

Network Positions and Propensities to Collaborate: An Investigation of Strategic Alliance Formation in a High-technology Industry

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The paper develops a network-based mapping of the technological positions of the firms in an industry and applies this model in a longitudinal study of the formation of alliances between organizations. In the analysis, the positions of high-technology firms in their competitive environment are stratified on two dimensions: crowding and prestige. Organizations in crowded positions are those that participate in technological segments in which many firms actively innovate, and prestigious firms are those with a track record of developing seminal inventions. The study's principal empirical findings are that firms in crowded positions and those with high prestige form alliances at the highest rates. The statistical analyses, performed on a sample of semiconductor firms during a six-year period, demonstrate that crowding and prestige predict alliance formations at the firm level (which organizations establish the greatest number of alliances) and at the dyad level (which particular pairs of firms choose to collaborate).*

To gain insight into corporate behavior and performance, organization theorists have begun to apply models of social structure to the analysis of economic markets. For example, White (1981) proposed a typology of markets as role structures, Burt (1992) studied the relationship between corporate profit margins and the positions of markets in networks of interindustry buyer-seller transactions, Podolny (1993) argued that status differences between firms affected producers' cost and price structures, and Davis and Greve (1997) demonstrated that firms' positions in director interlock networks patterned the diffusion of corporate governance practices. Although empirical applications in the sociology of markets have been diverse, the thread that draws together this body of work is the core contention that corporate behavior and performance are determined by the positions held by organizations in a broader, market-related context.

Researchers have used various types of recurrent relations between organizations to describe market structure, including director interlocks (Mizruchi, 1992) and economic exchange relations (Burt, 1992; Podolny, 1994). To better understand the strategies of organizations in a high-technology industry, this paper extends prevailing models of network structure to describe a relatively unexplored context: the technological structure of a market. The specific element of organizational conduct that I link to the locations of firms in this context is the proclivity to form strategic technology alliances. My objective is to demonstrate that the location of firms along dimensions of a market's structure influences firms' proclivity to enter strategic alliances, as well as the types of organizations with whom they establish relationships.

Strategic alliances—contractual asset pooling or resource exchange agreements between firms—have become a topic of considerable interest to scholars of organizations. Because alliances are now prevalent in many industries, and because they inherently challenge the notion that organizations are discretely bounded entities, researchers have labored to understand the antecedent conditions that lead to

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interfirm collaboration. Particularly in high-technology sectors, alliances appear to have become a routine strategic initiative. In addition to their pervasiveness and the questions that they pose for the location of organizational boundaries, empirical studies have now produced evidence that alliances affect corporate performance: they may contribute to firm growth (Powell, Koput, and Smith-Doerr, 1996), speed rates of innovation (Hagedoorn, 1993), forestall mortality (Mitchell and Singh, 1996), facilitate organizational learning (Hamel, 1991), and affect corporate reputations (Stuart, Hoang, and Hybels, 1999). Clearly, the accreting evidence of the instrumental significance of alliances underscores the importance of understanding the conditions under which they are formed.

Most of the work seeking to understand interfirm differences in propensities to establish alliances has asked, What motivates an organization to form an alliance? Oriented by this question, the literature has, with notable exceptions, developed and tested attribute-based explanations of the formation of interorganizational coalitions. According to this perspective, characteristics of organizations, such as their size or financial condition, predispose firms toward or against engaging in certain actions. In empirical work on strategic alliances, researchers have investigated whether a variety of firm attributes, including size, age, scope, and resource endowments affect firms' propensity to enter into alliances (Oliver, 1990; Barley, Freeman, and Hybels, 1992; Burgers, Hill, and Kim, 1993; Shan, Walker, and Kogut, 1994).

Rather than focus on organizational characteristics to predict alliance formation, I propose a positional explanation of the phenomenon, beginning with the premise that inherently interorganizational phenomena such as strategic alliances are driven in large part by the opportunities tied to a firm's position in its external environment (Burt, 1982; Mizruchi and Galaskiewicz, 1993). Accordingly, I orient the paper around the question, How does a producer's position in the market affect its propensity to enter into strategic coalitions? I follow this route because firms will enter alliances only when they possess exchange partners with whom they forecast a high probability of a strategically or financially beneficial collaboration, and the availability of such partners is very often the binding constraint on alliance formations. Particularly in light of the evidence that alliances are on balance beneficial to their participants, it is important to develop perspectives on their formation that recognize constraints on firms' ability to establish new coalitions.

TECHNOLOGICAL NETWORK POSITIONS AND ALLIANCE OPPORTUNITY SETS

Network theorists have previously investigated the structural antecedents of interfirm alliances. Scholars working within the "embeddedness" perspective associated with Granovetter (1985) have argued that an established network of interorganizational relationships is a resource that facilitates the establishment and governance of future alliances (Mizruchi and Galaskiewicz, 1993). One of the central ideas in this work is that social ties convey access to reliable, inexpensive information about the quality and trustworthiness of the

actors in a network (Burt, 1992). Either through shared third parties (Burt and Knez, 1995) or previous direct ties (Podolny, 1994; Gulati, 1995; Uzzi, 1997; Walker, Kogut, and Shan, 1997), information diffuses unevenly in an alliance or other type of network. In turn, access to first- or second-hand information about potential exchange partners reduces the costs of establishing new business associations, including the expense of searching for and screening potential associates. In empirical work on alliances in this tradition, the patterned diffusion of information about potential alliance partners through the existing intercorporate network is viewed as the mechanism that connects an established alliance network to the formation of new business associations (Gulati, 1995).

Instead of using the network of previously formed alliances as the derivative context that sparks the formation of new coalitions, I treat the technological structure of a market—a connected set of technological positions defined at the producer level—as the antecedent setting. I investigated, in particular, whether technological similarities and prestige distinctions among the firms in a focal industry affect horizontal alliance formations within that market. Hence, throughout the paper, I maintain the structuralist's emphasis on the ecological foundations of the relationship formation process, but in my analysis the exogenous context that drives the process consists of a set of interrelationships between the innovative activities of the organizations under study.

I develop this approach for two reasons. First, although theoretical discussions of embeddedness theory have been broadly concerned with how social and economic structures affect economic exchanges (Granovetter, 1985), empirical strategic alliance studies in this tradition have attended to the much more limited question of whether and how inter-organizational alliance networks, once formed, shape the establishment of relationships in future periods (e.g., Gulati, 1995; Powell, Koput, and Smith-Doerr, 1996). Because the causal motor in these studies has been the circumscribed diffusion of information through the network of prior cooperative activity, questions such as how newly founded organizations, new entrants into an industry, and firms that have not previously formed alliances gain first entry into the alliance network have been outside the purview of extant, empirical embeddedness studies. By contrast, because my focus is on technological positioning, prior alliance activity is not a prerequisite for collaboration in the empirical models I develop (although prior innovative activity is a precondition in my framework). The intention of the present analysis is neither to challenge the theory nor the evidence that prior alliance activity represents a significant basis for the development of new associations, but to argue that attention to the heterogeneities in the technological positions of producers can complement and extend existing work on embeddedness and further our understanding of alliance antecedents.

The second reason why I focus on technological positioning is simply because it influences whether, when, and to what extent firms have opportunities to establish beneficial strategic alliances. Because alliances are volitional relationships, a lack of access to a good set of willing exchange partners is a

limitation on many organizations' ability to put into place a productive cooperative strategy. The originators of intercorporate relationships are the factors that create opportunities for profitable associations, and the lack of these opportunities is the constraint on alliance entry. For this reason, I expect to discover that a meaningful proportion of the variance in formation rates can be attributed to factors that reflect the breadth of the set of collaborators available to a firm. Many of these factors relate to how a firm is situated in its market relative to other producers.

Technological Positioning: Crowding and Prestige

Two dimensions of technological positioning, *crowding* and *prestige*, underpin the paper's theoretical argument and the empirical models. Organizations occupy crowded technological positions when many other firms concentrate in their areas of technological specialty and so are undifferentiated from them. Technological crowding is therefore much like an organization-specific measure of competitor density (Baum and Singh, 1994; Podolny, Stuart, and Hannan, 1996): it reflects the degree to which the technological focus of a firm is shared by many other organizations. Crowding is both a property of organizations and of fine-grained market segments. When organizations occupy crowded positions, it is because many of the technological areas in which they participate are concurrently pursued by many competitors. For example, in the semiconductor industry, microprocessor and memory device technologies were areas of intensive innovative activity during the 1980s. As a result, the firms that worked in those two areas held crowded positions. In contrast, a smaller number of producers funded in-house gallium arsenide (GaAs) research and development programs, and even fewer specialized in developing ferroelectric thin film process technology. Hence, innovators in the areas of gallium arsenide and ferroelectric-processed chips encountered fewer direct competitors in their primary specialty than did microprocessor and memory chip producers.

