

COMPARING ALLIANCE NETWORK STRUCTURE ACROSS INDUSTRIES: OBSERVATIONS AND EXPLANATIONS

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Much research in strategic entrepreneurship has focused on the consequences of network structure for firm performance. Despite this emphasis, little is known about variation in network structure across industries, or about the antecedents of this variation. In a comparative study of alliance networks in 32 industries, we demonstrate substantial variety in network structure, and develop a typology of network structures. We then endeavor to explain this variation by focusing on dimensions of the products and technologies that characterize these industries—such as technological uncertainty and dynamism, product modularity, and architectural control—and associating them with underlying characteristics of network structure. We conclude with a discussion of implications of our findings for research in strategic entrepreneurship. Copyright © 2008 Strategic Management Society.

INTRODUCTION

Recent research has demonstrated that interfirm network structure can significantly influence firm-level performance outcomes such as growth (e.g., Powell *et al.*, 1996), innovation (e.g., Ahuja, 2000a; Schilling and Phelps, 2007), and access to venture capital (Sorenson and Stuart, 2001). Some of the most prominent mechanisms by which an interfirm network influences firm outcomes include shaping the flow of information and other resources between connected firms, providing signals of firm quality, and enabling reciprocity norms through shared third-party ties (Ahuja, 2000a; Gulati and Gargiulo, 1999; Owen-Smith and Powell, 2004; Schilling and

Phelps, 2007; Stuart, 2000; Uzzi, 1997). However, despite mounting evidence of the importance of alliance network structures, neither the variation in these structures nor the antecedents of this variation are well understood. There is very little research documenting systematic differences in alliance network structure, presumably because of the difficulty in doing so.¹ Only a few databases exist that track alliances for multiple industries in a consistent fashion, and harvesting the data from these alliances in a way that permits accurate network analysis is a nontrivial task.

Similarly, most extant studies addressing the question of where interorganizational alliance networks come from either limit their scope to a single or few

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¹ Some notable exceptions include Schilling and Phelps (2007), who analyze how the characteristics of 11 industry alliance networks affect patenting activity, and Verspagen and Duysters (2004), who compare the network structure of the chemicals and food and electrical equipment industries.

industries (e.g., Baum, Shipilov, and Rowley, 2003; Stuart, Ozdemir, and Ding, 2007), or to explaining the formation of dyadic alliances rather than the overall network (e.g., Gulati, 1999; Stuart, 1998). Here we have seen that alliance formations may be predicted by prior alliance activity (Powell *et al.*, 1996; Walker, Kogut, and Shan, 1997; Gulati, 1995)—by network ties in other contexts such as technical committees (Rosenkopf, Metiu, and George, 2001), director interlocks (Gulati and Westphal, 1999), patent-related technology landscapes (Mowery, Oxley, and Silverman, 1998; Stuart, 1998)—and by technological capabilities (Gulati and Gargiulo, 1999; Ahuja, 2000b). Again, this activity has been fruitful, but it does not address how these alliances aggregate into an overall structure, how these structures vary, or what broader industry characteristics may shape these alliance decisions.

To address these issues, we first assess whether there are significant and systematic differences in alliance network structure across different industries by developing and analyzing 32 industry alliance networks. We take care to construct and analyze the networks by consistent means, permitting us to compare these networks on such dimensions as size, connectivity, centralization, small-world properties, and others. We are then able to compare alliance network structure to other industry features, such as number of publicly held firms, change in total factor productivity, research and development intensity, separability of innovation activities, and concentration of architectural control. We combine this inductive approach with theoretical reasoning to develop a typology of alliance network structure, and propose a set of industry factors that shape network structure. We close by considering the implications of these findings for future research.

COMPARING NETWORK STRUCTURES

For the inductive portion of our study, we began by constructing a sample of industry alliance networks. From the full list of three-digit (1987 SIC) manufacturing industries, we excluded consumables (food and beverage and tobacco) and those industries that are ‘not elsewhere classified’ designations (i.e., catchall categories for miscellaneous products that are not otherwise classifiable under the SIC system), leaving 103 candidate industries

for our study. For these industries, strategy and entrepreneurship scholars assessed the levels of technology-focused characteristics, such as product modularity, value chain separability, proprietary standards, and architectural control. Using these assessments, we selected a total of 32 industries that demonstrated varying levels of these characteristics.

For our sample, alliance data were gathered using Thomson’s SDC Platinum database. The SDC data have been used in a number of empirical studies on strategic alliances (e.g., Anand and Khanna, 2000; Schilling and Steensma, 2001; Sampson, 2004).² For each industry, we gathered all alliances announced between 2001 and 2003 that included at least one firm whose primary SIC code (the four-digit SIC code in which the firm generates the largest portion of its revenues) matched the industry. Both public and private firms were included.

Alliance relationships typically last for more than a year, but alliance termination dates are rarely reported. This required us to make an assumption about how long the alliances lasted. We took a conservative approach and assumed that alliance relationships would last for three years, consistent with recent empirical work on the average duration of alliances (Phelps, 2003). Other research has taken a similar approach, using windows ranging from one to five years (e.g., Bae and Gargiulo, 2003; Gulati and Gargiulo, 1999; Stuart, 2000). Thus, we create the alliance networks based on a three-year window spanning 2001 to 2003. Each network was

²Like all other large alliance databases (e.g., MERIT-CATI, RECAP, Bioscan), SDC is incomplete in that it does not capture all announced alliances. However, it has been demonstrated that despite this incompleteness, the pattern of alliance activity across the major databases is remarkably symmetric. Furthermore, alliance network structure is highly resilient to this incompleteness, because the alliance databases (with the exception of Bioscan) are sampling on the *links* (the alliances) rather than the *nodes* (the organizations). This means that the likelihood of an organization making it into the sample is directly related to the number of alliances it publicly announces, reducing the likelihood of an important hub being overlooked. Furthermore, an organization’s size and prominence is directly related to both the number of alliances it is likely to have and the amount of press attention it is likely to receive, further reducing the likelihood of a major hub being overlooked, at least in the datasets that consider all forms of organizations (Schilling, 2007). This means that while network and main component size are undoubtedly underestimated, dimensions such as relative degree, centralization, clustering, etc., are fairly reliable so long as the sampling methodology is consistent across the networks being compared.

constructed as a binary adjacency matrix.³ Since we were concerned with whether a path existed from one firm to another and not with the effect of multiplex relationships, multiple alliance announcements between the same pair of firms in any time window were treated as only one link. Alliance relationships are considered to be bidirectional, resulting in an undirected unipartite graph (Newman, Strogatz, and Watts, 2001). Ucinet 6.23, a leading social network analysis software package, was used to obtain network structure measures on each of these networks (Borgatti, Everett, and Freeman, 2002), and Netdraw was used to create graphical pictures of the networks (Borgatti, 2002).

Table 1 lists relevant statistics for all 32 of our networks. The first two measures—change in total factor productivity and research and development intensity—capture the technological dynamism of the industry. The former—change in total factor productivity⁴—examines whether the rate of output from a given quantity of inputs has changed in an industry over time. Historically, total factor productivity has increased significantly across all industries, and part of this increase is typically imputed to be due to technological progress that enables factors of

production to be more effective or efficient (Crafts, 1996; Griliches, 1990; Terleckyj, 1980). This measure is available at the four-digit SIC level from the Bertelsman-Gray database available at the National Bureau of Economic Research, and we used a weighted average method to aggregate the data up to the three-digit level for the purposes of our study. The latter measure, research and development intensity⁵, has been repeatedly associated with the importance of innovation and technological change in an industry. To measure it, we used industry-level research and development expenditures divided by industry-level sales, both obtained from Compustat.

