Strategic Management Journal
Strat. Mgmt. J., **21**: 791–811 (2000)

INTERORGANIZATIONAL ALLIANCES AND THE PERFORMANCE OF FIRMS: A STUDY OF GROWTH AND INNOVATION RATES IN A HIGH-TECHNOLOGY INDUSTRY

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This paper investigates the relationship between intercorporate technology alliances and firm performance. It argues that alliances are access relationships, and therefore that the advantages which a focal firm derives from a portfolio of strategic coalitions depend upon the resource profiles of its alliance partners. In particular, large firms and those that possess leading-edge technological resources are posited to be the most valuable associates. The paper also argues that alliances are both pathways for the exchange of resources and signals that convey social status and recognition. Particularly when one of the firms in an alliance is a young or small organization or, more generally, an organization of equivocal quality, alliances can act as endorsements: they build public confidence in the value of an organization's products and services and thereby facilitate the firm's efforts to attract customers and other corporate partners. The findings from models of sales growth and innovation rates in a large sample of semiconductor producers confirm that organizations with large and innovative alliance partners perform better than otherwise comparable firms that lack such partners. Consistent with the status-transfer arguments, the findings also demonstrate that young and small firms benefit more from large and innovative strategic alliance partners than do old and large organizations.

Owing to some recent empirical studies, we are gaining an understanding of the factors that compel firms to enter strategic alliances (e.g., Nohria and Garcia-Pont, 1991; Gulati, 1995; Eisenhardt and Schoonhoven, 1996; Walker, Kogut, and Shan, 1997). With few exceptions, explanations of why firms establish alliances are directly linked to presumptions about the benefits of alliances to participant firms. In light of the natural association between cause and consequence in purposive theories of organizational behavior, however, it is surprising to find relatively few large-sample studies that confirm widely-espoused assumptions that strategic alliances are advantageous for participant firms (exceptions include Hagedoorn and Schakenraad, 1994; Shan, Walker, and Kogut, 1994; Powell, Koput and Smith-Doerr, 1996; and Mitchell and Singh, 1996).

This article has two objectives. First, to offer consultation regarding the conditions under which strategic alliancing is advantageous, it is first necessary to develop a nomothetic literature on the effects of alliances on firm performance and, in particular, on the contingencies that bear upon the alliance-performance link. Because I believe that there has been insufficient attention to the connection between the value of alliances and the characteristics of the firms in the partnership (and the interactions between partner characteristics), I will attempt to show in this study that the advantage of a portfolio of alliances is determined not so much by the portfolio's size, but by the

Key words: strategic alliances; firm performance; interorganizational networks; innovation; patents
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Received 12 January 1998
Final revision received 14 March 2000

characteristics of the firms that a focal organization is connected to. Second, theories of the functionality of alliances have devoted little attention to one of the most significant and one of the easiest to obtain of the potential advantages of intercorporate affiliations: under frequently-met conditions, alliances can significantly enhance (or devalue) the reputation of one or both of the participant firms. In this study, I investigate whether alliances with prominent partners upgrade a focal firm's reputation, which I infer from the relationship between attributes of a focal firm's alliance partners and its post-alliance performance (Rao, 1994; Wilson, 1985). These ideas are subjected to empirical scrutiny in a study of the effect of horizontal technology alliances in the semiconductor industry on two outcome variables: the rate of innovation and the rate of revenue growth of the firms in the industry.

Literature and theory

Firms establish alliances for many reasons (Gulati, 1998, offers a current review). Salient among the incentives to collaborate is the possibility of bringing together complementary assets owned by different organizations (Nohria and Garcia-Pont, 1991). For instance, two companies may establish an alliance when each one possesses strength in a different stage in a product's value chain, such as when one firm has manufacturing expertise and a second one controls a distribution channel. Second, firms may form coalitions to defray costs and share risk when they undertake high-cost (capital- or development-intensive) projects or very speculative strategic initiatives (Hagedoorn, 1993). It has also been suggested that the resources acquired from an alliance partner can facilitate a firm's efforts to alter its competitive position (Kogut, 1988), as well as that corporations in concentrated industries utilize alliances to collude or to gain market power at the expense of other competitors (Pfeffer and Nowak, 1976). Empirically, researchers have observed an association between the propensity to enter into alliances and a variety of organizational attributes, including firm size, age, scope, and resources (Shan et al., 1994; Burgers, Hill, and Kim, 1993).