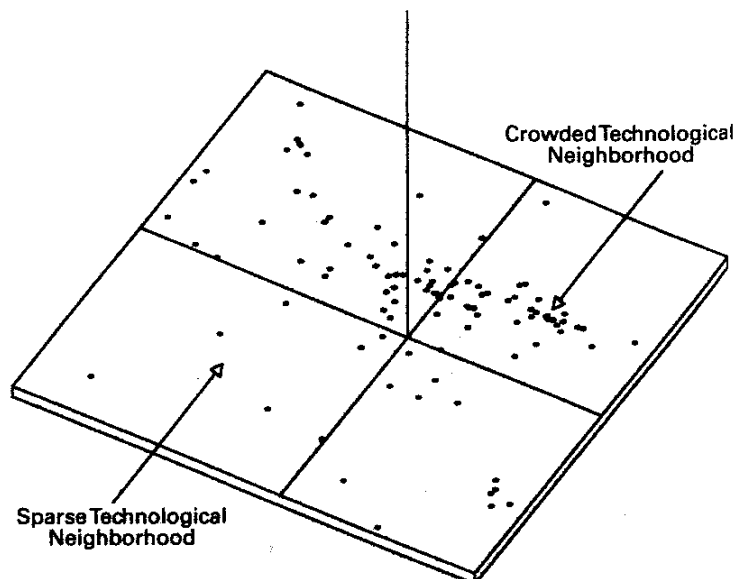
Actual differences in crowding among semiconductor firms are demonstrated in figure 1, which portrays the uneven population density of organizations across the regions of the two-dimensional technology space of the semiconductor industry in 1991. Each point in figure 1 corresponds to one semiconductor firm in my sample during the year 1991, and interpoint distances reflect technological distances between producers. The figure is the output of a multidimensional scaling (MDS) algorithm, which is a technique to generate a spatial image of the objects represented in a matrix of inter-object distances. The input for the MDS procedure was a firm-by-firm matrix of technological proximity scores (i.e., the elements in the matrix represented the overlap in innovative activities of all pairs of firms in the sample). Therefore, interpoint distances in the figure 1 spatial map are shortest for pairs of firms that had participated in similar technological areas. The purpose of the image is to convey the fact that the semiconductor firms in the sample for this study were irregularly dispersed across the technological landscape of the industry: a swarm of competitors converged around some organizations, while other firms were relatively distant from their nearest competitors. For example, the relatively

large areas of white space around the organizations in the vicinity of the "sparse neighborhood" in figure 1 participated in relatively unique combinations of technological segments, particularly when compared with the firms that were located in the region labeled as a "crowded neighborhood."

For three reasons, I expect that firms in crowded technological positions will form alliances more frequently than otherwise comparable organizations that make their living in relatively unpopulated areas of technology. First, distance between two firms in their technological foci can interfere with their ability to collaborate effectively. As a general rule, organizations are better able to evaluate and internalize the know-how of technologically similar firms. This is equivalent to asserting that limitations on absorptive capacity (Cohen and Levinthal, 1990)—the ability of organizations to assimilate new ideas and inventions from external sources—often hinders effective collaboration between technologically dissimilar firms.

Organization theorists often assume that standard operating procedures configured around a core production technology engender organizational inertia (Hannan and Freeman, 1984). In a related vein, the literature on organizational innovation emphasizes that firms that have built the routines and skills to innovate in specific technological areas are constrained in their ability to innovate in areas in which they lack prior experience (Nelson and Winter, 1982; March, 1988, Burgelman, 1994; Stuart and Podolny, 1996). Because an organization's routines and its base of development and production knowledge are contingent on its areas of technological focus, firms that work in similar niches tend over time to develop similarities in their operating protocols and knowledge foundations. The correspondence between technological focus and innovation skills affects alliance formation because firms that share an understanding of technologies and mar-

Figure 1. Dispersion of semiconductor firms in technology space in 1991.



ket segments are better equipped to exchange or jointly develop new technology (Cohen and Levinthal, 1990; Mowery, Oxley, and Silverman, 1998). The common stock of knowledge held by technologically similar firms both obviates the need for investments to understand and evaluate the technologies of alliance partners and facilitates the processes of transferring and integrating knowledge. For this reason, joint development work and technology exchange encounter fewer obstacles when they occur between organizations in the same technological neighborhood. It follows that firms in crowded areas of technology have many possible alliance partners.

While absorptive capacity considerations affect the feasibility of alliances, the fact that alliances can be forums for collusion and opportunities for knowledge and cost sharing affects which firms are most likely to benefit from them. Both for information exchange and cost sharing purposes, alliances may be most valuable when they are between firms that compete in a similar set of market niches. An ecological principle holds that when actors compete because they lack differentiation, they will enter into collusive arrangements "to limit, channel, or otherwise control the competitive relationship" (Hawley, 1986: 71; see also Laumann and Knoke, 1987: 220). Because unencumbered competition is often deleterious to the economic interests of competing firms, the benefits of alliances are often greatest when they open up collusive channels between directly competing firms. Moreover, because technology partnerships frequently entail personnel exchanges, they often kindle professional and social ties between staff members at different organizations, opening up long-lasting avenues for information exchange between two firms that may help to mitigate rivalrous interactions (Pfeffer and Leblebici, 1973).

Crowded technological areas are particularly fecund for inter-firm alliances because effort is continuously duplicated within them as undifferentiated firms independently invest in the development of related technologies. For example, in biotechnology it is common to find genomics firms racing to sequence the same gene. At each point in time, many of the firms in a technological area will be conducting R&D projects that are similar in objective to those being performed at one or more of their competitors. Because of this redundancy, alliances represent a means for firms in the same technological area to eliminate duplicative efforts by pooling capital and technical resources. In these circumstances, alliances may benefit participants by increasing the odds that the firms in a partnership will win the race or, because of complementarities in the knowledge assets of the two firms in a partnership, an alliance may improve the likelihood of an important discovery. Hence, the fact that technologically alike firms undertake similar R&D activities means that they may benefit from alliances in a way that fully differentiated firms cannot.

Finally, because they have an established presence in the technologies that represent one of the centers of activity in a market, other organizations may seek access to firms in technologically crowded positions for the purpose of functionally integrating, bundling, or otherwise associating their

products with one of a market's core products. Although absorptive capacity limitations may deter or waylay some of these "non-local" alliances, firms in crowded areas still may attract interest as potential alliance partners from organizations outside of their areas of concentration. For each of these reasons (duplication avoidance, collusion, absorptive capacity, and presence in the center of a market), firms in technologically crowded areas will have a large set of firms that foresee the possibility of productive collaboration with them. By the same reasoning, this interest is frequently reciprocated. I therefore predict:

Hypothesis 1: The greater the level of crowding of a firm's technological position, the higher the rate at which it will form technology development and/or exchange alliances.

The image of technological crowding is of a level field, but one through which innovative activity is irregularly dispersed. Most markets are characterized by the uneven spacing of producers across product niches, and crowding captures these differences at the organization level. In addition to exhibiting differences in crowding, high-technology firms are vertically stratified along a prestige axis. Firms accrue prestige in a process very much like the one in which scientists attain status. According to Merton (1973), scientists acquire status by producing research that opens up new scientific avenues, contributing work that becomes the foundation for many followers. Through a similar process, firms accrue technological prestige by developing path-breaking technological advances, defined as such because they become the foundation for imitation and elaboration by other firms. Hence, high-technology firms obtain prestige by forging new technological avenues and opening up possibilities for follow-on inventions (Podolny and Stuart, 1995). Moreover, just as every scientific specialty has a stratified prestige hierarchy, the firms in every industrial community may be characterized according to their position in a hierarchical ordering of status levels.

Technological prestige influences alliance formations because it affects the number of partners available to a firm and an organization's ability to secure favorable terms in alliance contract negotiations. Prestigious organizations are desirable associates because their strategic undertakings are focal points that draw the attention of external resource holders. Hence, potential customers and employees, the financial community, as well as the media and trade press are likely to become attentive to the initiatives of the affiliates of well-regarded firms. In this way, attention is directed and status is conveyed through interorganizational associations. Because an association with a prestigious actor may enhance the level of attention paid to a firm's endeavors, network and institutional theorists subscribe to the view that an economic actor's performance in its marketplace is affected by the status levels of its close associates (Baum and Oliver, 1991; Podolny, 1994; Stuart, Hoang, and Hybels, 1999). As a result, a firm's reputation and its ability to mobilize resources are likely to improve when it formalizes an alliance with a high-prestige partner.

The reputational consequences of strategic alliances are particularly important in high-technology industries, which are

contexts noted for pervasive uncertainty (Tushman and Rosenkopf, 1992). Because there is always considerable uncertainty surrounding the technical and commercial future of new innovations, firms that have well-known affiliates enjoy a significant advantage in contests for the recognition and acceptance of their products and processes (Rao, 1994; Podolny and Stuart, 1995; Stuart, Hoang, and Hybels, 1999). The reason for this is that high-prestige organizations have previously sponsored successful innovational paths; therefore, outside evaluators take into account the status of an innovation's sponsor to inform their estimates of the innovation's chances for market acceptance. These ideas were recently illustrated in an alliance between chipmaker Advanced Micro Devices (AMD) and IBM. AMD received an important boost when IBM, a high-status computer and semiconductor producer, decided to source the K6 microprocessor from AMD for use in one of its PC lines. Describing IBM's decision, a *Wall Street Journal* (1997) article stated:

IBM said it will use AMD's new K6 MMX chips in some future models IBM, the world's No. 2 PC maker, is by far AMD's most prestigious customer for the product. Analysts said the deal was just what investors had been hoping for, vindicating AMD's promises that a major PC company would become a K6 user. The news sent AMD's shares up \$5, or 13% James Firestone, general manager of IBM's consumer business, said [IBM] conducted exhaustive testing to make sure that the K6 met its standards for quality, reliability, and compatibility.

Even though supply alliances such as the IBM-AMD deal are often episodic, IBM's decision to source from AMD was an endorsement because of the extensive quality testing that predated IBM's commitment to the deal. Because it is routine to perform a thorough evaluation before entering into a cooperative venture, a technology alliance with a prestigious organization is a public certification of another firm's products or quality by a well-regarded enterprise.

