1988. Social capital in the creation of human capital. *Amer. J. Sociol.* **94** S95–S120.

Collis, D., G. Pisano. Intel Corporation: 1968–1997. Harvard Business School Case 9-797-137.

Davis, G. F., M. Yoo, W. E. Baker. 2003. The small world of the American corporate elite, 1982–2001. *Strategic Organ.* **1**(3) 301–326.

de Nooy, W., A. Mrvar, B. Batagelj. 2005. *Exploratory Social Network Analysis with Pajek*. Structural Analysis in the Social Sciences, Vol. 27. Cambridge University Press.

Gulati, R. 1995a. Familiarity breeds trust? The implications of repeated ties on contractual choice in alliances. *Acad. Management J.* **38**(1) 85–112.

Gulati, R. 1995b. Social structure and alliance formation pattern: A longitudinal analysis. *Admin. Sci. Quart.* **40**(4) 619–652.

Gulati, R., M. Gargiulo. 1999. Where do interorganizational networks come from? *Amer. J. Sociol.* **104**(5) 1439–1493.

Gulati, R., H. Singh. 1998. The architecture of cooperation: Managing coordination uncertainty and interdependence in strategic alliances. *Admin. Sci. Quart.* **43**(4) 781–814.

Han, S. K. 1994. Mimetic isomorphism and its effects on the audit service market. *Soc. Forces* **73**(2) 637–664.

Hansen, M. T. 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunit. *Admin. Sci. Quart.* **44**(1) 82–111.

Hargadon, A. B., R. I. Sutton. 1997. Technology brokering and innovation: Evidence from a product design firm. *Admin. Sci. Quart.* **42**(4) 716–749.

Henderson, R., K. B. Clark. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Admin. Sci. Quart.* **35**(1) 9–30.

Hsu, D. H. 2004. What do entrepreneurs pay for venture capital affiliation? *J. Finance* **59**(August) 1805–1844.

Kogut, B. 1988. Joint ventures: Theoretical and empirical perspectives. *Strategic Management J.* **9**(2) 312–332.

Madhavan, R., B. R. Koka, J. E. Prescott. 1998. Networks in transition: How industry events (re)shape interfirm relationships. *Strategic Management J.* **19**(5) 439–459.

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

Mizruchi, M. S. 1993. Cohesion, equivalence and similarity of behavior. A theoretical and empirical assessment. *Soc. Networks* **15**(3) 275–307.

Newman, M., S. Strogatz, D. Watts. 2001. Random graph with arbitrary degree distribution and their applications. *Phys. Rev. Part E* **64** 026118.

Nohria, N., C. Garcia-Pont. 1991. Global strategic linkages and industry structure. *Strategic Management J.* **12** 105–124.

Podolny, J. M. 1993. A status-based model of market competition. *Amer. J. Sociol.* **98**(4) 829–872.

Podolny, J. M. 1994. Market uncertainty and the social character of economic exchange. *Admin. Sci. Quart.* **39**(3) 458–483.

Podolny, J. M., D. J. Philips. 1996. The dynamics of organizational status. *Indust. Corporate Change* **5**(2) 453–471.

Podolny, J. M., T. E. Stuart. 1995. A role-based ecology of technological change. *Amer. J. Sociol.* **100**(5) 1224–1260.

Powell, W. W., K. Koput, L. Smith-Doerr. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Admin. Sci. Quart.* **41**(1) 116–145.

Powell, W. W., D. R. White, K. Koput, J. Owen-Smith. 2005. Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *Amer. J. Sociol.* **110** 1132–1205.

Raub, W., J. Weesie. 1990. Reputation and efficiency in social interactions: An example of network effects. *Amer. J. Sociol.* **96**(3) 626–654.

Rosenkopf, L., P. Almeida. 2003. Overcoming local search through alliances and mobility. *Management Sci.* **49**(6) 751–766.

Rosenkopf, L., A. Nerkar. 1999. On the complexity of technological evolution. Exploring coevolution within and across hierarchical levels in the optical disc technology. J. Baum, B. McKelvey, eds. *Variations in Organization Science: In Honor of D. T. Campbell*. Sage Publications, Thousand Oaks, CA, 169–183.

Rosenkopf, L., A. Nerkar. 2001. Beyond local search: Boundary-spanning, exploration and impact in the optical disk industry. *Strategic Management J.* **22**(4) 287–306.

Rosenkopf, L., M. Tushman. 1994. The Co-evolution of technology and organization. J. Baum, J. Singh, eds. *Evolutionary Dynamics of Organizations*. Oxford University Press, New York, 403–424.

Rosenkopf, L., M. Tushman. 1998. The co-evolution of community networks and technology: Lessons from the flight simulation industry. *Indust. Corporate Change* **7**(2) 311–346.

Rosenkopf, L., A. Metiu, V. P. George. 2001. From the bottom up? Technical committee activity and alliance formation. *Admin. Sci. Quart.* **46**(4) 748–772.

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

Schilling, M. 1998. Technological lock-out. An integrative model of the economic and strategic factors driving technology success and failure. *Acad. Management Rev.* **23**(2) 267–284.

Schilling, M., C. Phelps. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Sci.* **53**(7) 1113–1127.

Sorenson, O., T. E. Stuart. 2001. Syndication networks and the spatial distribution of venture capital investments. *Amer. J. Sociol.* **106**(6) 1546–1588.

Stuart, T. 1998. Network positions and propensity to collaborate: An investigation of strategic alliance formation in a high-technology industry. *Admin. Sci. Quart.* **43**(3) 668–698.

Stuart, T. 2000. Inter-organizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic Management J.* **21**(8) 791–811.

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

Tripsas, M. 1997. Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. *Strategic Management J.* **18** 119–142.

Tushman, M. L., L. Rosenkopf. 1992. On the organizational determinants of technological change: Towards a sociology of technological evolution. B. Staw, L. Cummings, eds. *Research in Organizational Behavior*, Vol. 14. JAI Press, Greenwich, CT, 311–347.

Uzzi, B., J. Spiro. 2005. Collaboration and creativity: The small world problem. *J. Sociol.* **111**(2) 447–504.

Uzzi, B., J. Spiro, D. Delis. 2002. Emergence: The origin and evolution of career networks in the broadway musical industry, 1877 to 1995. Working paper, Northwestern University, Evanston, IL.

Verona, G., E. Prandelli, M. Sawhney. 2006. Innovation and virtual environments: Towards virtual knowledge brokers. *Organ. Stud.* **27**(6) 765–788.

Vicari, S., G. von Krogh, J. Roos, V. Mahnke. 1996. Knowledge creation though cooperative experimentation. G. von Krogh, J. Roos, eds. *Managing Knowledge. Perspectives on Cooperation and Competition*. Sage Publications, London.

Wade, J. 1995. Dynamics of organizational communities and technological bandwagons: And empirical investigation of community evolution in the microprocessor market. *Strategic Management J.* **16** 111–133.

Walker, G., B. Kogut, W. Shan. 1997. Social capital, structural holes and the formation of an industry network. *Organ. Sci.* **8**(2) 109–125.

Watts, D. J. 1999. Networks, dynamics and the small world phenomenon. *Amer. J. Sociol.* **105**(2) 493–527.

Watts, D. J., S. H. Strogatz. 1998. Collective dynamics of "small world" networks. *Nature* **393** 440–442.

Zuckerman, E., D. Phillips. 2001. Middle status conformity: Theoretical restatement and empirical demonstration in two markets. *Amer. J. Sociol.* **107** 379–429.