Rather than investigate the antecedents of intercorporate partnerships, I treat the formation of alliances as exogenous in this study. I do so to focus on the question of whether and under what conditions firms that have a portfolio of strategic partnerships outperform those that do not. However, one area of the literature on alliance antecedents—the body of work suggesting that the potential to learn from a strategic partner is an important and increasing prevalent rationale for alliancing—directly informs the paper's predictions. A number of recent papers have conceived of alliances as instruments used by firms to acquire know-how and to learn new skills that reside within other organizations (Hamel, 1991; Powell et al., 1996; Hagedoorn, 1993; Hagedoorn and Schakenraad, 1994). There are likely two reasons for this recent emphasis. First, attention to the acquisition of know-how as an incentive to collaborate is driven by the concentration of alliance activity within particular sectors of the economy: high-technology industries are the arenas in which alliance activity has been most intensive in the recent past (Hagedoorn, 1993). A second and related point is that the emphasis on learning is both consistent and coincident with the gaining influence of knowledge- or competence-based conceptions of the firm (e.g., Nelson and Winter, 1982; Henderson and Cockburn, 1994).

As a reason to enter alliances, the potential to learn from partners highlights the fact that alliances are, in the first instance, *access relationships*. Just as scholars of social networks have observed that social ties purvey access to information possessed by one's contacts (Burt, 1992), so have alliance researchers recognized that strategic coalitions can convey access to the resources or know-how possessed by one's partners. For example, many of the R&D alliances between established pharmaceutical firms and dedicated biotechnology firms have been structured so that the pharmaceutical firm, in exchange for funding a research project at its biotech partner, acquires the right to observe the development process of the biotechnology firm (of course, it also obtains a claim to a large fraction of the revenue stream generated by the resultant discoveries). Similarly, many of the horizontal alliances in the semiconductor industry have been forged by corporations eager to acquire device or manufacturing technology from their strategic partners.

If learning specifically and gaining access to resources more generally are the sources of the advantage attained from alliances (in addition to being among the most compelling motives to enter them), then all potential alliance partners are not of equal value. In this study, I posit that well-endowed firms—for instance, those that possess a large stock of technological resources or those with extensive market coverage—are the types of alliance partners that can produce the best ex post results for their associates. Moreover, I suggest that attributes of a focal firm are likely to interact with the characteristics of its alliance partners to influence the relationship between its collaborative activity and subsequent performance.

Existing research has established that alliances often have positive effects on a number of different measures of corporate performance. For example, McConnell and Nantell (1985) showed that the equity markets reward parent companies' share prices when they announce joint ventures. Baum and Oliver (1991) and Mitchell and Singh (1996) treated mortality as the performance variable and showed that alliances raised organizational survival rates. Uzzi (1996) showed that apparel firms with strong ties to business groups enjoyed improved life changes. Taking a different approach, Singh and Mitchell (1996) demonstrated that the mortality rate of a focal firm increased when its strategic partner ceased operations or established a new alliance with a different firm. Studying a sample of young firms in the biotechnology industry, Powell *et al*. (1996) found that companies which had formed many alliances experienced accelerated growth rates. In one of the few studies that has investigated whether the configuration of exchange relations affected firm performance, Chung (1996) found that patterns of exchange relations between investment banks affected the volume of firms' security underwriting activity. Finally, Hagedoorn and Schakenraad (1994) demonstrated a positive relationship between entry into technology alliances and innovation rates.

Although the evidence rests heavily on the side that alliances engender superior performance, the extent to which characteristics of a firm's strategic partners mediates the link between alliances and performance remains a largely unexplored area of research. I argue that because alliances are formed to achieve access to partner-firm resources, the benefit gained from a portfolio of strategic alliances is determined in part by attributes of the partner firms that make up the portfolio. No doubt, it is the contingency between the quality of a partner and the dividends of an alliance that underlies the costly and time consuming search and screening processes that many firms follow when selecting strategic partners.[1] More generally, it is an axiom in the social networks literature that the potential advantages of a relationship depend upon the social and material capital possessed by the contact (cf. Burt, 1992: chs. 1 and 2). However, despite the consensus that firms enter strategic alliances to acquire know-how or other resources, there is little large-sample research that has documented the importance of partner characteristics for alliance outcomes.