The previous argument explains the certification advantages of alliances with prestigious enterprises; however, because alliances are discretionary relationships, it is important to consider whether this interest is likely to be reciprocated. From the perspective of a high-prestige firm, the inducements to form an alliance are likely to depend on the status of a potential alliance partner. When two high-prestige firms agree to form an alliance, the benefits of partnership include considerable publicity and consumer interest when the alliance is announced and when it reaches important milestones, even surpassing that which would accrue to the solo strategic initiatives of a high-prestige firm. In contrast, when alliances are between organizations that occupy significantly different statuses in the prestige hierarchy, the low-prestige member is likely to need to proffer generous financial terms and/or access to promising development-stage technologies to entice a high-status firm into an exchange relation. The recent IBM-AMD supply agreement illustrates this point; the *WSJ* article cited above went on to note, "Analysts were unsure of the financial effect on AMD, since it may have offered IBM unusually attractive financial terms that could reduce its profit margins on the K6." Clearly, IBM understood the value of its endorsement to AMD and therefore insisted

on favorable transaction terms before committing to the agreement.

More generally, when there is an asymmetry in the statuses of potential alliance partners, the high-prestige firm's interest in a venture is likely to stem from the fact that its superior bargaining position enables it to secure favorable contract terms. The fact that prestige is partially transferable in the context of interorganization exchange relations and that sponsorship and reputations are important in high-technology markets suggests that significant value can be created in alliances involving high-prestige, high-technology firms. As the holder of one of the valuable resource in alliance transactions, high-prestige firms are enticed into strategic coalitions because they are able to retain a large share of the value created in the partnership. The general hypothesis is that prestigious enterprises have the greatest number of opportunities to establish collaborative relations under terms that appeal to them:

Hypothesis 2: The greater the level of a firm's technological prestige, the higher the rate at which it will form technology development and/or exchange alliances.

The first two hypotheses are agnostic about the shape of the relationships between crowding and prestige and the propensity to form strategic alliances. Relevant to the form of these relationships is the fact that many considerations limit the number of alliances that a firm will choose to form within a fixed interval. The size of an organization held constant, adding collaborators beyond a certain point may result in a dilution of focus as an organization's development efforts become thinly spread across many different projects. Coupled with the fact that firms will prioritize their alliance opportunities so as to pursue the best ones first, this suggests that there may be diminishing benefits to forming additional coalitions within a fixed time interval. Moreover, negotiating alliance terms and resolving conflicts with partners can require a significant amount of executive time (Harrigan, 1985). Because upper management time is at a premium, there is a carrying capacity on the number of cooperative ventures that can be negotiated and managed within a period of time. Furthermore, with each increase in the number of coalitions formed by a firm, the potential for conflicts of interest multiplies. Since information and technical know-how are exchanged in technology alliances, some organizations will choose not to partner with a firm that is tied to other organizations that they wish to keep at a distance. This reluctance stems from the concern that proprietary knowledge will be leaked to third parties through a common node.¹ Because of these factors, I hypothesize:

Hypothesis 3: Increases in the level of technological crowding will increase the formation of technology development and/or exchange alliances at a decreasing rate.

Hypothesis 4: Increases in the level of technological prestige will increase the formation of technology development and/or exchange alliances at a decreasing rate.

Crowding and prestige may also interact to affect alliance establishment. High-prestige firms are accomplished innovators, whose public recognition derives from their track records of developing important inventions. They have well-

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When Firm 1 establishes a partnership with Firm 2, it simultaneously enters into two-step connections with all of Firm 2's current alliance partners and with the organizations that Firm 2 takes on as partners during the course of its relationship with Firm 1. Naturally, the converse is true as well: by dint of an alliance, Firm 2 would be two steps away from each of Firm 1's collaborators. As a result, the potential for extensive leakage of proprietary know-how is a deterrent to collaborations with firms that have many ongoing strategic partnerships.

developed, in-house technical capabilities that partially extricate them from the absorptive capacity constraints that would otherwise limit their choice set of technology alliance partners to firms with similar innovation profiles. A high-prestige firm's extensive stock of technical know-how derived from prior, successful technology development programs enables it to evaluate and assimilate ideas and inventions even when they are outside of the domains in which the firm has previously worked. The implication of this is that crowding may be a stronger driver of the alliance formation rate among firms that lack technological prestige: low-status firms, because they are less likely to possess the skills to work productively with collaborators from outside of their proximate technological vicinity, are more dependent on their neighbors in technology space as potential collaborators. In contrast, because high-prestige firms have greater absorptive capacity, they are more likely to search beyond the areas of their existing technological foci when considering candidates for technology development alliances. Therefore, the size of the local technological neighborhood will have less of an effect on the alliance formation rate of high-prestige than of low-status firms:

Hypothesis 5: The higher the level of a firm's technological prestige, the lower the effect of crowding on the rate at which it will form technology development and/or exchange alliances.

The above hypotheses have been framed at the firm level, but they could be recast as predictions about the relationships between the technological positions of two firms and the likelihood of alliances between them. For ease of exposition, I have formulated the hypotheses at the firm level rather than at both levels of analysis, but in the methods and results sections I do introduce and discuss findings from tests of a series of analogous hypotheses formulated at the dyad level. Performing the analyses at both levels of analysis not only strengthens confidence in the findings, it also clarifies the mechanisms that lie behind the observed effects.

METHOD

Sample

To test these hypotheses, I compiled a database that documents the alliance histories of a large sample of semiconductor (SC) firms. The SC industry is a suitable context for testing the hypotheses for two reasons. First, it consists of a heterogeneous population of firms that vary in size, scope, age, and innovation strategy. Second, because there have been many alliances in the industry, it offers ample variation for testing the hypotheses. All firms for which annual semiconductor sales were available during the analysis period (1986–1992) were included in the sample. This sampling criterion was imposed because SC sales is a critical control variable in the statistical models. Dataquest, a consulting and information services firm, supplied the revenue data. The Dataquest database was supplemented with sales figures from the Integrated Circuit Engineering Corp.'s annual reports. In total, there were 150 companies in the sample, although some were not present for all years. Two-thirds of the firms in the sample had headquarters in the U.S.; the remainder were divided between Europe, Japan, and other

Southeast Asian nations. As a group, the firms in the sample accounted for 90 percent of the total, worldwide SC production volume in 1991. The sample consists of the firms with the largest sales volume in the industry. Dataquest tracked all merchant SC firms with annual sales in excess of \$10 million. After a firm reached \$10 million in sales, Dataquest continued to track that firm even if its sales dropped below \$10 million in a subsequent year.

Strategic technology alliances between semiconductor firms. I limited the empirical analyses reported here to the rate of formation of horizontal, reciprocal technology alliances. To conform to this definition, an alliance must have satisfied two criteria: both of the firms in the agreement must have been SC producers, and the deal must have been to exchange or develop technology. Therefore, the dependent variable excluded all vertical partnerships, such as those between a microelectronics firm and a manufacturer of semiconductor production equipment. The analyses also excluded alliances solely focused on vertical links in the semiconductor value chain, such as marketing agreements. These screens were imposed to exclude coalitions that were likely to be of minor strategic significance or those that were motivated by considerations unrelated to technological positioning.

I also excluded all one-way technology licensing alliances, for two reasons. First, product licenses were often granted by SC firms attempting to promulgate a technical standard. Because of the importance of compatibility among users of certain types of semiconductor devices, such as microprocessors and telecommunications chips, licensing strategies in some segments of the industry were closely tied to firms' efforts to establish their devices as standards (Wade, 1995). Second, a norm in the industry has been for manufacturers to license "second sources" to produce their proprietary chips. This practice developed very early in the industry's history when customers insisted on second sources to insure a reliable supply of a device and to promote price competition between manufacturers (Tilton, 1971). For both reasons, license agreements were excluded to reduce the noise in the data.

After the imposition of these restrictions, the coalitions in the data were joint product development agreements, joint ventures, and technology exchanges. All of the alliances in the database were reported in public sources, primarily the *Predicasts* indexes, articles in *Lexis/Nexis*, *Infotrak*, *Electronic News*, *Electronic Buyer's News*, *Electronic Engineering Times*, *Electronics*, *Electronic Business*, as well as company SEC filings. Table 1 presents brief descriptions of eight randomly selected alliances to provide a feel for the data.

Measures and Analysis

Researchers have studied the interorganizational relationship formation process at two different levels of analysis: the dyad and the firm. Some scholars have treated the dyad as the unit of analysis, assuming that each pair of organizations in a sample or population is at risk of forming a tie (e.g., Lincoln, 1984; Mizruchi, 1989; Podolny, 1994; Gulati, 1995). Dyad models are designed to answer questions about how

Table 1

Sample Alliances*

Firm 1	Firm 2	Date	Agreement description
Synergy Semi	Toshiba	01/1991	Joint research on high-speed ECL chips (ultra-fast ASICs)
Philips-Signetics	Fujitsu	06/1990	Share manufacturing and design technology for LAN chip sets
Sony	AMD	04/1987	Jointly develop 64K and 256K SRAM (memory) chips
Oki Electric	Catalyst Semi	07/1986	Jointly develop non-volatile memories (CMOS EPROM and EEPROM chips)
Texas Instruments	Hitachi	12/1988	Jointly develop 16 MB DRAM (memory) chips
AT&T	Mitsubishi	10/1991	Jointly develop, manufacture, and market gallium arsenide ICs
NEC	AT&T	03/1990	Exchange design technology for gate arrays and ASICs
WaferScale	National Semi	06/1990	Jointly develop high-speed, high-density EEPROM devices

* Firm and deal order are random. Date is the time of first announcement of the alliance. Descriptions are based on accounts appearing in the popular press.

relationships between a pair of actors affect the chance that the pair's members will form a relationship of a different type, in this case a dyadic alliance. Other alliance studies have treated the organization as the unit of analysis and so have modeled the rate at which the organizations in a sample formed new relations (e.g., Kogut, Shan, and Walker, 1992; Powell, Koput, and Smith-Doerr, 1996). Firm-level models address the propensity of organizations to form relationships, without taking into account the identities of their affiliates.