The next measure, average separability of innovation activities, captures the degree to which the industry is considered to be characterized by innovation activities that can be separated across multiple firms (as, for example, when the industry is characterized by interfirm product modularity). To create this measure, we developed two rating instruments. First, we created a list of the 103 manufacturing industries described previously. The two researchers independently rated every industry as high in separability (1), low in separability (−1), or neither (0). The resulting set of ratings exhibited a coefficient alpha of 0.71, suggesting very high interrater reliability (Nunnally, 1978). Thus, we aggregated these scores across the two researchers to create a single index ranging from −2 to 2. Second, we gave copies of the list to a set of 13 scholars in strategy and entrepreneurship, asking them to identify the 10 they felt exhibited the highest levels of separability of innovation activities.⁶ These

³ A binary adjacency matrix is a square matrix with nodes (e.g., firms) as rows and columns. The entries in the adjacency matrix, x_{ij} , indicate which pairs of nodes are adjacent (i.e., have a relationship). In a binary matrix, a value of 1 indicates the presence of a relationship between nodes i and j , while a 0 indicates no relationship.

⁴ Total factor productivity (TFP) growth is a version of the Solow residual (Solow, 1957). A series of studies of economic growth conducted at the National Bureau of Economic Research attracted attention to the role of technological change when it was shown that the historic rate of economic growth in GDP could not be accounted for entirely by growth in labor and capital inputs. Though many researchers have attempted to explain this residual away in terms of measurement error, inaccurate price deflation, or labor improvement, in each case the additional variables were unable to eliminate this residual growth component (Terleckyj, 1980). Gradually a consensus emerged that despite idiosyncratic measurement effects, the residual largely captures technological change (Crafts, 1996; Terleckyj, 1980). Though this residual is primarily used at the national level, a number of researchers have used TFP growth at the industry level to model the relationship between such productivity growth and other variables (e.g., Griliches and Lichtenberg, 1983; Jorgenson, 1984; Siegel and Griliches, 1991). The TFP growth index is calculated as the growth rate of output (real shipments) minus the revenue-share-weighted average of the growth rates of capital, production worker hours, non-production workers, non-energy materials and energy. The TFP growth measure used here is the percent average compound growth rate from 2000–2005 for each industry (based on two-digit SIC) as obtained from the Bureau of Economic Analysis. This measure has been used in a number of other studies to capture the rate of industry-level technological change (e.g., Nelson, 1988; Sterlacchini, 1989).

⁵ Industry-level research and development intensity (R&D intensity) captures the degree to which firms in an industry focus on innovation activities and is an oft-cited predictor of technological innovation rates (e.g., Godoe, 2000; Mariani, 2004). For the industry-level measure used here, we gathered R&D expenditure and sales data on every publicly held firm in each of the industries. For each industry, we divided the average R&D expenditures by the average sales. It was important to calculate the averages for R&D expenditures and sales prior to dividing the former by the latter to prevent unusually large outliers from biasing the measure. This is because if R&D intensity is calculated at the firm level and then averaged, the resulting number can be skewed upward dramatically by firms that have spent on R&D but not yet earned revenues.

⁶ In the survey, respondents were asked to nominate the 10 industries with the highest level of either a) ‘... modularity within the products that characterize the industry. *Modularity* is defined as the degree to which a product’s components may be separated and recombined’, or b) ‘... separability of innovation activities along the value chain (product design, process design, manufacturing, marketing, etc.) for the products that characterize the industry. *Separability* is defined as the degree to which these activities can be distributed among multiple actors/facilities.’

Table 1. Descriptive statistics for the industries and their alliance networks

Industry	Chg in TFP, 1997–2002 ¹	R&D intensity, 2001	Avg separ- ability score	Avg arch. control score	Alliance networks							Nodes in main comp.	
					Nodes	Industry firms in alliances	Avg alliances per industry firm	Alliance part. rate ²	Network central- ization	Harmonic mean path length	Weighted overall clust. coef.		Small- world quot.
Broadwoven fabric mills, cotton (221)	−0.004	0.00	−0.76	−1.06	17	7	1.06	0.30	6.67%	14.29	0.00	0.00	3
Carpets and rugs (227)	0.002	0.00	−0.56	−0.76	3	1	2.00	0.06	0.00%	1.00	1.00	2.37	3
Women's and children's outerwear (233)	−0.015	0.23	0.29	−1.06	15	7	1.33	0.27	21.98%	8.40	0.38	4.72	5
Fur goods (237)	−0.029	0.00	−0.16	−0.76	2	1	1.00	0.17	0.00%	1.00	0.00	0.00	2
Logging (241)	0.000	0.00	−1.12	−0.70	6	3	1.67	0.27	40.00%	1.61	0.00	0.00	6
Wood buildings and mobile homes (245)	−0.024	0.00	0.15	0.00	2	1	1.00	0.11	0.00%	1.00	0.00	0.00	2
Household furniture (251)	0.009	0.32	0.51	−0.50	15	9	1.33	0.19	21.98%	8.33	1.50	18.79	5
Public building and related furniture (253)	0.003	1.62	−0.40	0.00	7	3	1.14	0.33	20.00%	4.76	0.00	0.00	3
Paper mills (262)	0.017	0.68	−1.12	−0.40	23	16	1.04	0.24	4.76%	20.41	0.00	0.00	3
Industrial inorganic chemicals (281)	−0.017	1.60	−0.76	−0.15	167	59	1.89	0.74	9.82%	50.00	0.49	6.96	18
Drugs (283)	−0.014	13.77	−0.40	1.26	913	568	1.62	1.08	1.80%	71.43	0.20	22.11	248
Tires and inner tubes (301)	0.003	3.06	−0.61	−0.15	29	17	1.80	0.41	11.80%	9.62	0.27	2.57	8
Footwear, except rubber (314)	−0.030	0.00	0.15	−0.76	12	3	1.00	0.08	0.00%	10.99	0.00	0.00	2
Flat glass (321)	0.012	0.00	−1.12	−0.70	15	9	1.73	1.00	13.46%	5.88	0.27	1.95	5
Cement, hydraulic (324)	−0.028	0.00	−1.12	−0.40	30	15	2.00	0.20	11.08%	13.16	0.91	5.07	6
Iron and steel foundries (332)	0.004	0.19	−1.12	−0.05	76	30	1.61	1.30	7.39%	17.86	0.21	4.98	26
Nonferrous rolling and drawing (335)	0.000	1.63	−1.12	−0.70	55	20	1.14	0.19	22.69%	11.11	0.36	5.37	23
Cutlery, handtools, and hardware (342)	−0.003	1.62	−0.20	−0.40	24	11	1.00	0.50	15.81%	7.14	0.29	3.57	11
Engines and turbines (351)	0.041	3.47	0.51	1.56	104	23	1.00	0.96	9.22%	11.11	0.64	5.60	36
Computer and office equipment (357)	0.075	6.93	2.02	0.36	383	113	1.00	0.34	11.19%	18.52	0.37	19.94	173
Refrigeration and service machinery (358)	−0.002	1.60	0.20	0.00	57	29	1.00	0.50	10.36%	33.33	0.62	8.91	8
Electric lighting and wiring equipment (364)	0.001	1.20	0.51	−0.70	84	22	1.00	0.33	14.90%	8.33	0.40	5.92	41
Household audio and video equipment (365)	0.007	5.58	1.62	0.30	278	58	1.00	0.82	15.25%	7.63	0.05	6.62	180
Communications equipment (366)	−0.057	13.52	1.22	0.76	342	120	1.33	0.48	5.53%	41.67	0.56	14.53	82
Electronic components and accessories (367)	−0.019	11.01	0.66	0.20	503	228	1.06	0.38	6.62%	33.33	0.37	27.76	162
Motor vehicles and equipment (371)	0.007	3.93	1.12	1.16	464	239	1.54	0.88	7.74%	21.74	0.35	22.74	203
Aircraft and parts (372)	0.001	4.77	1.17	1.56	143	62	1.58	1.77	5.73%	43.48	0.62	7.50	17
Ship and boat building and repairing (373)	0.028	1.54	−0.25	−0.05	40	18	1.47	0.53	16.73%	14.29	0.63	6.09	10
Guided missiles, space vehicles, parts (376)	−0.011	3.15	0.15	2.06	52	13	1.00	2.60	33.26%	5.00	0.54	5.44	32
Medical instruments and supplies (384)	−0.008	9.99	−0.20	0.45	222	80	1.44	0.41	2.60%	125.00	0.34	7.84	9
Photographic equipment and supplies (386)	0.004	6.24	0.32	0.20	45	2	1.27	0.05	6.67%	10.53	0.51	5.12	18
Watches, clocks, watchcases, and parts (387)	−0.012	0.40	0.47	0.30	26	15	1.43	1.00	20.33%	6.62	0.57	3.78	9

¹ Bertelsman-Gray TFP data for 1997 to 2002; weighted averages (weighted by value of shipments) used to aggregate four digit up to three digit.² Alliance participation rate calculated as number of industry firms participating in alliances divided by number of publicly held firms listed in that primary SIC per the Compustat Global database.

nominations were then aggregated into a count for each industry (industries that received no nominations received a zero). These scores were compared to the index created by the researchers, yielding a coefficient alpha of 0.76—again suggesting very high interrater reliability. Therefore, we normalized the count and aggregated it with the researcher index to create a single composite *average separability score*. Not surprisingly, computers and household audio and video equipment, which are often used as archetypal examples of interfirm product modularity, both scored very highly on this separability measure.