As a first step toward generating this kind of evidence, it will be necessary to characterize the firms in a focal industry according to their quality, skill level, or resources in domains of business activity that are critical for competitive success in that particular market. Firms at the apex of the ranking in a domain possess the highest quality or greatest amount of resources in that domain; for example, they may have the foremost technological capabilities, leading-edge production technology, the largest customer base, or a premier brand image. Regardless of the empirical locale, the industry's incumbents will be stratified in terms of the quantity and quality of the resources in their possession. My first two hypotheses posit associations between the statuses of a focal firm's alliance partners in an industry's key resources hierarchies and the size of the change in the focal firm's post-alliance performance.[2]

The empirical locale for this paper is a high-technology industry and most of the alliances that I study are technology-related (for example, joint

[1] For instance, when Applied Materials was searching for a Japanese joint venture partner to support its initial entry into the business of designing equipment for the production of active matrix liquid crystal displays (high resolution flat panel displays), it engaged McKinsey & Co. to evalute 130 Japanese companies before ultimately selecting Komatsu as its alliance partner. This is just one example of the high search costs firms often incur when they screen potential alliance partners.

[2] Of course, the most important domains for determining competitive success will vary considerably across contexts. In consumer products industries such as packaged foods and over-the-counter medicines, key resources and skills may be, respectively, brand names and consumer marketing capabilities. In contrast, in high-technology industries they are likely to be state-of-the-art manufacturing facilities and a leading R&D organization.

product development agreements). Given the setting and types of interfirm coalitions, I investigate how the standing of alliance partners on two dimensions—degree of innovativeness and extent of market coverage—affect the post-alliance performance of the firms that are partnered with them. With respect to the first dimension, if learning is one of the primary motives for alliances as emphasized in the literature on cooperative technology strategies, or even if learning is the unintended by-product of relationships established to serve quite different purposes, then the benefits of a portfolio of collaborative relations will depend upon the technological competencies of the alliance partners that make up the portfolio. Other factors held constant, alliances with the most skilled innovators are the most viable opportunities to learn new routines and acquire advanced technical know-how.[3] Because innovative firms possess the highest quality technological capabilities, I expect that the know-how acquired from highly innovative alliance partners should contribute to a firm's ability to develop new technology in a subsequent period. Therefore, I predict:

Hypothesis 1: The greater the technological capabilities of a high-tech firm's alliance partners, the higher the rate of innovation of that firm.

In addition to the chance to acquire technological know-how from a collaborator, technology alliances may also represent present opportunities to enter new market segments and to service new customers (Mitchell and Singh, 1992). This suggests that revenue growth is another area of performance that may be affected by alliances because strategic partners can facilitate entry into new market niches (Kogut, 1988) and because the members of an alliance may gain business from their collaborator's customers, particularly when partnerships lead to jointly-developed products. For instance, in the semiconductor industry strategic alliances with platform sponsors historically have been the only route by which firms could gain entry into a proprietary technology standard, such as a microprocessor architecture, that was controlled by a different organization (Kogut, Walker, and Kim, 1995; Wade, 1995). When a firm obtains a large alliance partner, the revenue potential of the association is likely to be significant because the partner is tied into a large revenue stream. This just reflects the common wisdom that partnerships with the well-connected and well-endowed offer greater rewards than do alliances with business associates that lack resource. Because they may provide access to extensive distribution channels, long-standing customer relations with influential end users, or a widely-adopted technology platform, large strategic partners are more valuable than small associates. I predict:

Hypothesis 2: The greater the revenues of a high-tech firm's alliance partners, the higher the rate of sales growth of that firm.

The rationale for the first two hypotheses is that alliances are access relationships, and so strategic ties with well-endowed partners are, on balance, the most valuable associations. In addition to purveying access to resources such as technological know-how and new customers, alliances often play a second but in no sense ancillary role: they can elevate the reputations of participant firms in the eyes of existing and potential customers and the financial community (Podolny, 1994; Rao, 1994; Stuart, Hoang, and Hybels, 1999). Moreover, because a good reputation is thought to be a rent-generating asset (Wilson, 1985; Fombrun and Shanley, 1990), strategic alliances also affect firm performance through their influence on an organization's reputation.