The formation of interorganizational relationships is influenced by both firm and dyadic factors. In a network of actors, the probability of a relationship between the two nodes i and j is a function of nodal properties (characteristics of actors i and j) and dyadic properties (direct and indirect characteristics of the relationship between i and j). In any particular network, it is a matter for empirical resolution how the variance in the relationship formation process is split between nodal attributes and dyadic relationships. The implication for this study is that some proportion of the variance in the technology alliance formation process can be attributed to firm characteristics measured either as internal organizational attributes or as properties of a firm's position in its market, and some of the variance to relationships between particular pairs of firms, such as the extent to which two organizations participate in the same niches in a market.

Because I have framed the hypotheses in terms of firm propensities, I emphasize analyses at the corresponding level of analysis, but I also report and discuss the findings of a dyad analysis. The dyad-level analyses help to clarify the mechanisms that drive the empirical results, particularly those that relate to the crowding variable and the crowding-by-prestige interaction. For instance, one of the reasons that crowding is expected to increase alliance formations is that there are incentives for firms jointly involved in the same technological

areas to form alliances to eliminate duplicative R&D investments and to manage an assumed competitive relationship. The implication of this is that pairs of firms that have directly overlapping innovative activities should be more inclined to establish a collaborative relation than otherwise comparable dyads of non-overlapping firms. Hence, the arguments that I have made suggest that firms in crowded positions will form more alliances, but also that their partners will be technologically similar firms. If high technological overlap does not increase the odds of an alliance between two firms, then the mechanisms that I have posited cannot explain alliance formation even if results show that technological crowding accelerates the rate of alliance establishment at the firm level. Thus, the dyad-level models afford a more precise test of the crowding-related hypotheses.

Modeling firm-level alliance formations. I have operationalized the dependent variable in the firm-level models as a count of the number of technology alliances formed by each organization in the sample during each year in the observation window. Hence, the data are a panel of observations on organization-years. I report random effects Poisson models incorporating a robust variance estimator. Poisson regression assumes that the event count is drawn from the single parameter Poisson distribution, which can be expressed as:

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!} \quad (1)$$

where the parameter λ_{it} represents the mean and the variance of the event count. It is assumed that $\ln \lambda_{it} = \beta'x_{it}$ (the relationship between the rate and the independent variables is log linear).

The random effects estimator differs from the usual Poisson because it allows the error terms across firm-years to be correlated. The model assumes a within-firm correlation matrix R with elements equal to one on the main diagonal and to ρ off of the diagonal. I estimated equation (1) utilizing the White/Huber robust estimator of variance. The robust estimator yields consistent standard errors even when the residuals across firms are not identically distributed or the correlation within firms is not as hypothesized by the random effects model.

Poisson regression rests on the assumption that the mean and variance of the event count are equivalent (Hausman, Hall, and Griliches, 1984). Because this assumption is often violated, I also estimated the alliance formation models with two different methods to verify that the results are not sensitive to the assumptions of the estimator. First, I fit negative binomial models to the firm-level data set because they do not assume equivalence between the mean and variance of the event count (but unfortunately they do not incorporate a within-firm correlation structure). Second, I estimated the hazard of alliance formation using continuous time event history analysis. This method assumes that alliances are repeatable events and that all firms are at risk of forming an alliance during the period in which they are observed.² The discussion of the results notes the few instances in which there were discrepancies in the findings between the three estimators.

2

Parametric hazard rate models require an assumption about the form of duration dependence. I estimated piecewise exponential models (using a split spell structure to update time-changing covariates) because this parameterization allows the rate of alliance formation to vary in an unconstrained manner across a number of different time periods (Blossfeld and Rohwer, 1995). A reviewer for this paper preferred Poisson regression to the event history models because the exact dates on which alliances were formed were not known for more than 20 percent of the alliances (in these instances, only the year was known). The hazard rate analysis required the random assignment of dates when I knew only the year in which an agreement was reached.

Modeling alliances in organizational dyads. To estimate the dyad models, I first created annual, symmetric firm-by-firm alliance matrices, in which the ij th cell in each of the matrices was a 1 if there was an alliance in the ij th pair of firms in the year t . I then constructed a vector consisting of all of the cells in one triangle of each of the annual matrices and pooled these vectors across years to arrive at the dependent variable for the dyad analysis. The dependent variable is therefore an indicator denoting the presence ($= 1$) or absence ($= 0$) of an alliance in each dyad-year.

Implicit in full-network dyad models is the assumption that a focal actor has some probability of partnering with any of the other actors in a network (the number of firms in my data varies by year from 137 to 144). For example, there were 137 firms in the sample during 1991, so by the assumption of the model, each firm had the potential to partner with any of its 136 alters. Therefore, the number of dyads in 1991 was the number of unordered pairs in the sample, 9,316 [$N*(N - 1)/2 : 137*136/2$]. Of these, the firms in 97 pairs formed an alliance and so were coded 1.

To estimate the dyad models, I used a random effects probit regression with a robust variance estimator (in the panel probit model, the random effects estimator allows error terms across dyad-years to be correlated). Formally, the model is:

$$\Pr(Y_{ij,t2} = 1) = \Phi(\alpha + \beta'X_{ij,t1} + u_{ij}) \quad (2)$$

where $\Pr(Y_{ij,t2} = 1)$ is the probability of an alliance between firms i and j at time $t2$; Φ represents the Gaussian cumulative distribution; $X_{ij,t1}$ is a matrix of time-changing independent variables that represent attributes of each dyad (for example, the combined sales of the firms in the dyad); u_{ij} are unobserved, time constant effects not captured by the other independent variables; and α and β are coefficients to be estimated. All covariates describe a dyad and are lagged by one year. The interpretation of the coefficients in the dyad model are as effects on the probability of an alliance between two firms.

I estimated a number of variants of equation (2) to show that the findings are not sensitive to the assumed risk set or the method. First, instead of assuming that all possible dyads in the sample were at risk of forming an alliance, I defined the risk set (the observations that were included in the analyzed data matrix) to include only dyad-years in which both firms possessed at least one patent. The reason for this was that firms without a record of proprietary innovation may have been much less likely to form technology development alliances. Including firms without patents could substantially inflate the number of observations (potential dyads) with pairs of firms that were highly unlikely to form an alliance. After removing the no-patent dyads, the number of observations in the data set fell by 50 percent, but the number of alliances fell by only 14 percent (i.e., 86 percent of the observed alliances were among pairs of firms in which both members of the coalition held semiconductor patents). Excluding no-patent firms substantially reduced the number of organizational pairs in the model but did not change the results.

Second, one concern with dyad models is that the observations within each cross section may be interdependent because each actor in the network appears in multiple dyads, creating a common-actor effect (Lincoln, 1984). Network autocorrelation is similar to unobserved heterogeneity in panel data: if all firm-level attributes that influence alliance formation are included in the model, no unmeasured effects of common firms would remain. One strategy for addressing the non-independence issue is therefore to include dummy variables denoting each of the firms in the network (Mizuchi, 1989, 1992). Much like a fixed effects model, this procedure is performed by including firm dummy variables in the covariate matrix. For each dyad-year, the dummy variables corresponding to the two firms in the dyad are coded as 1 and all other firm dummies are coded as 0. I found that the coefficients on the variables of interest remained significant in models that included firm dummy variables.

Third, in one of the reported dyad models, I included the autoregression control variable advocated by Lincoln (1984). To remedy the problem of network autocorrelation, Lincoln suggested that dyad models should contain a variable that is defined for the ij th dyad as the mean of the dependent variable across all dyads that included either firm i or j in the current year t , excluding the ij th dyad. The rationale for this variable is that it captures within-year nodal effects (firm effects) that are not otherwise included in the model. Therefore, the autoregression variable is an additional unobserved heterogeneity control. This variable serves to clean the coefficients on the other explanatory variable of the propensities of the two firms in a dyad to form alliances within each time period.

Independent variables: Patent-based measures of technological positioning. The hypotheses require measures of technological crowding and prestige. To compute these variables, I drew on prior work that conceives of a technological arena as a network. Following Podolny and Stuart (1995), nodes in this network are the inventions of organizations, and ties are the technological commonalities that connect consequent inventions to the antecedents upon which they build (therefore, I refer to these ties as "technological building relations"). The advantage of representing a technological area as a network is that it enables one to use generalized expressions of the crowding around and prestige of an actor's position to operationalize the constructs needed for this analysis. Because technological crowding and prestige are properties of firms' locations in a network of inventions, I refer to them as positional variables. Moreover, because the raw data from which both measures are derived consist of a network of ties that cross organizational boundaries, crowding and prestige are ecological properties: they are defined by how the activities of one firm relate to the activities of other organizations.

The data to construct the technological network for the microelectronics industry were all semiconductor inventions that have been patented in the U.S. I used domestic patents

because the U.S. is the world's largest technology marketplace, and it has become routine for non-U.S.-based firms to patent in the U.S. (Albert et al., 1991). To acquire a patent, an inventor must submit to the U.S. Patent Office an application that describes a non-obvious and industrially useful invention. A legal requirement to obtain a patent is that applicants must generate a list of citations to all previously granted patents that made technological claims similar to those claimed in their applications. This process is supervised by patent examiners, who maintain the integrity of the citation process by verifying that the list of references included in each patent application is complete before a patent can be issued. The function of the citation requirement is to establish the scope of the patent under evaluation: inventors can only claim patent rights to the unique aspects of their inventions. To establish uniqueness, each application must identify how the proposed invention extends on all patented technological precursors. For this reason, patent citations have been likened to markers in intellectual property space: they delineate technological adjacency relations between inventions (Jaffe, Trajtenberg, and Henderson, 1993). In the technological network that I have constructed to represent the semiconductor industry, patents are nodes, and patent citations are the ties that delineate technological links between the nodes.