We performed a similar procedure for the next measure, *average architectural control*. This measure attempts to capture when a few firms have significant power over the technology design or component compatibility within an industry. To measure this, we again used a researcher rating index (the coefficient alpha between ratings by the two researchers was 0.75), and nominations⁷ from the set of scholars (the coefficient alpha between the scholar count and the researcher index was 0.64). We again normalized the latter and aggregated it with the former to create a single measure of average architectural control. The three industries that scored highest in terms of architectural control were guided missiles, aircraft and parts, and engines and turbines—all industries that exhibit very high minimum efficient scale and may necessitate large players for several stages of product development, manufacturing, or system integration.

The remaining measures are network statistics. The measures indicate that there are wide differences in the size and structure of alliance networks across the industries. The first measure—nodes—is a count of all of the players implicated in the industry alliance network, while the second—industry firms—is a count of the firms in the network for whom that industry is their primary SIC. As shown, our networks range in size from a single industry firm engaged in a single alliance with a nonindustry firm (e.g., wood buildings and homes) to networks

with hundreds of industry firms engaged in alliances both within and beyond the industry. The next two measures, number of alliances per industry firm and alliance participation rate, both tap into the emphasis on alliance activity in the industry. The first is the average number of alliances individual industry firms engage in, measured as a direct count of the number of alliances engaged in by each industry firm, averaged over the industry. The second is a measure of the relative rate of participation in alliances by firms in the industry, measured as the number of industry firms engaged in alliances divided by the number of firms in that industry worldwide, as reported by Compustat Global.⁸ The average number of alliances ranges from a low of 1.00 to a high of 3.75 (engines and turbines), and participation ranges from a low of 0.05 to a high of 2.60 (for guided missiles, where more firms in the industry participate in alliances than there are publicly held firms in the industry).

Network centralization captures the degree to which some firms have many more alliances than others in the industry, scaled by the maximum value this measure can take on. It is measured as:

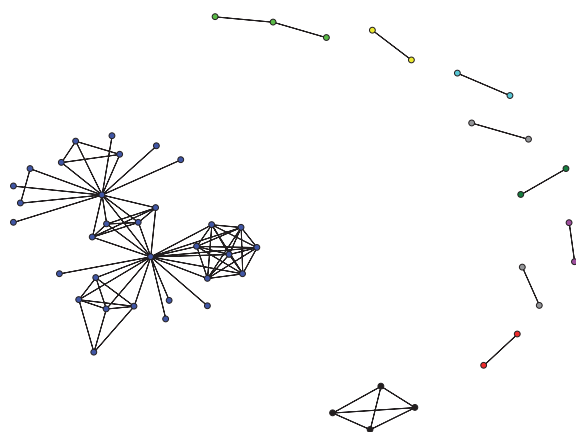
$$\frac{\sum (c_{\max} - c_i)}{\text{Max}(\sum (c_{\max} - c_i))}$$

where $c_{\max}$ is the maximum degree centrality of any node in the network, and c_i is the degree centrality of node i . This measure can take on a value of 0.00 (where all nodes have the same degree centrality) to 100 percent for a star graph where one node is connected to all the others nodes, but those nodes are connected only to the center of the star. In our networks, this measure ranges from 0.00 to values as high as 33.26 percent (for guided missiles) and 40 percent (for the logging industry). Both of these high centralization industries are depicted in Figure 1. The graphical visualization of the guided missile network is particularly exquisite, showing four large cliques connected by two main hubs (Lockheed Martin and Thales SA).

⁷In the survey, respondents were asked to nominate the 10 industries with either a) '... the highest concentration of architectural control among the firms in the industry. *Architectural control* refers to the ability of a firm(s) to define specifications for both the individual subsystems of a product as well as the integration of these subsystems to form the end product,' or b) '... the highest level of proprietary technological standards governing the products that characterize the industry. *Proprietary technological standards* refer to interface specifications that are company owned.'

⁸Since there is no definitive count of the number of private and public firms that compete in an industry worldwide, we divided the number of industry firms engaged in alliances by the number of publicly held firms in the industry worldwide as reported by Compustat Global. While the latter decidedly understates the size of the industry by counting only publicly held firms, it provides some scaling for industry size that at least enables us to get a sense of relative participation rates.

a) Guided missiles



b) Logging

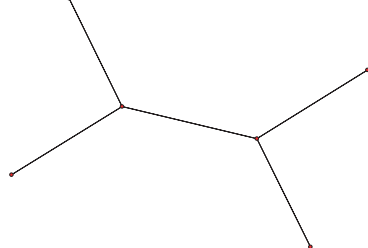


Figure 1. Highly centralized networks: guided missiles, logging

The next three measures pertain to small-world properties. The first, harmonic mean path length, measures path length in a disconnected network by scaling the infinite distances (those between nodes for which there exists no path) to the size of the network (Newman, 2000).⁹ The second, the weighted overall clustering coefficient, represents the percentage of a firm's alliance partners that are also partnered with each other, weighted by the number of each firm's partners, averaged across all firms in the network. The third, the small-world quotient, is a ratio of the weighted overall clustering

coefficient of the network over the clustering coefficient that would be expected in a random graph of similar size and degree, divided by the ratio of the harmonic path length of the network over the path length that would be expected in a random graph of similar size and degree:

$$\frac{\left(\frac{\text{Weighted overall clustering coefficient}_{\text{actual}}}{\text{Clustering coefficient}_{\text{random}}} \right)}{\left(\frac{\text{Harmonic path length}_{\text{actual}}}{\text{Path length}_{\text{random}}} \right)}$$

As shown, there is tremendous range on these measures across the industries, going from small-world quotients of 1.00 (e.g., footwear, logging) to 27.76 (electronic components). Finally, the last column gives the number of nodes in the largest component of the network. This ranges from two (for networks consisting only of disconnected dyads) to 248 (for pharmaceuticals).

Graphical visualizations of networks

Visual depictions of alliance network structure are relatively rare, as most researchers rely on reporting some summary statistics of their networks, or simply analyze the more microlevel alliance formations as described earlier. Some notable exceptions include Powell *et al.*'s (2005) 'network movie,' which shows the yearly evolution of the set of collaborations among multiple actors in the life sciences arena over a 12-year period, and Rosenkopf and Padula's (2007) four snapshots of alliance network structure in their study of networks in the mobile communications industry. The graphics in both studies are complex and fascinating, yet the very feature that enables the development of the graphics—that is, the intensive study of one industry—also leaves the reader wondering about the generalizability of the results. Do other industries demonstrate these same structures? Is the structure in Rosenkopf and Padula similar to or different than the one Powell *et al.* demonstrate? If so, how? Are the observable differences due to design choices on the part of each research team as they chose to portray their networks, or do they reflect more substantive differences? The only way to assess this effectively is through systematic comparative study of multiple networks.

To this end, nine network structures are displayed in Figure 2. The graphs are created by spring embedding the nodes based on their path lengths from one

⁹The length of the path connecting two nodes, A and B, is the minimum number of intermediate nodes that must be traversed in reaching A from B. If no path exists between a pair of nodes, the path length is said to be infinite. To accommodate the fact that many of the nodes in our networks have infinite path length, we calculate the harmonic path length by first inverting each distance between every pair of nodes, averaging all of these inverted distances, and then inverting this average. Because the inverse of infinity is well defined (zero), the harmonic mean path length provides a measure of the distance between nodes that scales for the number of pairs of nodes that are not connected by any path.