A corporate reputation is a set of attributes that observers perceive to characterize a firm (Weigelt and Camerer, 1988). My assertion is that intercorporate alliances convey status to a focal firm when its partners include large, highly skilled or otherwise well-known organizations, particularly when the focal enterprise is itself

[3] Although the context was quite different, Lin, Ensel, and Vaughn (1981) developed an argument similar to this one. Noting that job seekers often obtain leads for employment opportunities through social contacts (e.g., friends, friends of friends, and so forth), Lin *et al*. found that the higher the occupational prestige of the contact, the greater the probability that the job seeker would obtain a high prestige position. Hence, at least in the job search process, ties to individuals at the top of the prestige (resource) hierarchy are more valuable than ties to those in a lower rank. Indeed, it has been widely observed that connections to high-prestige or otherwise accomplished actors provide access to information that may help to achieve a desired results.

relatively unknown. Therefore, in addition to the transfer of tangible and knowledge-based resources, interfirm affiliations may convey social status. To develop this argument, I build upon a sociological literature asserting that the status of an actor can be affected by the statuses of its close associates.

Sociologists have argued that *when there is uncertainty about the quality of someone or something*, evaluations of it are strongly influenced by the social standing of the actors associated with it (Merton, 1968 [1973]; Podolny, 1994). The reason that this dynamic may apply in alliance contexts is that highly regarded organizations are likely to meticulously evaluate a potential alliance partner before entering into a collaborative venture with it, and this evaluation acts as a certification of the quality of the partner. For three reasons, surviving the due diligence of a well-known organization serves as a signal (Spence, 1974) of quality for the lesser-known of the firms in an alliance. First, prominent organizations are likely to be selective in their choice of strategic partners in order to preserve their own reputations, which may be damaged if they transact with low-quality or disreputable firms. Second, highly regarded organizations are likely to be perceived as reliable evaluators that are capable of discerning quality differences among potential partners. Third, prominent organizations typically have many potential strategic partners, and therefore their partners—by virtue of being selected—typically were deemed more desirable than a number of alternates. For these reasons, a firm's important constituents (customers, the financial community, the media) will view the gaining of a large or prestigious alliance partner as an endorsement of its quality (Stuart et al., 1999).

There are many documented instances of a product or firm of unknown quality gaining an enhanced image because of its association with prominent alters. For example, the rate of diffusion of new innovations and of new drugs appears to depend upon whether prominent actors (firms or physicians, respectively) have previously adopted the invention or medicine (Podolny and Stuart, 1995; Burt, 1987). In other words, broader perceptions of product quality have been shown to depend upon the reputation of those who have adopted the product. Similarly, it has been shown that when organizations are endorsed by institutions such as licensing organizations or trade associations, they gain an advantage in their subsequent attempts to acquire resources (Baum and Oliver, 1991; Aldrich and Auster, 1986).

The effect on a firm's reputation of acquiring well-known alliance partners will be particularly significant if the firm occupies a precarious competitive position—for example, if it is young or small. The reason is that evaluators rely upon signals of an organization's abilities when they possess few indicators to inform their inferences about the firm's quality, and when they are unsure about the firm's future prospects. Potential customers, suppliers, employees, collaborators and investors tend to be knowledgeable about the reliability and ability of large and old enterprises (Stinchcombe, 1965; Hannan and Freeman, 1984), either because they have previously transacted with them or because old and large organizations have verifiable reputations. Similarly, it is typically safe to assume that large and old organizations will continue to survive in one capacity or another. In contrast, much less is known about young and small firms and the future of these organizations is far from certain. Potential customers, suppliers, and employees—particularly those that are risk averse—will be more confident of the quality and more likely to transact with a young or small firm after it has been implicitly certified by a prominent alliance partner.

Based on the preceding arguments, I expect that when a young or small firm gains a well-regarded alliance partner, its reputation will be enhanced in the eyes of its public. Because time-varying perceptual data on the assessments of an organization's reputation by its constituents do not exist for most firms, my strategy for testing hypotheses about the effect of alliances on reputations is to follow the literature in assuming that improvements in a firm's reputation will manifest as enhancements in its performance. Therefore, I test for a relationship between alliance partner prominence and improvements in a firm's reputation by investigating how the former affects the performance of an organization. Following the argument that intercorporate ties are status-enhancing only when there is uncertainly about a firm's true quality, I test for the effect of alliances on reputations by investigating whether large or innovative alliance partners have a particularly strong effect on the performance of young and small firms. If the effects of having well-known alliance partners are invariant across measures of the uncertainty (age and size) of focal firms, then I can reject the hypothesis that prominent affiliations enhance reputations. I predict:

> *Hypothesis 3: The greater the technological innovativeness of a high-tech firm's alliance partners, the higher the rate of sales growth of that firm* particularly if it is young or small.