Patent citation data have been used in social science research for at least two purposes. First, scholars in the applied technology and the economics literature have used citation counts to measure the importance of inventions. Studies have shown that highly cited patents are inventions perceived by experts in a technological area to have been the most important inventions in that area (Albert et al., 1991). Because patent citations manifest technological similarities between inventions, the second use of citation data has been to identify the firms that have been developing similar technologies (Jaffe, Trajtenberg, and Henderson, 1993).

U.S. semiconductor patents. I collected all U.S. semiconductor patents for the analysis. First, I identified approximately 2,400 distinct patent classes that contain semiconductor product, device, and design inventions. I retrieved the 50,000 patents in these classes from the 1993 Micropatent CD series, which included all U.S. patents issued between 1975 and 1993 (details of the procedure and the list of 2400 classes are reported in Stuart, 1995). For the 150 firms in the sample, I constructed detailed family trees, using the *Directory of Corporate Affiliations*. These corporate ownership relations were used to assign subsidiaries' patents to their corporate parents.

Technological crowding: Structural equivalence in a patent network. To compute the two firm-level measures of technological positioning, I first configured the patent data in a binary, patent-to-patent citation matrix. Cells in the citation matrix were a 1 when the column patent cited a previously issued row patent. To compute technological crowding at the level of the firm, I began with an operational definition of the technological proximity of two patents. I assumed that two patents were technologically similar to the degree that

they were structurally equivalent in the patent citation network. As defined by Lorrain and White (1971), two nodes in a network are structurally equivalent when they have identical ties to the same third nodes. Applying this definition to the citation network, two patents are structurally equivalent when they cite the same antecedent inventions. Because a patent citation denotes the fact that a consequent invention has built upon an antecedent patent, structurally equivalent patents represent technically similar inventions. Therefore, when a patent has many structural equivalents, it is in a crowded region of the patent network.

With this definition in hand, the next step was to aggregate up to the level of the organizational pair. I represented each organization in the citation network as the set of all U.S. patents that were assigned to it. Small semiconductor firms, such as Cyrix, possessed only a handful of patents during the analysis period; large innovators, such as Texas Instruments, had developed hundreds of patented semiconductor inventions. Moving from the patent-level to the firm-level, I assumed that the technological overlap of two firms was an average of the overlaps of the patents in their portfolios. Specifically, two organizations occupied overlapping technological positions when their patent portfolios cited the same antecedent patents (i.e., when the two firms were structurally equivalent in the citation network). Following Stuart and Podolny (1996), a measure of the degree to which a firm j crowds the position of a focal firm i during a period t , denoted α_{ijt} , is:

$$\alpha_{ijt} = \frac{\sum_p C_{ipt} C_{jpt}}{\sum_p C_{ipt}} \quad (3)$$

where p indexes all existing semiconductor patents, $C_{i,jp}$ was coded as 1 if the patents of firm i, j included a citation to an existing patent, p , and it was coded as 0 otherwise. Hence, a unit was added to the numerator of equation (3) every time that a patent that firm i cited was also cited by firm j . The denominator is just the total number of patent citations made by firm i 's patent portfolio. The interpretation of α_{ijt} is therefore the proportion of firm i cites that were also made by j .

Finally, to move from the level of overlap between a focal firm and each of its alters to the overall technological crowding of a firm's position, I summed the dyadic overlap scores over all firms in the industry. The overall crowding of firm i 's position at period t , denoted A_{it} , is

$$A_{it} = \sum_j \alpha_{ijt} \quad i \neq j, \quad (4)$$

To compute technological crowding scores, a decision rule was needed for how to update the variable through time: crowding may change if a firm alters its areas of focus or if other firms enter and exit its niche. The prior year was too short an interval to describe an organization's technological crowding at time period t ; to do so would be to assume that firms' technological foci are renewed annually. By the same

logic, it would be inaccurate to compute the measure on the basis of old patents; to do so would be to ignore the fact that firms' technological foci do change. Therefore, I used a five-year, moving window to compute technological crowding. I chose five years because this was the approximate length of the product life cycle in the semiconductor industry. From equations (3) and (4), the technological overlap coefficients (the α_{ijt}) and the composite crowding scores (A_{it}) were computed from all patent activity during the previous five years, $t-5$ to $t-1$.³ To insure that the findings were not an artifact of the time window, I reestimated all models with crowding defined over three- and seven-year moving windows. The duration of the time window had little bearing on the results.

The composite technological crowding score, A_{it} , was included in the firm-level models to test hypothesis 1, that firms in crowded technological positions form alliances at high rates. In the dyad models, the crowding hypothesis had to be recast in terms of how the relationship between two firms' technological activities affected the probability of an alliance between them. In these models, I looked directly at whether two firms that were structurally equivalent in the patent citation network were more likely to form an alliance than were two firms that were embedded in non-overlapping areas of the network. This test is an important addition to the firm-level analysis, because if absorptive capacity constraints favor technologically localized alliances (coalitions between firms in the same technological vicinity) or if alliances are frequently established to combine what otherwise would be competing R&D programs, as I have argued, then I should find that firms with structurally equivalent technological positions (measured as the sum of the asymmetric alpha coefficients for the two firms in a dyad, $\alpha_{jit} + \alpha_{jit}$) were more likely to form an alliance.⁴

Technological prestige: Indegrees in a patent network.

Knoke and Burt (1983) stated that an actor is prominent to the degree that its network position makes it visible to other actors, and it is prestigious when it is the object of relationships from other actors in a network of directed ties. Among the many measures of prestige, the most parsimonious is an actor's indegree or choice status. Indegree is a count of the number of relations directed to a focal actor. Adopting this intuition to the patent citation network, a prestigious innovator would be a firm with a patent portfolio that is highly cited by other innovators (Podolny and Stuart, 1995). Because patent citations reflect technological building relationships, highly cited patents are those that have served as important building blocks. Just as highly cited papers enhance the prestige of a scientist, I assumed that highly cited patents created prestige for their developers. Accordingly, I defined the technological prestige of a semiconductor firm as:

$$D_{it} = \frac{\sum_j C_{jit}}{L_t} \quad i \neq j, \tag{5}$$

where D_{it} denotes the prestige of firm i at time t , C_{jit} was coded as 1 when a patent of firm j cited a patent of firm i during the interval t , and L_t was the total number of patent

3

To provide a sense for the numbers of patents and citations involved in computing the technological crowding measure, the median patent cited four previously issued patents in the database, and the mean patent cited 4.5 previously issued patents. Hence, there was some skew in the citation distribution, although the majority of patents cited between 3 and 8 antecedents. As an example of the numbers of patents held by the firms in the database, the mean firm in the year 1990 possessed 114 patents with an application date between 1985 and 1989 (the window for computing crowding in 1990). Given a mean of 4.5 citations per patent, the mean firm made 513 citations during the five-year window. Hence, the denominator for the mean firm in equation (2) was 513.

4

Because the alliances that I studied were treated as symmetrical relationships (I modeled unordered firm pairs) and because distance is also a symmetrical property (the distance that separates firm i from firm j is the distance that separates j from i), I tested the crowding hypothesis with a symmetrical measure of dyadic technological overlap. In the models that I report, I summed the asymmetric alpha coefficients from equation (3) to derive a measure of dyadic technological overlap. The alternative was to define dyadic overlap as the proportion: [(Number of patents cited both by firms i and j) ÷ (Number of patents cited by firm i + Number of patents cited by firm j)]. Or, formally expressed using the notation defined in equation (3):

$$\alpha_{ijt} \equiv \alpha_{jit} = \frac{\sum_p C_{ipt} C_{jpt}}{\sum_p C_{ipt} + C_{jpt}}$$

The results from using this measure are nearly identical to those using the sum of the alpha coefficients.

citations accruing to all semiconductor firms during the interval t . Thus, a firm's prestige score at t was the proportion of all patent citations made during the interval t that were to patents assigned to that firm.⁵ The restriction $i \neq j$ was imposed so that patent self-citations did not contribute to a firm's prestige level. The denominator was included in equation (5) to adjust for changes in the total volume of citations accruing to the sampled firms over time. Because of the adjustment, the variable is a proportion that has a time-invariant interpretation. Following the rationale outlined in the discussion of the measure of technological crowding, D_{it} was computed over five-year, moving windows. For example, Intel's prestige in 1991 was the number of patent citations that it received from all patents with application dates between 1986 and 1990, divided by the total number of patent citations received by all firms in the sample during the same time interval. The models were also estimated with prestige computed over three- and seven-year windows. Again, the length of the time window had little bearing on the results, except as noted below.

The second hypothesis predicted that prestigious firms would form alliances at the highest rate. To test this, the variable D_{it} was included in the firm-level alliance formation models with the expectation of a positive effect on the rate. In the dyad models, I operationalized the second hypothesis by including the prestige level of the most prestigious of the two firms in the dyad.⁶

Control variables. The models control for a number of organizational attributes that prior research has singled out as factors that affect alliance formation propensities. All control variables were constructed as one-year lags. Firm size, measured as annual semiconductor sales, was added to all models. Because they have more employees, larger firms may have wider-reaching industry contacts, leading to more extensive personnel networks and greater knowledge of alliance opportunities (Eisenhardt and Schoonhoven, 1996). Moreover, size may also influence the appeal of an organization as an alliance partner—larger firms have greater market coverage and so convey access to a substantial segment of the industry's customer base. The models also included the age of firms' semiconductor operations, measured as the time since initial entry into semiconductors, for diversified firms, and as the time since founding, for dedicated semiconductor producers. Given the pace of technological change in the industry, older firms are likely to view alliances as a means to access new technological developments.