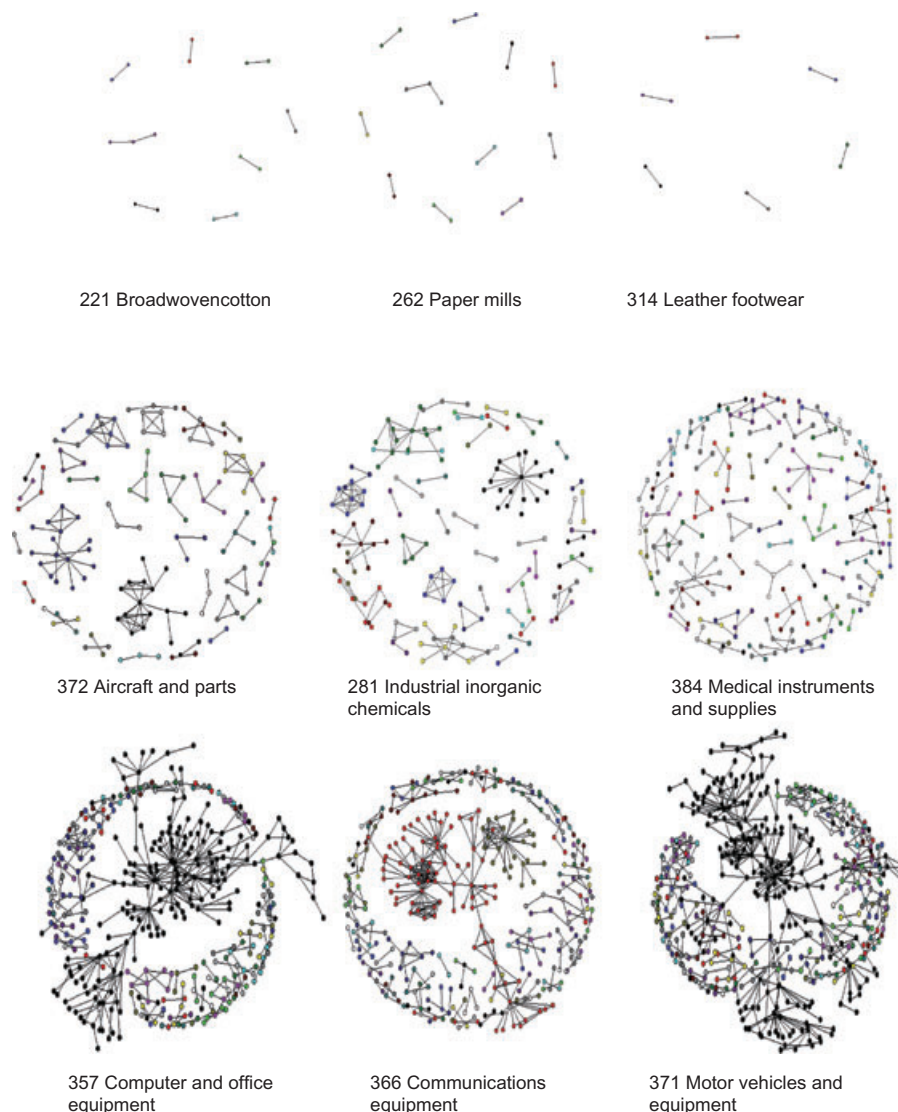


Figure 2. Nine industry alliance networks—graphical visualizations

another. This process brings nodes closer together that are directly connected or share a number of mutual connections, while pushing apart nodes that are not connected or are connected via a long path. Due to space constraints, this process often results in a ring (or crescent) of the dyadic pairs of nodes that are not connected to any other nodes, as is most obvious in the bottom row of networks (computers, communications, motor vehicles). The large spider-shaped webs in these networks represent single large components (sets of nodes that are connected to each other by a path).

Contrasts between the three rows are immediately apparent, and we label three network types

accordingly. The first row of networks (broadwoven cotton, paper mills, leather footwear) is characterized by small size (between 12 and 23 members) and very low connections among the nodes (average network degree between 1.00 and 1.06).¹⁰ Hence, we call networks of this type *disconnected*. In sharp contrast, the bottom row (computers, communications, motor vehicles) contains networks of

¹⁰ Average network degree is not shown in Table 1 due to space constraints. The number of alliances per industry firm differs from average network degree in that 1) it is constrained only to industry firms, and 2) it counts an alliance announcement only once irrespective of the number of parties to the alliance.

Table 2. A typology of alliance network structures

Type	Network size	Alliance intensity	Small-world statistic	Size of main component	Relative size of main component
Disconnected	Low	Low	Low	Low	Medium
Hybrid	Medium	Medium	Medium	Medium	Low
Spiderweb	High	High	High	High	High

large size (between 342 and 464 members) with a much higher level of connectivity among the nodes (average network degree between 2.26 and 2.50). This connectivity gives rise to an identifiable main component, and due to its shape, we call networks of this type *spiderwebs*. The middle row (aircraft, chemicals, medical instruments) contains networks of moderate size (between 143 and 222 members) with a moderate level of connection among the nodes (average network degree between 1.35 and 1.89). Here, no component dominates the graph, but many separate clusters of nodes are identifiable. We call networks of this type *hybrids*.

The small-world statistic appears to vary with the size and average degree of these network types. As size and average degree increase, so too does the small-world statistic (zero for all three disconnected networks, between 6.96 and 7.84 for hybrid networks, and between 14.53 and 22.74 for spiderweb networks). The sources of this variation in the small-world statistic, however, differ across the three types. For disconnected firms, there is no clustering. The zero-valued small-world statistic is generated by the zero-valued clustering coefficient. In contrast, the hybrid and disconnected networks exhibit higher, and largely indistinguishable, clustering coefficients (between 0.34 and 0.62 for hybrid networks and between 0.35 and 0.56 for spiderweb networks). Here, the source of the variation in the small-world statistic among these two network types is the harmonic path length, which obtains a range of moderate values (2.87 to 3.03) for spiderweb networks, but a range of high values (5.98 to 7.11) for hybrid networks.

One other topic of note with regard to these networks types and their differences pertains specifically to the main component. While the size of the main component appears to vary with the size of the network (between two and three for disconnected networks, nine and 18 for hybrid networks, and 82 and 203 for the spiderweb networks), once we control for the size of the network, the percent

of network nodes in the main component follows a different pattern. Specifically, the lowest relative size of the main component is found in the hybrid networks (ranging from four to 12 percent of nodes), while the disconnected networks obtain a moderate relative size (ranging from 13 to 18 percent of nodes). Not surprisingly, the spiderweb networks exhibit the highest relative size for the main component, ranging from 24 to 45 percent.

It is also worth noting that the network centralization does not separate as neatly among the three network categories as most of the other measures. Specifically, among these nine networks, centralization ranges from 0.0 to 6.7 percent for the disconnected networks; 5.5 to 11.19 percent for the spiderwebs, and 2.6 to 9.8 percent for the hybrids.

Table 2 summarizes the distinctions between the three types of networks along the dimensions we have examined. Though the typology relies on arbitrary distinctions between levels of connectivity to create categories, it provides intuition for us to visualize seemingly different networks. In the next section, we examine some industry characteristics that may determine these differences.

HOW DO TECHNOLOGY CHARACTERISTICS DETERMINE ALLIANCE NETWORK STRUCTURE?