> *Hypothesis 4: The combined sales volume of a high tech firm's alliance partners will have a more substantial effect on the rate of sales growth of that firm* if it is young or small.[4]

Setting, sample, and data

The ideas I have exposited are best explored empirically in the context of a large sample of firms drawn from a single industry. Limiting the analysis to a single industry insures that the dimensions on which alliance partners are characterized will be of comparable importance. Moreover, because the data requirements for testing the hypotheses are quite high (the models depend upon time-series alliance, patent, and revenue data for all of the firms in an industry), a multi-industry design was not practical.

For four reasons, I have chosen to draw the sample from the semiconductor industry. First, as noted by Hagedoorn (1993) and others, companies in the microelectronics industry have formed many hundreds of *horizontal* strategic alliances (i.e., agreements between two firms in the industry). There have been a sufficient number of alliances in the industry to allow for a large sample study of the effects of horizontal alliances on corporate performance. Second, the industry has been driven by innovation, meaning that the surest path to commercial success has been to develop new technologies (e.g., Tilton, 1971; Wilson, Ashton, and Egan, 1980). Because technological innovation is viewed as a priority by most of the firms in the industry, the industry is an appropriate context to explore the role of alliances as a strategy for learning from and gaining access to the technological capabilities of strategic partners (Hypothesis 1). Third, the microelectronics industry is well suited for this study because the firms in it routinely patent their inventions. This is an important consideration because patent data are necessary to operationalize a number of the variables in the analysis. Finally, the industry consists of a very heterogeneous population of firms, from small, dedicated producers to large and diversified electronics conglomerates. Therefore, the industry offers ample variation for testing the hypotheses.

The sample that I have analyzed included the semiconductor companies followed by Dataquest, a consultancy and information services firm, during the period from 1985 to 1991. Dataquest used information on product shipments to compile revenue figures for a large number of semiconductor producers. Because sales volume is the dependent variable in the sales growth models (Hypotheses 2, 3, and 4), the sample was limited to the set of organizations tracked by Dataquest.[5] The one instance in which the Dataquest data base was supplemented was for the small number of captive semiconductor producers. Sales figures for the captive producers were available in the Integrated Circuit Engineering Corp.'s annual *STATUS* volumes. Adding the captive producers to the Dataquest data, I built a sample of 150 companies, although some of the firms in the sample were founded during the analysis period and so are not represented in all years of the data. These firms hailed from the U.S., Europe, Japan, and other Southeast Asian countries, and the sample accounted for over 90 percent of the worldwide semiconductor production volume in 1991.

In addition to the sales figures, I required data on the strategic alliances and the patents of the firms in the industry to construct the variables

[4] The final two hypotheses are limited to sales growth because stakeholders' perception of a firm's reputation are not likely to influence its rate of innovation in the short term. Over a longer time period, however, a firm's reputation will influence its innovation rate by affecting its ability to recruit and retain high-quality human resources and to secure the funds and market position necessary to launch major innovation projects. Because my data span only a six year window, I am not able to look in detail at processes that operate over long periods of time (e.g., how interfirm relationships formed a number of years into the past affect a firm's current rate of innovation).

[5] Many of the organizations in the sample participated in multiple business lines (e.g., IBM, Siemens, and Hitachi) and many were privately-owned. While corporate-level sales figures could be ascertained from public sources for the publicly-traded firms in the sample, longitudinal *semiconductor* only sales volume data were quite difficult to obtain even for many of the publicly-owned firms. For this reason, I had to rely upon the revenue data from Dataquest.

for the analysis. I recorded all publicly-reported alliances formed between semiconductor producers during an 11 years period. To preserve the consistency of the measures of partner attributes, I chose to focus only on horizontal (intra-industry) alliances: the data excluded all partnerships involving a semiconductor firm and a second organization outside of the industry, such as a software producer. The sources for the alliance data included the *Predicasts* indexes (U.S., Europe, and International), articles in *Lexis/Nexis, Infotrak, Electronic News, Electronic Buyer's News, Electronic Engineering Times, Electronics, Electronic Business*, as well as company SEC filings. The data, consisting of more than 1600 dyadic alliances, include five types of collaborative relationships: joint product development agreements, joint ventures, technology exchanges, licensing, and marketing agreements.[6]

I also collected all U.S. semiconductor patents assigned to the firms in the sample. I chose to use domestic patents because the U.S. is the world's largest technology marketplace. Because a firm must patent in a country to gain intellectual property protection in that geography, non-U.S.-based firms regularly patent in the U.S. (see Albert *et al*., 1991). To assemble the patent data, I first identified approximately 2400 distinct U.S. patent classes which contained semiconductor product, device, and design inventions. I then retrieved the patents in these classes from the Micropatent *1994 Patent Abstract* CD, which included all U.S. patents issued between 1975 and 1993. For each patent document, I recorded three pieces of information that were necessary to construct the variables for the analysis: the date of application, the corporate assignee, and the list of prior art (patent) citations. For the 150 firms in the sample, I then constructed detailed family ownership trees using the *Directory of Corporate Affiliations*. These corporate ownership relations were used to assign subsidiaries' patents to their corporate parents.