Some of the firm-level models included controls for accounting measures of slack resources and financial performance. While a number of recent studies have found no effects of accounting measures of performance on alliance formations, the SC industry is one in which major new R&D projects require vast resource outlays. Therefore, financially constrained or poorly performing firms may have formed alliances because they required access to the capital resources of other firms to finance major development projects. As a measure of slack, I used the debt-to-debt-plus-equity ratio. Firms with high ratios were assumed to face greater cash constraints. I also included return on assets (ROA) as a performance mea-

5

Another class of prestige indices are eigenvector measures, which allow the influence of a cite on a focal firm's prestige to depend on the prestige of the citing firm (Bonacich, 1987). In other words, the contribution to firm i 's prestige of a cite from firm j is weighted by the level of j 's prestige. For a network of firms, it is possible to compute weighted prestige scores by solving a simple linear equation system. For the patent network, the correlation between firms' prestige measured as indegrees (equation 3) and Bonacich's (1987) weighted prestige measure was .93. In light of the high correlation between the two, I opted to employ the former measure. Results were comparable using both measures.

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The assumption behind this specification is that the likelihood of an alliance in a dyad is higher when at least one of the two firms has high prestige because the gains from association are greater when a high-status actor is involved. In the dyad models, it is possible to test for whether prestige asymmetries between the two firms in a dyad affect the likelihood of an alliance. Podolny (1994) and others have argued that high-status firms favor alters of similar status in their selection of exchange partners—a preference that would lead to status homophily in exchange relations. For the reasons previously discussed, I believe that in high-technology industries there are many situations in which an alliance between status-asymmetric firms will benefit both organizations. I do not test for the effect of prestige asymmetries on the likelihood of an alliance because I do not have strong prior expectations for the direction of the effect (see note 7, below).

Alliance Formation

sure. Because financial statements were only available for publicly traded U.S. companies, all private and non-U.S.-based firms had to be excluded from the models that included these control variables.

Because some of the firms in the sample were privately held, I included an indicator variable coded as 1 if a firm was publicly owned. In high-technology industries, alliances may be an alternative to both internal and external capital markets as a method of raising funds for technology development purposes. Therefore, publicly traded firms may be less inclined to enter alliances.

A number of the firms in the sample did not possess any patents. Based on the formulae for operationalizing crowding and prestige, firms without patents will have realizations of 0 on both variables. Rather than exclude these firms (24 percent of the organization-years in the sample), their records were identified with a "no-patent" dummy variable until the time at which they secured one or more patents. To insure that the results were not driven by the no-patent firms, I also performed the analysis on a subsample that included only firms with patents.

A number of studies have reported increases in alliance formations during the 1980s (see Hagedoorn, 1993). The trend in the semiconductor alliance data was not linear, and the number of alliances established by sample members did not fluctuate dramatically during the years of this analysis. Still, the formation of cooperative ventures may have depended on industrywide economic conditions. Therefore, I controlled for environmental factors that varied over time but were constant across firms by including annual, calendar-year dummy variables.

Finally, the models included an endogenous occurrence dependence variable, operationalized as the total number of alliances that each organization had formed during the previous five years. Including the number of times that an event being modeled has occurred in the past is one way to control for unobserved heterogeneity in event models (Heckman and Borjas, 1980). The first five years of the alliance data, 1982 to 1986, were only used to construct occurrence dependence variable for the first year of the analysis, 1987.

RESULTS

Table 2 reports the 15 firms with the greatest number of semiconductor alliances. For each firm, the table reports the average number of alliances per year and the organization's rank in the industry's prestige hierarchy. Although all but 36 of the 150 firms in the sample formed at least one technology development alliance during the analysis period, the firms in table 1 were involved in almost 50 percent of the alliances in these data and averaged slightly more than five coalitions per year, compared with the average of .71 alliances per year formed by the 135 firms in the sample that do not appear in table 2. From the table, it is apparent that there was a core set of central firms in the semiconductor industry's strategic alliance network. Moreover, this set was high in technological prestige: 9 of the 10 highest prestige firms in the industry appear in table 2, and all of the firms in

the table ranked in the top quintile of the prestige distribution. The identities of the central players in the industry's alliance network show that forming coalitions was not a strategy chiefly used by weak firms: the organizations in table 2 were among the largest and most innovative of those in the industry.⁷

Table 3 reports means and a correlation matrix for the variables in the models, while table 4 reports the estimates from the random effects Poisson regressions of the firm-level alliance rate. Because the models are multiplicative, I discuss the partial effect of a variable as a multiplier rate. The baseline model (1) in table 4 contains only the vector of control variables. The results show that firms that had no patents were significantly less likely to form technology alliances than those with patents. Publicly traded firms and older firms exhibited higher alliance rates, but neither variable reached the 5-percent significance level. The coefficient on firm size is also positive, but the effect is not significant. The lagged alliance count is a positive and significant predictor of the alliance rate.

Model 2, which adds to the baseline model the technological crowding variable, supports hypothesis 1: the parameter estimate for technological crowding is significantly positive, showing that increases in crowding multiplied the rate of alliance formation. According to the parameter estimate, a one standard deviation increase in crowding multiplied the rate by a factor of 1.22 ($= \exp^{.1318 \times 1.46}$). In unreported models, I included the crowding variable computed using three- and seven-year moving windows (instead of the five-year window); in both cases, the effect of crowding remained positive and significant.

Table 2

Fifteen Firms with the Most Alliances*

Firm	Alliances per year (average)	Prestige rank
Texas Instruments	9	4
Motorola	8	5
Intel	7	7
Fujitsu	6	6
AT&T	6	8
Philips	6	12
National Semi	6	15
Hewlett Packard	6	22
IBM	5	1
Hitachi	5	2
Siemens	5	13
AMD	5	16
Thomson	4	14
NEC	4	9
Mitsubishi	4	10
Firms 16-50	1.8	
Firms 51-100	.60	
Firms 101-150	.05	

* Total of 1,088 alliances. Prestige ranks are based on the status ordering of firms during the last year of the data (1992). Rank 1 (IBM) was the highest prestige firm in the sample, and so on down. The lowest prestige firm in the sample held a rank of 141. Alliances per year indicates the average number of alliances formed by firms during each year in the data.

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Although I do not delve into these patterns in this paper, the alliance data contain many ties between two central firms and many associations between one central and one peripheral firm when the center is defined to include the 25 firms that were highest in technological prestige. In other words, there were many alliances between two high-prestige firms and many alliances between one high- and one low-prestige firm, but few coalitions between two low-prestige firms.

Table 3

Means, Standard Deviations, and Correlations for Variables in Firm-level Models (830 firm-years)

Variable	Mean	Sigma	1	2	3	4	5	6	7	8	9	10	11
1. Firm is public	.809	.392	-										
2. Firm has no patents	.243	.429	-.16	-									
3. Lagged alliance count	5.90	1.01	.21	-.27	-								
4. Firm age	18.32	12.84	.36	-.18	.43	-							
5. Firm sales (\$M)	33.0	725.0	.10	-.17	.72	.28	-						
6. Tech. crowding (A_{it})	1.721	1.461	.14	-.59	.34	.15	.16	-					
7. Tech. prestige \times 1000 (D_{it})	5.922	14.22	.14	-.15	.58	.38	.69	.12	-				
8. Return on assets	.0377	.125	NA	-.11	-.01	.01	.04	.03	.04	-			
9. Debt-to-(debt + equity)	.167	.249	NA	.27	-.20	-.11	-.10	-.22	-.11	-.29	-		
10. Crowding-squared	5.921	6.377	.09	-.45	.24	.00	.07	.89	.01	.05	-.06	-	
11. Prestige-squared \times 1000	237.2	1046	.07	-.07	.19	.15	.64	.02	.89	.02	-.02	-.03	-
12. Prestige-by-crowding	.015	.034	.16	-.16	.45	.37	.78	.14	.87	.03	-.12	.03	.86

Model 3 adds the technological prestige variable to the model with crowding and the controls. The positive, statistically significant parameter estimate on this variable supports the second hypothesis: high levels of technological prestige increased the alliance formation rate. According to the model 3 estimates, a one standard deviation increase in prestige multiplied the alliance formation rate by a factor of 1.25. In unreported models, prestige had a similar effect when the variable was computed using a three- and a seven-year window.

Hypotheses 3 and 4 predicted that prestige and crowding would have nonlinear effects on organizations' alliance formation rates. In particular, the argument that firms will experience diminishing benefits from alliances on the margin implies that the alliance formation rate will increase at a decreasing rate with upward changes in crowding and prestige. To test these ideas, models 4 and 5 in table 4 added quadratic terms for the technological crowding (model 4) and prestige (model 5) variables. Apparently consistent with the hypotheses, the quadratic terms are negative in the two models. According to the model 4 estimates, the crowding multiplier reaches a maximum at a value just shy of the highest value of the variable observed in these data. In contrast, the prestige effect is approximately linear within the observed range of the variable, and the prestige multiplier does not reach a maximum until the variable exceeds by three times its highest observed value. Additionally, the quadratic prestige term was negative but insignificant when I estimated negative binomial and hazard rate models with the model 5 covariate vector. Thus, the evidence for a nonlinear prestige effect is weak.