Alliances enable firms to pool, exchange, and jointly create information and other resources (Eisenhardt and Schoonhoven, 1996; Gulati 1998), and, thus, are an important factor in technological innovation. Collaborating can enable a firm to obtain necessary skills or resources more quickly than developing them in-house. It is not unusual for a company to lack some of the complementary assets required to transform a body of technological knowledge into a commercial product. Given time, the company can develop such complementary assets internally. However, doing so extends cycle time. Instead, a company may be

able to gain rapid access to important complementary assets by entering into strategic alliances or licensing arrangements (Hamel, Doz, and Prahalad, 1989; Pisano, 1990; Shan, 1990; Venkatesan, 1992; Schilling and Steensma, 2001). Second, collaborating with partners can be an important source of learning for the firm. Close contact with other firms can facilitate both the transfer of knowledge between firms and the creation of new knowledge that individual firms could not have created alone (Baum, Calabrese, and Silverman, 2000; Liebeskind *et al.*, 1996; Mowery *et al.*, 1998; Rosenkopf and Almeida, 2003). By pooling their technological resources and capabilities, firms may be able to expand their knowledge bases, and do so more quickly than they could in absence of collaboration. Third, one of the primary reasons that firms collaborate on development project is to share the costs and risks of the project. This can be particularly important when a project is very expensive or its outcome is highly uncertain (Hagedoorn, Link, and Vonortas, 2000). Finally, firms may also collaborate on a development project when such collaboration would facilitate the creation of a shared standard. Collaboration at the development stage can be an important way of ensuring cooperation in the commercialization stage of a technology, and such cooperation may be crucial for technologies in which compatibility and complementary goods are important.

In this section, we examine three technology dimensions that we argue have a significant influence on the formation of alliances and, hence, the structure of the overall network. First, we consider how technological dynamism and uncertainty in an industry encourage firms to form alliances and, thus (other things being equal), may lead to more alliance activity overall. Second, we examine how the degree of separability of innovation activities (due to, for example, product modularity) enables coordination between firms via alliances rather than hierarchical integration. Third, we anticipate that the degree to which architectural control in an industry is governed by a small number of firms will significantly influence the structure of the overall alliance network. Each of these three dimensions is discussed in turn.

Technological dynamism and uncertainty

Rosenkopf and Tushman (1994) proposed that rates of interorganizational linkage formation are greatest during eras of technological ferment. When

technology is changing rapidly, firms may make greater use of alliances in their innovation activities. As mentioned previously, alliances can be an important mechanism for firms to obtain knowledge or other complementary assets more quickly than developing them in-house (Liebeskind *et al.*, 1996; Rosenkopf and Almeida, 2003; Schilling and Steensma, 2001; Shan, 1990; Venkatesan, 1992).

Furthermore, to the degree that firms are uncertain about the direction of technological change, alliances may become more attractive because they provide considerable flexibility compared to in-house integration of activities. The firm can choose between partners that differ in their competencies, increasing the firm's range of production options. Additionally, because alliances are often nonexclusive and temporary, the firm can change its mix of partners over time, both increasing the firm's flexibility and exposing its partners to some of the discipline of market incentives. Through an alliance, a firm can establish a limited stake in a venture while maintaining the flexibility to either increase the commitment at a later date or shift these resources to another opportunity (Kogut, 1991; McGrath, 1997). In essence, firms can use these modes as transitional governance forms and as a means to gain an early window on emerging opportunities that they may want to commit to more fully in the future (Mitchell and Singh, 1992). Finally, alliances enable firms to share the risk of a venture, which can be particularly important when a technology requires large-scale investment or faces a highly uncertain future.

All the arguments suggest that when the industry environment is characterized by dynamism and uncertainty, firms may be motivated to make greater use of alliances, leading to 1) a higher proportion of firms in the industry being actively engaged in alliances, and 2) a higher rate of alliance activity per firm. To explore the effects of technological dynamism and uncertainty, we examine both the rate of change of total factor productivity and the level of research and development intensity for each of our 32 industries. Five industries obtain high¹¹ levels of both rate of change of total factor productivity as well as level of R&D intensity. The convergence of these two different indicators suggests that these industries experienced significant technological

¹¹ For each measure, we divided our set of industries into tertiles: high, medium, and low. Thus, 10 industries were included in each of the high and low categories.

dynamism and uncertainty during the study period. These industries include: computer and office equipment, engines and turbines, household audio and video equipment, motor vehicles and equipment, and photographic equipment and supplies. Notably, the pharmaceuticals and communication equipment industries both had exceptionally high R&D intensities (13.77 percent and 13.52 percent, respectively), but both had experienced declines in total factor productivity over the 1997 to 2002 period.

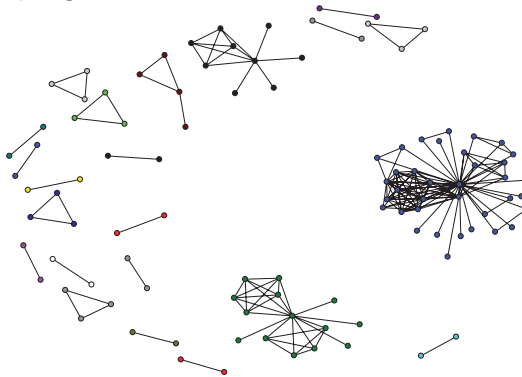
Consistent with the arguments we made earlier, all but one (photographic equipment and supplies) of the five industries that rank highly on both our measures of technological dynamism also obtain high levels of alliances per industry firm, and all but two (computer and office equipment and photographic equipment and supplies) obtain a high percent of industry firms that participate in alliances. Visual inspection of the networks for the engines and turbines, household audio and video equipment, and motor vehicles and equipment industries in Figure 3 shows that each exhibits a hybrid or spiderweb structure. On the other end of the spectrum, there were five industries in the low tertile for both measures of technological dynamism (hydraulic cement, leather footwear, fur, women's and children's outerwear, and wood buildings), and all except one of these (hydraulic cement) also scored in the lowest tertile for both alliance participation rates and number of alliances per industry firm. Visual representations of the leather footwear and the women's and children's outerwear industry networks are shown in Figure 4. These networks are clearly of the disconnected type.

As mentioned earlier, the pharmaceutical and communications equipment industries both had very high R&D intensity, but had negative changes in total factor productivity. As shown in Figure 5, both have very extensive alliance networks with spiderweb properties (indeed, the pharmaceutical industry has a significantly larger alliance network than any other industry we examined). The pharmaceutical industry makes the top tertile for alliance participation rate, but not number of alliances per industry firm, and the communications equipment network makes the top tertile for number of alliances per industry firm, but not for alliance participation rate.

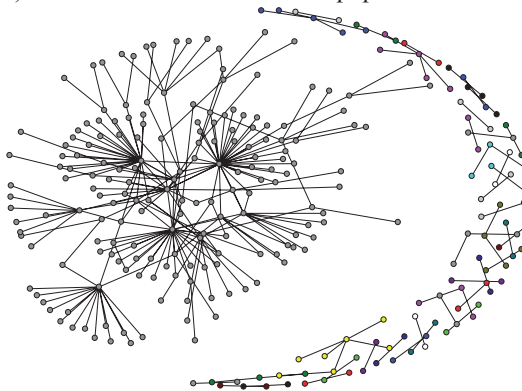
In sum, both theory and evidence suggest the following:

Proposition 1: Technological dynamism and uncertainty will be positively related to the

a) Engines and turbines



b) Household audio and video equipment



c) Motor vehicles and equipment

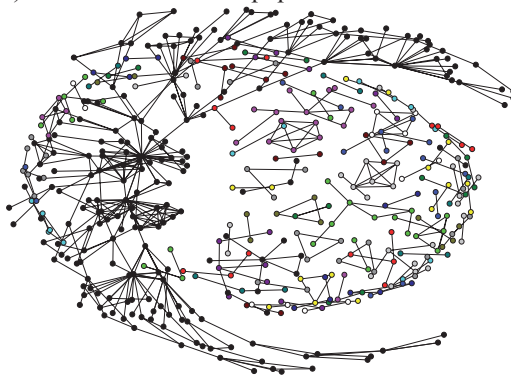


Figure 3. Industries ranking high for technological dynamism: engines and turbines, household audio and video equipment, motor vehicles and equipment

proportion of the firms in the industry that engage in alliances.

Proposition 2: Technological dynamism and uncertainty will be positively related to the average number of alliances formed by each firm in the network.