While there has been some question about the reliability of patents as innovation indices (Levin *et al*., 1987), there is evidence that firms in the semiconductor industry actively file for patents. As the strength of U.S. intellectual property protection has increased and a number of the firms in the industry have begun to appeal to the courts to defend their intellectual property positions,[7] semiconductor firms have raised the priority of patenting (Rivette, 1993). The proclivity of domestic and international firms to patent semiconductor technologies in the U.S. is evidenced by the fact that the six firms that had received the greatest number of U.S. patents in 1996—IBM, Motorola, NEC, Hitachi, Canon, and Mitsubishi—each had substantial semiconductor operations, and four of these firms were headquartered outside of the U.S.

Data and variables

Characteristics of alliance partners

The four hypotheses posit relationships between summary attributes of a firm's alliance partners and its ex post performance, measured either as a rate of innovation or as a rate of sales growth. In particular, I have argued that large and technologically innovative firms are the alliance partners that will lead to the most substantial performance

[6] I have estimated the models using two different criteria for including alliances. First, I estimated models that included all types of agreements in the computation of the alliance-based independent variables. Second, I restricted the alliance data to just three of the five types of agreements: joint ventures, joint product development agreements, and technology exchanges. The reason to impose this screen is that these three forms are the more durable, more intensive, and often the more strategically significant of the five types of alliances. The reported results are from the models including all partnerships, but the findings are similar to those resulting when only the three more durable and intensive alliance types are used to compute the alliance-based covariates. I have chosen to report the estimates from the models that include all alliances because the data on alliance type are occasionally missing for partnerships between small and non-U.S.-based firms. Therefore, excluding alliances by type may introduce systematic measurement error by lowering the realizations on the alliance-based variables for small firms and enterprises headquartered outside of the U.S.

[7] In 1982 the Congress established the Court of Appeals for the Federal Circuit in Washington DC specifically to hear patent cases. The new court has fortified patent protection in the semiconductor industry by consistently ruling against challenges to patent claims (Almeida and Rosenkopf, 1997). Adding to the strategic importance of patents, a number of firms in the industry, such as Intel and Texas Instruments, have been particularly vigilant in litigating perceived violations of their intellectual property. As the incidence of patent infringement suits in the industry has grown, patenting as a defensive strategy has become considerably more important because a large and extensive patent portfolio helps to defend against infringement charges. For example, when DEC recently accused Intel of infringing on its early microprocessing patents, Intel's extensive patent portfolio enabled it to file a counter suit charging infringement by DEC.

gains. Therefore, to test the hypotheses it is necessary to derive measures of the innovativeness and the size of the firms in the semiconductor industry so that each organization's alliance partners can be described on those dimensions.

I have used patent citation data to construct innovativeness scores for the sampled firms. One of the requirements of a patent application is to list citations to all previously-granted patents which made technological claims similar to those claimed in the application. This process is tantamount to mandating that patent applicants identify and acknowledge the existing, patented inventions that are technologically nearest to their inventions. It is then the obligation of the patent examiner to verify that the list of references in the patent application, known as the 'prior art,' is complete. When a patent application is granted, the patent issues with the list of prior art citations, including all citations added by the patent examiner.

Just as citations between journal articles reveal the transmission of ideas between papers, patent citations trace technological ancestries. Central nodes in the patent citation network (i.e., highly cited patents) therefore represent highly influential innovations. Patent citation data have been used to measure the importance of inventions in the economics literature (Trajtenberg, 1990), the applied technology literature (Albert *et al*., 1991) and work on the sociology of technology (Podolny and Stuart, 1995). Perhaps the most direct evidence of the validity of patent citations as a measure of the quality of innovations comes from studies such as Albert *et al*. (1991), which uncovers a very high correlation between the number of citations received by a set of patents and the rankings by technical experts in the relevant field of the importance of these inventions (see also Carpenter, Narin, and Woolf, 1981).