The final hypothesis predicted that, because high-prestige firms have the knowledge stock required to work outside of their areas of past specialization, a given level of crowding would have a stronger effect on the alliance formation rates of low-prestige firms. This hypothesis was tested with an interaction variable between crowding and prestige. Model 6 in table 4 includes the interaction variable and shows support for the fourth hypothesis. The crowding-by-prestige interaction is negative and significant, demonstrating that the magnitude of the crowding effect was stronger for firms with low prestige. To illustrate the interaction, suppose that

Table 4

Maximum Likelihood, Random Effects Poisson Estimates of Firm-level Technology Alliance Formation Rate*

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)†	(8)	(9)‡	(10)§
Constant	-.8594** (.3034)	-1.016** (.2747)	-1.071** (.2766)	-1.319** (.2506)	-1.120** (.2571)	-1.087** (.2231)	-5052* (.2435)	-1.054** (.3040)	-8812** (.2637)	-3227 (.3701)
Firm is public	.5421* (.3011)	.4800* (.2868)	.4778* (.2801)	.4889* (.2774)	.5079* (.2964)	.4951* (.2824)	.2688 (.2469)	.9602** (.3399)	.3576 (.3028)	-
Firm has no patents	-.3545** (.1807)	-.2237 (.1804)	-.2261 (.1861)	-.2213 (.1812)	-.2413 (.1931)	-.2613 (.1996)	-.3729** (.1756)	-	-	-.4537* (.2452)
Lagged alliance count	.0406** (.0071)	.0402** (.0067)	.0391** (.0071)	.0398** (.0064)	.0361** (.0073)	.0418** (.0071)	.0421** (.0053)	-	.0388** (.0068)	.0541** (.0119)
Firm age	.0115 (.0070)	.0110 (.0071)	.0085 (.0071)	.0020 (.0055)	.0020 (.0060)	.0062 (.0060)	.0080 (.0067)	-	.0084 (.0072)	-.0060 (.0083)
Firm sales (\$M)	.0001 (.00007)	.0001 (.00006)	.0005 (.00007)	.0004 (.00008)	.0002 (.00008)	.0002 (.00005)	.0009 (.00008)	-	.0002 (.00008)	-.0002 (.00012)
Technological crowding (A_{it})	-	.1318** (.0524)	.1313** (.0527)	.4537** (.1003)	.1501** (.0512)	.1405** (.0526)	.1210** (.0593)	-	.1131** (.0489)	.1746** (.0831)
Technological-crowding-squared	-	-	-	-.0592** (.0115)	-	-	-	-	-	-
Technological prestige (D_{it})	-	-	15.32** (4.073)	14.33** (3.494)	32.78** (10.69)	42.02** (12.95)	7.328* (4.434)	32.77** (4.768)	13.55** (4.001)	18.43** (4.692)
Technological prestige-squared	-	-	-	-	-210.8* (125.3)	-	-	-	-	-
Prestige-by-crowding	-	-	-	-	-	-12.16** (5.818)	-	-	-	-
Debt-to-debt+equity ratio	-	-	-	-	-	-	-	-	-	-.0609 (.2878)
Return on assets	-	-	-	-	-	-	-	-	-	-.0488 (.0544)
N (total organization-years)	830	830	830	830	830	830	830	830	627	318
Total number of organizations	150	150	150	150	150	150	150	150	141	63
Average number of years per firm	5.53	5.53	5.53	5.53	5.53	5.53	5.53	5.53	4.45	5.05
Pearson chi square	1305.11	127.93	1233.67	1238.13	1224.93	122.27	1492.66	2248.38	994.47	421.70

* $p < .10$; ** $p < .05$.

† Robust standard errors in parentheses. All models include unreported calendar year effects.

‡ In model 7, the dependent variable includes license alliances in addition to development alliances.

§ In model 9, firm-years with no patents are excluded (therefore, the no-patent dummy is omitted).

¶ In model 10, all privately held firm-years are excluded (therefore, the public dummy is omitted).

there is a firm at the mean level of crowding (1.72) and at zero prestige. The effect of crowding on this organization would be to multiply the alliance formation rate by a factor of 1.27 ($= \exp^{.1405 \cdot 1.72 - 12.17 \cdot 1.72 \cdot 0}$). Suppose now that a second organization, is also at the mean level of crowding (1.72) but, unlike the first firm, it possesses the mean level of prestige (.0059). The effect of crowding on this organization would be to multiply the alliance formation rate by a smaller factor of 1.13 ($= \exp^{.1405 \cdot 1.71 - 12.17 \cdot 1.72 \cdot .0059}$).⁸ Therefore, crowding had the strongest effect on the alliance formation rates of low-prestige firms.

The four remaining models in the table are reported to show that the crowding and prestige effects are extremely robust. First, the dependent variable in model 7 is a count of the total number of technology alliances, including both license and development/exchange alliances (license alliances are added to the dependent variable). Both crowding and prestige remain significant predictors of the alliance rate, although prestige drops to the 10-percent significance level (two-way test). Second, because there are two bivariate correlations near .70 and nontrivial correlations between sales, age, prestige, the no-patent dummy, and the lagged alliance count, I estimated a model that included only crowding, prestige, and the publicly traded dummy variable. Model 8 demonstrates that the significant effects of the substantive variables are not due to collinearity among the explanatory variables: crowding and prestige remained highly significant. Model 9 reports the results from the full model estimated on a sample that excludes the 203 no-patent firm-years. Again, crowding and prestige remain substantively and statistically significant predictors of the alliance formation rate.

Finally, model 10 includes the measures of slack resources and of financial performance for the publicly traded U.S. semiconductor producers for which these data were available. In model 10, neither debt-to-debt-plus-equity nor ROA has a statistically significant effect on alliance formations, while the influence of crowding and prestige are robust despite the 60-percent reduction in sample size. None of the other measures of financial status proved to be significant or to alter the effects of prestige and crowding.

Dyad model results. Table 5 presents means and a correlation matrix for the variables in the dyad analysis. As control variables, I included sales, expressed as the sum of the sales volumes of the two firms in a dyad. I also added the no-patent dummy variable, coded as 1 if either or both of the firms in a dyad possessed no patents. Finally, the reported models contain a dyad-level occurrence dependence variable operationalized as a count of the number of alliances formed by the two firms in a dyad during the previous five years. In unreported models, I included control variables for the combined age of the firms in a dyad, as well as measures of the difference between the ages and sizes of the two firms in each dyad. Including these variables did not change the results on the technological positioning variables. To test the hypotheses, I included the level of technological overlap of the two firms in a dyad ($\alpha_{ijt} + \alpha_{jit}$ for each ij pair), the prestige score for the most prestigious of the two firms in a dyad, and the interaction of these two variables.

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The reported alliance rate multipliers for the first (1.27) and second firms (1.13), however, are the partial effects of crowding. In this example, the alliance rate multiplier for the first organization from the joint effect of crowding and prestige remains unchanged (1.27), but it rises to 1.44 for the second firm ($\exp^{.1405 \cdot 1.71 + .42 \cdot .0059 - 12.17 \cdot 1.72 \cdot .0059}$). Although the crowding effect is stronger for low- than for high-prestige firms, the combined effect of crowding and prestige on the alliance formation rate multiplier is larger for high-prestige firms.

I also performed a comparison of means for the prestige and overlap variables by dichotomizing all dyad-years into those with a realized alliance and those without an alliance. In almost 59,000 observations on dyad-years, there were 544 joint ventures, joint product development, and technology exchange alliances. Comparing the means of the technological overlap and prestige variables in the dyad years that had

Table 5

Means, Standard Deviations, and Correlations for Variables in Dyad-level Models*

Variable	Mean	Sigma	(1)	(2)	(3)	(4)	(5)
1. Sales of the dyad (\$M)	.697	1080	—				
2. i or j no patents	.505	.49	-.27	—			
3. Prestige score for the highest of two firms in dyad	.011	.018	.67	-.25	—		
4. Prestige-by-overlap × 1000	.701	3.204	.48	-.24	.56	—	
6. Technological overlap of firms in dyad ($\alpha_{ijt} + \alpha_{jit}$)	.019	.082	.44	-.36	.45	.45	.49

* Database contains 58,973 dyad-years (an average of 9,829 dyads per year in a six-year time series).

an alliance with the means of those variables in the dyads that did not have one, there were clear differences. Among the 544 alliance dyads, the means of the overlap and prestige variables were .11 and .031; among the 58,429 unrealized dyads, the means were, respectively, .018 and .0106. A test for differences in means across the two groups yielded *p*-values well below .001 for both variables. Hence, before controlling for additional factors, dyads that formed an alliance appear to have consisted of two technologically proximate firms with (at least) one high-prestige member.

Table 6 reports the random effects probit estimates for the dyad models. Model 1 includes three control variables and the technological overlap measure. The results demonstrate that two structurally equivalent firms in the patent citation network (firms with high technological overlap) were significantly more likely to form an alliance than were dyads consisting of firms that worked in distinct technological areas. This finding is consistent with the arguments that absorptive capacity limitations and the opportunity to combine similar R&D programs created the incentive for alliances between firms that were embedded in the same sections of the patent citation network.

Model 2 adds the prestige score for the most prestigious of the two firms in a dyad. The positive, significant coefficient on the prestige variable is consistent with the findings of the firm-level models: alliances were more likely in dyads in which at least one of the firms had high prestige. Model 3 in table 6 presents the test of a dyad-level expression of hypothesis 4, that crowding will have a weaker effect on the alliance formation rate of the highest-prestige firms. Recast at the dyad level, this assertion would state that direct technological overlap has a smaller effect on the odds of a strategic alliance between the two firms in a dyad when at least one of the organizations has high technological prestige. Accordingly, model 3 includes an interaction term between the prestige of the highest-status firm in each dyad and the level of technological overlap between the two firms in the dyad.