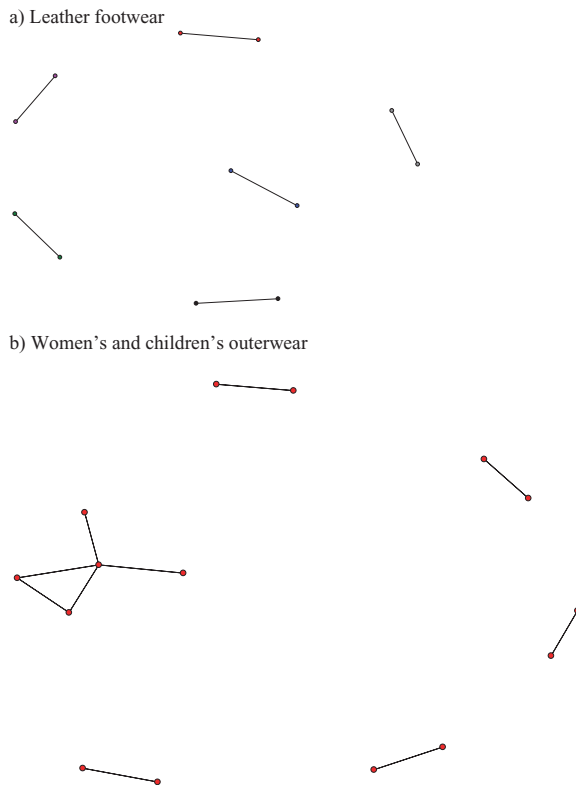


Figure 4. Industries ranking low for technological dynamism: leather footwear, women's and children's outerwear

Separability of innovation activities

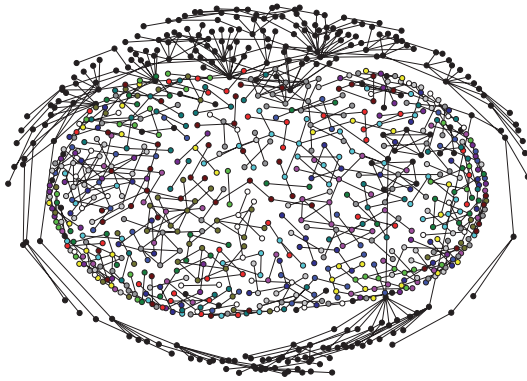
Whereas technological dynamism and uncertainty provide motivation for firms to pool their efforts and break down the complexity of a technological system into more manageable pieces, it is the separability of innovation activities that determines the ease or effectiveness of doing so (Baldwin and Clark, 2000; Schilling, 2000; Schilling, 2004). Tushman and Rosenkopf (1992) distinguished between assembled product systems and the less complex nonassembled ones, arguing that assembled systems engender more community activity. In some product systems, components may require such extensive interaction—and that interaction may be so directly influenced by the design or nature of that component—that any change in the component requires extensive compensating changes in the other components of the system, or functionality is lost (Sanchez

and Mahoney, 1996).¹² For such systems, it can be very difficult to separate innovation activities in a way that permits multiple firms to act in parallel. In other product systems, however, the components (or processes involved in the development of those components) are relatively independent—permitting either sequential stages or parallel activities to be performed by separate firms. For example, in a study of the development of the B-2 'Stealth' bomber, Argyres (1999) describes how four firms (Northrop, Boeing, Vaught, and General Electric) were able to use advanced information technology and a set of negotiated standards to increase the separability of the aircraft's design. As a result, each company was able to assume design responsibility for a different section of the aircraft and achieve coordination through a shared 'technical grammar,' rather than hierarchical control.

One of the key factors that can increase the separability of innovation activities is product modularity. Modularity is a continuum describing the degree to which a system's components may be separated and recombined (Schilling, 2000). It refers both to the tightness of coupling between components and the degree to which the rules of the system architecture enable (or prohibit) the mixing and matching of components (Baldwin and Clark, 2000). Since all systems are characterized by some degree of coupling (whether loose or tight) between their components, and very few systems have components that are completely inseparable and may not be recombined, almost all systems are, to some degree, modular. Some systems are, however, much more modular than others. For example, though personal computers were originally introduced as all-in-one packages (such as Intel's MCS-4, the Kenback-1, the Apple II, or the Commodore PET), they rapidly evolved into modular systems that enable the extensive mixing

¹²An excellent example of this may be seen in software systems. In many software systems, there are thousands of interdependent programs because of redundancies in the code, or because of shared data. Any design change results in a cascade of required changes in other programs, known as a 'ripple effect' (Fichman and Kemmerer, 1993). Because of this, many stakeholders in this industry are advocating the adoption of object-oriented programming, despite the major investment in new skills and new systems this will require for many firms. With object-oriented programming, software modules are designed to be encapsulated so that they do not require the sharing of data, and the range of their interdependencies with other modules is limited to those intended by the interface. Encapsulation allows information within the module to be hidden—modules can interact without requiring full knowledge of the contents of each module.

a) Pharmaceutical industry



b) Communications equipment industry

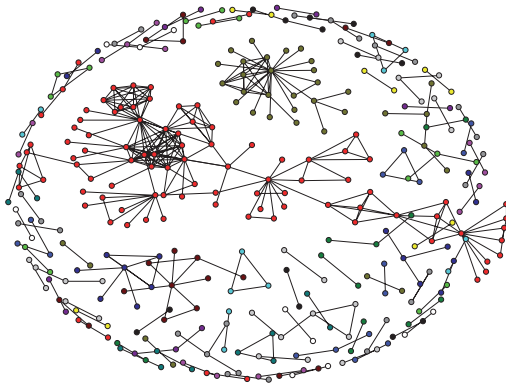


Figure 5. The pharmaceutical and communications equipment industries

and matching of components from different vendors. Standardized interfaces in both hardware and software enable many different producers to develop compatible components with relatively little coordination. In its extreme, modularity could lower the rate of alliance formation by eliminating the need for firms to interact at all (e.g., when compatibility can be achieved by conformance to a perfectly standardized nonproprietary interface), but it is far more typical for interfaces to be imperfect or to incorporate elements of proprietary control, requiring firms to engage in some form of negotiation and collaboration (such as licensing, standards consortiums, etc.).¹³

¹³Notably, the two industries in our study most commonly cited as examples of industries with strong network externalities—communications equipment and computers—exhibit low alliance participation rates, but high rates of alliances per firm. It is likely that modularity reduces the need for certain firms to participate in alliances.

Four of the five industries discussed in the previous section as ranking high on technological dynamism also exhibited high separability or modularity of the technology, as ranked by both sets of raters: computer and office equipment, household audio video equipment, motor vehicles and equipment, and engines and turbines. As observed previously, three of these industries (household audio video equipment, motor vehicles, and engines and turbines) demonstrate high levels for percent of industry firms that participate in alliances and number of alliances per industry firm. On the other extreme, of the 10 industries ranked lowest in terms of separability and modularity by both sets of raters, five were also ranked in the low tertile for either alliance participation rate or number of alliances per industry firm, though only one—paper mills—ranked in the bottom tertile for both. As previously shown in Figure 2, it exhibits a disconnected network with only a single triad.

Based on our theoretical discussion and anecdotal evidence, we expect that separability of innovation activities will be positively associated with both the proportion of firms in the industry that are engaged in alliance activities and the rate of alliance activity per firm.¹⁴

Proposition 3: Separability of innovation activities will be positively related to the proportion of the firms in the industry that engage in alliances.

Proposition 4: Separability of innovation activities will be positively related to the average number of alliances formed by each firm in the network.

Concentrated architectural control

Even in industries in which innovation activities are highly separable, the control over the architecture of the final system may be highly concentrated within the hands of a single (or few) firms. When an industry is characterized by such concentrated architectural control, this will have a significant influence over its

¹⁴Cowan, Jonard, and Zimmerman (2007) model the effect of *decomposability* on collaboration structure, suggesting that decomposability increases density and decreases structural holes. Of course, their modeling environment controls for network size, which has strong effects on these measures. In our case, with networks of varying size across industries, we examine the more basic measures of size (proportion) and degree (average alliances per firm).

alliance network structure. Tushman and Rosenkopf (1992) distinguished between 'closed' (geographically bounded) and 'open' (unbounded) assembled systems. Clearly, unbounded systems (such as telecommunications networks) require standardized interfaces to operate and grow effectively. The extent to which these unbounded systems are governed by open or proprietary standards will determine the concentration of architectural control. In general, concentrated architectural control will be more common in industries in which a dominant standard interface incorporates proprietary elements.