Assuming that the most important patented inventions are those that are highly cited in future patents, then the most innovative firms in an industry are those that have developed a significant fraction of the highly-cited patents. Accordingly, I compute the innovativeness of a firm as a composite, citation-based measure of the importance of the individual patents in its portfolio. Specifically, I define the innovativeness of a given semiconductor firm (denoted as i) during a particular time period (denoted as t) *as the proportion of prior art citations included in the universe of U.S. semiconductor patents applied for in year t that refer to patents that are assigned to firm i*.[8] I denote the innovativeness of a firm i at a time t as d_{it}. For each time period in the data series, an $Nx1$ vector $\mathbf{d_t}$ contains the innovativeness scores of the N firms in the sample.[9]

With measures of the innovativeness and size (which I have operationalized as annual semiconductor sales volume) of all semiconductor firms as well as a record of the alliance activity in the industry, it is possible to construct time-varying, summary measures of the innovativeness and size of the semiconductor alliance partners of each of the firms in the sample. To compute these measures, I first created a set of time-changing alliance matrices, labeled $\mathbf{W_t}=[w_{ijt}]$. The $\mathbf{W_t}$ are NxN (firm-by-firm) symmetrical matrices. The elements of the alliance matrices (the w_{ijt}) are defined as a positive value when the ijth pair of firms had formed an alliance during period t, and as '0' if there was no alliance between firms i and j in t.

The innovativeness (size) of the semiconductor alliance partners of each of the firms in the sample at period t is the product of the alliance matrix at t at the corresponding vector of innovativeness (size) scores for the firms in the industry. Hence, I define the vectors $\mathbf{p_t}$ $(\mathbf{v_t})$ as: $\mathbf{p_t} = \mathbf{W_t d_t}$, $\mathbf{v_t} = \mathbf{W_t s_t}$ where $\mathbf{W_t}$ are the binary alliance matrices and $\mathbf{d_t}$ $(\mathbf{s_t})$ are the innovativeness (sales) vectors. Therefore $\mathbf{p_t}$ $(\mathbf{v_t})$ are time-changing $Nx1$ vectors containing the summed innovativeness (size) scores for the alliance partners of each of the firms in the sample during each year t. Hypothesis 1 predicts that firms which enjoy access to technologically-advanced alliance partners will innovate at a greater rate than otherwise compara-

[8] I have also constructed a number of different permutations of this variable by altering the treatment of time. For instance, I have computed innovativeness scores as future citations to current-period patents, in addition to measuring innovativeness as current-year citations to previously-issued patents. Fortunately, all of the measures I have computed were correlated above 0.90.

[9] As an alternative to weighting each organization's patent portfolio by future patent citations, one could just use a count of the number of patents received by a firm as an innovation index. Conceptually, the difference between the two is that the raw patents count does not weight the quantity of patents by the best available measure of their importance. However, empirically the two measures are often highly correlated (above 0.80 in the data for this paper), and the raw patent count is much more expeditiously constructed.

ble firms that do not enjoy access to innovative affiliaties (in other words, a positive coefficient on the $\mathbf{p_t}$ variable in models of innovation rates).[10] Hypothesis 2 predicts that firms with large alliance partners will grow at a greater rate than otherwise comparable firms that do not possess alliance partners with extensive market coverage (a positive coefficient on $\mathbf{v_t}$ in the sales growth models). Hypotheses 3 and 4 predict that possessing large and innovative alliance partners, although beneficial for all firms, will have the greatest effect on the growth rates of young and small firms.

The one outstanding issue in the computation of the characteristics-of-alliance partner variables concerns the lag structure. Learning from another organization and then integrating that knowledge into a firm's own routines or technologies may take time. Similarly, it requires time for an alliance to lead to jointly-developed products and for a focal organization to gain access to a collaborator's customer base or entry into new market niches. Therefore, including only the alliances formed during the prior year in models of current-year performance may not allow a sufficient interval of time for the benefits of a cooperative strategy to manifest in observable performance measures. To address this issue, I have chosen to define the alliance matrix for year t to incorporate all alliance activity that had occurred during the previous five-year period, that is during t-1 to t-5.[11]