Table 6

Random Effects Probit Regression Models of the Likelihood of an Alliance in a Dyad-year*

Variable	(1)	(2)	(3)	(4)
Intercept	-2.567** (.0330)	-2.582** (.0330)	-2.619** (.0330)	-2.619** (.0330)
Sum of sales of firms in the dyad (\$M)	.00017** (.00001)	.00014** (.00001)	.00014** (.00001)	.00009** (.00001)
One or both firms in dyad have no patents	-.3723** (.0444)	-.3754** (.0454)	-.3652** (.0455)	-.2438** (.0621)
Count of alliances between firms in dyad, last 5 years	.3038** (.0336)	.3096** (.0329)	.3092** (.0329)	.2886** (.0338)
Technological overlap of firms in dyad ($\alpha_{ijt} + \alpha_{jit}$)	.7380** (.1770)	.6031** (.1831)	1.518** (.2549)	1.139** (.2642)
Prestige score for the highest of two firms in dyad	-	2.860** (.7846)	4.851** (.8774)	2.393** (1.037)
Prestige-by-overlap interaction	-	-	-21.62** (5.801)	-14.088** (6.1069)
Total alliances formed by i and j during t (excluding <i>ijt</i> th dyad)	-	-	-	.1144** (.0057)
Total crowding around firms in dyad (excluding $\alpha_{ijt} + \alpha_{jit}$)	-	-	-	.02118 (.0138)
Number of dyad years	58973	58973	58973	58973
Number of dyads	11288	11288	11288	11288
Pearson chi square	59328	58365	58341	49119
Number of alliances	544	544	544	544

** $p < .05$.

* Robust standard errors in parentheses.

The coefficient on the interaction term is negative, which establishes that a given (non-zero) level of technological overlap between two firms had a weaker effect on the probability of an alliance when one of the firms in the dyad had high prestige. Thus, high-prestige firms were more likely than low-prestige firms to be involved in alliances with alters that specialized in technological areas that were distinct from their areas of concentration. The magnitudes of the coefficients indicate that direct overlap always had a positive effect on the probability of an alliance, but it was quite small for dyads that contained one of the highest-prestige firms. This result can be explained by the fact that the strong technological competence bases of firms with highly cited patent portfolios enables them to evaluate and integrate the ideas and inventions of technologically dissimilar firms. It appears that high-prestige firms were more likely to use alliances as bridges into areas of technology that were distant from the areas of their prior innovative activities.

The final model in table 6 introduces two additional control variables. First, model 4 controls for the combined, composite crowding of the technological positions of the two firms in the *ijt*th dyad, excluding the direct technological overlap between firms *i* and *j* (or, $A_{it} + A_{jt} - \alpha_{ijt} - \alpha_{jit}$). Second, the model also incorporates the autoregression variable that controls for the propensities of the two firms in each dyad to form alliances during the contemporaneous time period. Including these two variables rules out an alternative explanation for the structural equivalence finding in the dyad models: the effect could be spurious because firms in crowded

positions form more alliances (we know this from the firm-level results), and those in crowded positions are more likely to be structurally equivalent with their competitors (true by the definition of crowding in equation 4). Without these two control variables, the dyad findings could be an artifact of a firm-level crowding effect. The results in model 4 show, however, that even after controlling for the aggregate crowding around the two firms in a dyad and their propensities to form alliances during the current year, structural equivalence in the citation network still increases the probability of an alliance.

DISCUSSION AND CONCLUSIONS

My purpose in this paper has been to demonstrate that there is a demographic component to alliance formations: the opportunities to form strategic coalitions vary across technological positions. After proposing a simple mapping of organizational positions in the technological structure of a producer network, the paper has extended work on the structural antecedents of strategic alliances by demonstrating the importance of technological positioning in the alliance formation process. Specifically, in addition to our understanding of how the established alliance network facilitates the formation of new interorganizational associations, we can now include the crowding and prestige of a producer's network position among the structural factors known to underlie relationship formations. Moreover, it is now an empirical fact that firms with many previous alliances benefit from a form of relationship or social capital that provides them with privileged access to potential exchange partners. Therefore, contextual characteristics such as crowding and prestige that convey access to alliance partners will also indirectly affect future coalition formation through their impact on the level of social capital held by firms.

There are five points that I wish to emphasize in conclusion. First, many scholars have suggested that the proliferation of interorganizational alliances marks the emergence of a new and superior organizational architecture, the so-called "network form." Accordingly, researchers have demonstrated that alliances can facilitate learning, enhance status or legitimacy, and contribute to organizational growth. But in light of the widely espoused advantages of the network organization, particularly in high-technology industries, one is left to wonder why all firms do not embrace the alliance strategy. One possible answer to this question is that structural positions create—and therefore also limit—organizations' abilities to implement cooperative strategies successfully. I have emphasized crowding and prestige as measures of structural positions because I had anticipated that the two variables would reflect differences between organizations in the breadth of the set of potential strategic partners available to them. The more general observation is that access to the right exchange partners is an essential prerequisite to fashioning a productive cooperative strategy. The results of the paper convincingly uphold the notion that the position of a firm in a broader technological context is one factor that influences alliance formation rates. Therefore, even if the network strategy is perceived to be advantageous, only some of

the organizations in an industry will hold positions that enable them to execute the strategy successfully.

Second, I have distinguished attributes of organizations from their positions in a market context, but this distinction can be equivocal. For example, technological prestige is a positional variable because it is engendered by flows of deference between firms, and so it has relational foundations (Podolny, Stuart, and Hannan, 1996). But the reason for these flows of deference is, at least in part, that an organization has contributed an on-going stream of notable innovations to the technological frontier of its industry. No doubt, the ability to develop this stream of innovations—a precursor to the accrual of prestige as I have measured the variable—reflects the presence of a strong, internal technology-development capability, which must be considered an attribute of an organization. Hence, the positional variable “prestige” and the attribute variable “capability” are closely related. Given this association, prestige could have affected alliance formations because it measured technological capability, it could have done so because it measured social standing and the capacity to elevate the status of partner firms, or it could have worked through both mechanisms. It is important to develop empirical tests to adjudicate between these alternative mechanisms.

The third point that merits emphasis is that prestige overwhelmed sales revenue in its effect on alliance formations, suggesting that prestigious organizations enjoy access to a broad array of firms as potential business associates and that there is no comparable effect of size. I argued that one of the principal reasons for this finding is that prestigious firms are attractive associates because they can convey status to a partner firm (Stuart, Hoang, and Hybels, 1999). I also speculated that the benefits to a high-status firm of alliances with lower-prestige partners often derive from the implied asymmetry in bargaining power between the two organizations in contract negotiations, a point that was demonstrated in the previously discussed AMD-IBM alliance. Should this suspicion withstand empirical scrutiny, it has two implications that should be verified. First, high-prestige firms enjoy an advantage that stems from their unique capacity to certify in the public's eye the initiatives of lesser-known firms. This is in a very real sense a money-making resource, because it allows high-prestige firms to use alliances to source competitors' technologies on favorable financial terms. Second, the flipside of this observation is that endorsements in the form of prestige-asymmetric affiliations may come at a price for the firms that receive them. Because high-prestige firms can set the terms of the alliances that they enter, their partners often give a great deal away to gain the certification implicit in the formation of an alliance with a well-known and well-regarded organization. From the vantage point of the low-prestige firm, whether the endorsement value of a tie supersedes the financial or access costs that it incurs to gain the endorsement is a question that merits investigation.

The fourth point is that technological positioning is sure to change over time as a result of the pattern of technology alliance formation in an industry. Computing crowding and prestige meant deriving the technological positions of the

firms in the semiconductor industry from the technological relationships among their innovative (patenting) activities, but technological structure was exogenous in the empirical models of alliance formation: it was assumed to be prior to and a driver of the relationship formation process. Of course, this assumption was made valid by imposing a lag structure in the empirical models so that the technological positioning variables were measured prior to the time of alliance formation. Nonetheless, because technology alliances are so often forums for the exchange of ideas and for the joint development of new knowledge, they influence the subsequent elaboration of technology in the industry. For example, Intel is a company that appears to have used alliances as a vehicle for entering market segments (such as graphics chips) that are adjacent to its core microprocessor business. Therefore, in industries in which alliance formation is commonplace, it would be useful to develop ideas and to generate evidence concerning how interorganizational associations shape the evolution of technological structure.

Finally, I conclude with a cautionary remark about the generalizability of the results. Because this was a single-industry study and because the semiconductor industry has certain unique characteristics, it would be inadvisable to generalize the findings beyond the present context until the results can be replicated in other contexts. For example, one potentially confounding feature of the semiconductor business is that alliances in the industry were sometimes formed to develop devices that would succeed commercially only if they were adopted as standards. I have tried to reduce the influence of technology standards in these analyses by excluding license alliances, but if standards-oriented development alliances were more likely between technologically overlapping firms (if the crowding hypothesis interacted with a characteristic of the empirical setting to produce one of the core results), then the findings of this study may not generalize beyond the semiconductor industry. Therefore, claims about the generalizability of the findings will need to await replication of the two-dimensional positional framework in other industry contexts.

Although there can be no guarantee that the findings will be replicated in other contexts, the two-dimensional characterization of corporate positions should have general application. One of the paper's objectives has been to contribute to the burgeoning literature aimed at trying to understand organizational conduct and strategy through the lens of network models of industry structure. Seen as general descriptors of the positions of organizations in producer networks, crowding and prestige are likely to prove useful in studies of other industries and in analyses of different outcome variables. Differences in crowding and prestige can be described with many different types of relational data, including migrations of workers between firms, strategic alliances themselves, networks of interlocking board memberships, product reviews and product characteristics data, and so on. Therefore, while the findings of a single industry study may not be replicable, prestige and crowding are broadly relevant relational properties. I am confident that they will be shown to be significant in studies of other organizational strategies and in low-technology industries as well.

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