There is often considerable ambiguity in the extant literature about what is meant by 'open' versus proprietary systems, largely because various domains of management research use the term 'open' in different ways (Gacek and Arief, 2004). Proprietary systems are defined here as those based on technology that is company owned and protected through patents, secrecy, or other mechanisms. In the information systems literature, the term 'open standards' does not necessarily mean that the underlying technology is unprotected. For example, the Open Group standard-setting body defines open systems as computers and communications environments based on *de facto*¹⁵ and formal interface standards, but these standards may be proprietary in the sense that they were developed, introduced, and are maintained by vendors (Chau and Tam, 1997). The degree to which rivals or complementary goods producers can access, augment, or distribute a proprietary technology varies along a continuum in accordance with the degree of control imposed by the technology's developer. Anchoring the two ends of the continuum are wholly proprietary technologies, which are strictly protected and may be accessed, augmented, and distributed only by their developers, and wholly open technologies which may be freely accessed, augmented, and distributed by anyone. If a firm grants or sells the right to access, augment, or distribute its technology for commercial purposes, but retains some degree of control over the technology, this is termed a 'partially open' technology. Many technologies that are termed 'open' in common parlance are actually only partially open.

When a firm retains some proprietary control over a technology, it may be able to exert some degree of architectural control over the system in

which the technology is embedded (Schilling, 2000). As pointed out by Prybeck, Alvarez, and Gifford (1991), a firm that possesses proprietary control over an important component in a system can restrict market access by offering that component only as part of a total product system. If potential entrants to the industry must be able to provide an entire system (rather than just individual components), integrated systems may act as a significant barrier to entry and lower competitive intensity, particularly if one proprietary component of the integrated system is highly desired by customers and can be protected from compatibility with other providers' components. The firm can also control the rate at which the technology is upgraded or refined, the path it follows in its evolution, and its compatibility with previous generations. If the technology is chosen as a dominant design, the firm with architectural control over the technology can have great influence over the entire industry. Through selective compatibility, it can influence which other firms do well and which do not, and it can ensure that it has a number of different avenues from which to profit from the platform. The literature on increasing returns suggests that these dynamics will be accentuated in industries where there are strong forces encouraging the adoption of a single dominant design, such as in industries that exhibit network externalities (Arthur, 1994; Schilling, 1998).

Of course, platform leadership is but one form of architectural control. Concentrated control over product architecture is also found in industries where products are assembled into systems by what can be called *integrators*. So, for example, automobile and aircraft manufacturers assemble multiple subsystems to produce their products, and most of these subsystems are outsourced to specialized producers. These integrators control the overall design of the system, and subsystem producers must conform to the integrator's system requirements since the integrator controls access to the end users. For complex, capital-intensive products, the number of integrators is typically limited relative to the number of complementors, and the integrators' access to the end users creates a great deal of bargaining power for the integrators (Coff, 1999). Here, the integrators do not need to control or even master the subsystem technologies, yet they maintain bargaining power through design and control of the overall system architecture.

When one or a few firms have significant architectural control in an industry, they will tend to be

¹⁵ A *de facto* standard is defined similarly to a *dominant design*—it is the emergence of a standard through market selection.

engaged in a disproportionately high number of alliances in the industry, creating hubs that account for a significant portion of the network's overall connectivity. For example, in software, the dominance of Microsoft's Windows gives the firm immense influence over the design of software applications for personal computers. Makers of complementary software must work to ensure that their products are compatible with Windows, resulting in a large number of joint R&D alliances and licensing agreements between Microsoft and other software producers. Thus, Microsoft is a very large hub in the software industry.

Alliance networks tend to have skewed degree distributions because larger and more prestigious firms tend to attract and sustain a far greater number of alliances than smaller or less prestigious firms (Stuart, 1998). Both size and visibility tend to attract alliance partners, while size gives the larger firm greater resources with which to manage alliance relationships. Concentrated architectural control amplifies this effect, leading to networks with extremely skewed degree distributions.¹⁶

Notably, such hubs can also shorten a network's average path length. Hubs that are connected to many other nodes contract the network by providing a short path between all of the nodes to which they are connected. The extreme is a star graph, where a single node in the network connects every other node, leading to an average path length that will always be under two. Thus, we might expect industries with high architectural control to also exhibit strong small-world properties. This characteristic is of particular interest to many management researchers because the average path length of a network is often a crucial determinant of the

dynamics of the network. In networks in which information, power, disease, etc., diffuse, the length of the path determines how long transmission will take, the likelihood of the transmission being completed, and the degree to which whatever is being transmitted retains its integrity (Schilling and Phelps, 2007).

To explore these arguments in our data, we examine three industries that were rated high in architectural control: aircraft and parts, communications equipment, and motor vehicles and equipment. All three also exhibit exceptionally skewed degree distributions (see Figure 6). We used SPSS curve fit estimation to assess the relationship between degree and frequency and found that all three fit a power law function with R squares above .90 with significant scale-free degree exponents. In the aircraft industry, Boeing and Rolls-Royce plc played key hub roles. In the communications equipment industry, the key hubs were Alcatel SA, Oki Electric Industries, and Nokia. In the motor vehicles and equipment industry, Toyota was, by far, the largest hub, followed by Mitsubishi Corp.¹⁷ All three of these industries also ranked in the top 10 for small-world quotients (7.5, 14.53, and 22.74 respectively). In fact, of the 10 industries ranked highest in terms of architectural control, six (aircraft, pharmaceuticals, motor vehicles, communications equipment, medical instruments, and computer and office equipment) also make the top tertile for small-world quotient.

At the other extreme, of the 10 industries ranked lowest in terms of architectural control, most had very small networks with nearly uniform degree distributions (of degree one), and six made the lowest tertile for small-world quotients. For example, both footwear and broadwoven cotton fabric mills (pictured previously in Figure 2) fall into this category: both are rated very low for architectural control, have nearly uniform degree distributions whereby nearly every node has a degree of one, and exhibit small-world quotients of zero.

In sum, we propose the following:

Proposition 5: Industries with concentrated architectural control will have alliances with more highly skewed degree distributions than industries without concentrated architectural control.

¹⁶ Scale-free networks are a particular kind of highly centralized network with a skewed degree distribution. Specifically, a network is only considered to be scale free if the distribution of links across nodes follows a power law. There are, however, highly centralized networks that are not scale free in that the distribution of their links across nodes does not conform to a power law; it is even possible to have a highly centralized network with a uniform degree distribution. For example, consider a network wherein there are no redundant paths, and a single central node has four links to four other nodes, and each of those nodes has three links to three other nodes, and each of those nodes has three other links to three other nodes, and so forth. Such a network might represent a traditional organizational hierarchy, with the founder or CEO playing the role of the first node. In this network, the first node lies on the shortest path between many of the pairs of nodes in the network, giving this network high centralization even though every node in the network has the exact same number of links.

¹⁷ Notably, despite the fact that these industries exhibited scale-free degree distributions with large hubs, none scores high for overall network centralization, ostensibly because there are multiple hubs rather than a single hub.

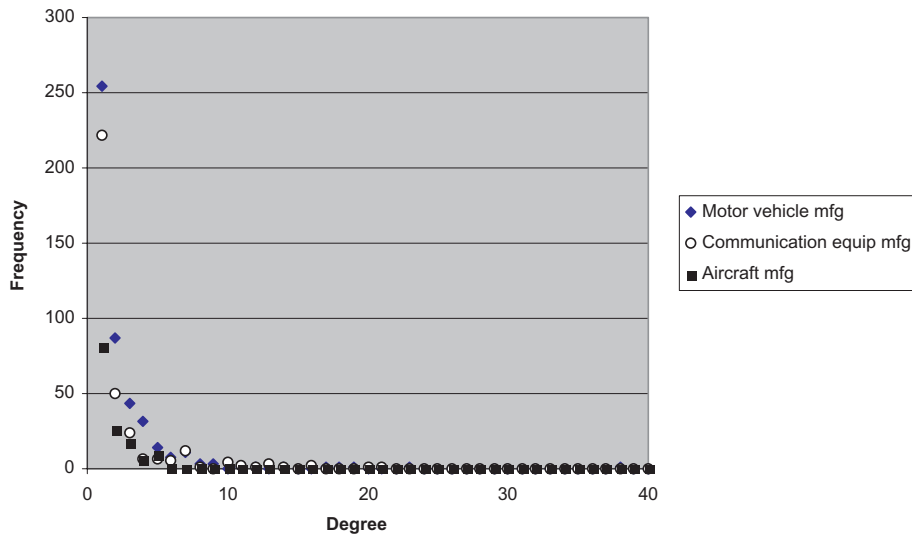


Figure 6. Degree distributions for the motor vehicles and equipment, communications equipment, and aircraft and parts industries

Proposition 6: Concentrated architectural control will tend to be associated with small-world properties.

DISCUSSION

Before we discuss any implications of our study, we must acknowledge two limitations. In order to create 32 networks systematically in a reasonable time frame, we made some design choices to keep the data collection demands manageable. First, each alliance network was generated from a three-digit SIC code and included firms located primarily within the SIC code, as well as their partners (who in many cases are located in a different primary SIC code). Thus, from a three-digit SIC perspective, many *cross-industry* alliances are included. Future research should examine whether our findings are robust when considering four-digit or even two-digit industry classifications, and future research should consider whether the relative breadth or narrowness of any particular SIC code may affect findings. Second, our network data is cross-sectional, in that only three years of alliance formations are included for each industry. Any imputation about network evolution can only be induced from the between-industry variation in our sample. An ideal study would include network snapshots at several times over the lifecycle of an industry.

These limitations notwithstanding, our work has demonstrated that there is substantial variance in alliance network structure across industries. Visually, notable contrasts are observable between spiderweb, disconnected, and hybrid types of network structures. Furthermore, we have suggested that several underlying technological characteristics of the industry, such as dynamism and uncertainty, separability, and architectural control can be usefully associated with these structures.

There are several implications of these findings, some of which are particular to strategic entrepreneurship, and others of which may be more broadly applied to the field of network studies. To begin, our research shows there are significant differences in the rate (and, presumably, importance) of alliance activity across the industry networks, and this leads to significant differences in the overall connectivity of the networks. If the recent extensive theorizing about the network acting as a medium for the exchange of information and other resources is correct, the network connectivity of an industry has important implications for the alliance strategies pursued by new entrants. For example, in industries that are disconnected, it may not matter that much whether or how new firms engage in alliances. By contrast, in industries we would characterize as having a large spiderweb network, there may be a significant difference between the amount of information and resource flow between firms that are

connected to the main component and those that are not. Thus, in these industries, it may be very important that new entrants attempt to forge alliances that connect them to this main component, and better still if they can forge alliances that help them achieve a more central position in this component. On the other hand, the size of these networks and the presence of large hubs tends to make these networks highly stable over time (Schilling, 2007), lessening the likelihood that a new entrant's alliance strategy will enable them to rapidly achieve a highly central position or significantly alter the alliance landscape. Thus, the entrant's efforts to connect to the main component act primarily as an 'admission ticket' (Powell *et al.*, 1996) to have access to roughly the same information that other participants have access to, helping them obtain competitive parity rather than conferring a superior position. In the networks we have labeled hybrids, where there are multiple significant clusters that are not connected to each other, a new entrant's alliance activity can take on even greater significance. For example, if a new entrant focuses their effort on striking alliances with partners from different clusters, the new entrant might be able to become a knowledge broker between formerly disconnected communities of firms, dramatically altering the alliance landscape (and concomitant information and resource flow) of the industry.

Future research should examine the entry strategies utilized by firms in various network structures, as well as analyze their success. For example, Ahuja and Polidoro (2003) examine both the contract terms and the subsequent alliances formed by firms initially entering the alliance network in the chemicals industry. Their preliminary results suggested that new entrants accept less attractive alliance deals, and that these new entrants are not able to parlay their initially low network status into more attractive network positions. Is such a finding generalizable to all high-tech industries, or is it limited to industries that are nonseparable, like chemicals? Examples of firms such as Electronic Arts—which accepted a highly unfavorable alliance with Nintendo only to parlay that into a much more attractive one with Sega later on—raise the possibility that certain network structures enable more movement than others, which must be addressed by future research. Similarly, Gawer and Cusumano (2002) have suggested that in industries with concentrated architectural control, three strategies exist: platform leaders, *wannabes*, and complementors. For new entrants in

these industries, are all three viable strategies or are they consigned to exploitable positions as in the chemicals industry?

At the industry level of analysis, which industries facilitate entrepreneurial entry, and how much of this can be associated with network structure? Do hybrid or spiderweb structures induce more entry? Rosenkopf and Padula (2007) find that new entrants to mobile telecommunications networks frequently enter via multiparty deals. Again, is this a generalizable finding, or specific to industries with strong standards?

Beyond implications of various network types for entry, it is also useful to consider how these types may be related to performance. Schilling and Phelps (2007) have considered effects of network structure across 11 different industries, finding that network structures that exhibit both high clustering and low average path lengths are associated with higher levels of firm and industry innovativeness. Of course, studies like these are susceptible to the endogeneity critique raised by Stuart and Sorenson elsewhere in this issue. Nonetheless, as our methods in these areas improve, it will become important to more fully understand the connections between industry performance, variance in firm-specific performance, and firm entry into these networks; most specifically, how these interrelated characteristics may look very different across the structural types.

Next, our industry-specific findings may indicate support for a weaker version of what has been called *network endogeneity* (Gulati and Gargiulo, 1999). A strict form of network endogeneity suggests that networks are inertial over time, because as network actors seek to form new alliances, they are enabled or constrained by their preexisting network positions. Others have critiqued this position because it does not provide an explanation for how nonnetwork members might join the network (Ahuja, 2000b; Rosenkopf *et al.*, 2001; Rosenkopf and Padula, 2007). To reconcile these opposing views, consider that the aggregate network structure of an industry may be inertial over time, even though different actors may enter or exit the particular network positions. Since our work highlights the technological characteristics of the industry as determinants of network structure, it supports the notion that network structures may be relatively fixed over extended periods of time, while allowing actors that are technologically advanced (or backward) to move through these alliance structures. Therefore, an extension of this research

can explore longitudinal variation in alliance participation as well as overall network structure.

Finally, our work raises some substantial concerns about the recent excitement about *small worlds* in the social network literature. Two characteristics of this literature merit attention. Small worlds are formally defined as networks that simultaneously exhibit low average path length and high clustering, and most researchers have focused on the main component of a network to assess these measures (though Schilling and Phelps (2007) represent a notable exception). Our networks make it clear that limiting analyses to the main component of a network is a risky endeavor, even for the higher connectivity networks. Additionally, it is theorized that small-world structures simultaneously offer social capital benefits due to clustering and also information transfer benefits stemming from low path length. Many alliance networks exhibit these statistical characteristics, yet the underlying network structures generating these characteristics can be quite different. For example, both centralized and decentralized networks can generate substantial small-world statistics. Yet, the Watts (1999) characterization of small worlds quite specifically requires that they also be decentralized—it is, after all, unsurprising to find that centralized networks have short path lengths. In fact, the shortest possible path length is achieved via a star graph whereby a single node connects all the others. Decentralization is also a key attribute to support the small-world theorizing about information flow, because the combination of decentralization and a short path length typically means that there are many routes for information to reach the same destination. In contrast, in a centralized network, a single (or few) node(s) may serve as the central connecting point between many nodes, and these central actors may have neither the capacity nor the motivation or economic interest in sharing information. So in the recent rush to classify many networks as small worlds based on the clustering/path length ratios and to generalize these findings to all industries, our data demonstrate that many alliance networks are quite centralized and, as such, may not offer the benefits that are theorized.

In summary, our focus on comparative network structure has allowed us to demonstrate a variety of network structures and speculate as to the determinants of this structure. With these issues established, it is our hope that researchers will continue to make strides assessing how strategic entrepreneurship can best occur in each of these specific network contexts.

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