I experimented with two weighting schemes to modify the influence of alliances that occurred in the past (in addition to estimating models that used no weights). First, I (linearly) depreciated the contribution of older alliances to the summary measure of each firm's alliance partners. I constructed a measure such that alliances which occurred five years prior to the current year received a weight of 0.2, those that were established four years ago received a weight of 0.4, and so on until the lagged year, which received a weight of 1.0. I then multiplied each alliance matrix by the corresponding size and innovativeness vectors. Conversely, based upon the logic that effective interorganizational learning requires the development of relationship-specific knowledge-sharing routines (Lane and Lubatkin, 1998; Dyer and Singh, 1998), I also experimented with a weighting scheme that depreciated the contribution of alliances which were formed within the past three years (by assigning agreements that were formed within the last three years a weight of 0.5, versus 1.0 for older agreements). The results were weakest in the latter weighting scheme, when more recent agreements were assigned a reduced weight (although the coefficient magnitudes differed relatively slightly across the weighting schemes). The reported results are from the models in which the influence of older alliances was linearly depreciated.

Estimation

Modeling innovation rates

The outcome variable in the test of the first hypothesis, that organizations which possess technologically advanced alliance partners innovate at a higher rate, is a count of the number of new semiconductor patents applied for by each organization in the sample in each year of the analysis period. This variable is bounded at zero, can assume only integer values, and consists of observations on the same firms at multiple points in time. I have modeled the data using a random effects Poisson estimator with a robust variance estimator, (i.e., it does not assume within-firm observational independence for the purpose of computing standard errors). Poisson regression assumes that the event count is drawn from the single parameter Poisson distribution, which can be written as:

$$\Pr(Y_{it} = y_{it}) = \frac{\exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!} \tag{2}$$

[10] The specification of $\mathbf{p_t}$ ($\mathbf{v_t}$) and the models to be estimated are similar to a general class of social influence models of the form: $y = \rho Wy + x\beta + e$. In these models, y typically refers to an attitude or opinion held by the actors in a network, W is often known as a structure matrix because each w_{ij} measures the influence that actor j has on the opinion of actor i, and x is an nxk matrix of k covariates. In other words, the value of y_i is assumed to be influenced by a weighted combination of the opinions (y_j) of other actors.

[11] The existing literature helps to define the lag structure. Pakes and Griliches (1984) modeled firms' current-year patenting as a function of five lags of annual R&D spending. They found that contemporaneous R&D spending and the 5th-year lag were the two significant predictors of current patenting. They also estimated the mean R&D project gestation lag to be 1.6 years (the time from when an R&D project is begun until it first generates a revenue stream). Pakes and Schankerman (1984), which reports estimated gestation lags by a few major industry groupings, contends that the mean gestation lag in electronics is only 0.84 years. Based on these findings, I have chosen a five-year window to compute the alliance-based covariates. The window begins at a one year lag.

where the parameter λ_{it} represents the mean and the variance of the event count. It is assumed that ln $\lambda_{it2} = \beta' x_{it1}$. Hypothesis 1 is tested by including as a regressor p_{it}, the summed innovativeness score of a firm's alliance partners, in the patent rate models.[12]

In addition to the innovativeness of a firm's alliance partners, the patent rate models control for a number of firm characteristics. First, the models include a raw count of the number of technology alliances formed by each firm during the previous five years. It may be that firms that have formed a greater number of technology alliances innovate at a higher rate simply because the decision to enter alliances is a reflection of a firm's commitment to an innovation-focused technology strategy (in other words, that the number of alliances formed by the firm is a proxy for an underlying and unobserved strategic disposition). By controlling for the total number of alliances, I am able to separate the effect of characteristics of a firm's alliance partners from the effect of the number of alliances the firm has formed. Second, the models include the size of each firm measured as its annual semiconductor sales. Because larger firms typically possess greater resources to invest in R&D, larger firms are likely to innovate at a higher rate (Cohen and Levin, 1989, review the literature on the relationship between firm size and innovation).[13]

The models also include annual dummy variables to account for time-changing factors, including macroeconomics conditions, that may have affected the industry as a whole. These dummies control for omitted factors that have constant effects on the organizations in the sample but vary over time. They also serve to capture any secular trends in the incidence of patenting. Hence, the regression coefficients in all models can be interpreted as within-year effects.

Finally, to control for firm heterogeneity in the propensity or ability to patent, I have included in the patent rate models a variable that reflects historical differences across organizations in their patenting behavior: all models contain a count of the number of semiconductor patents granted to each organization from 1975 until the year prior to the dependent variable. Including the number of times that the focal event has previously occurred for each firm is a common method of controlling for unobserved heterogeneity (Heckman and Borjas, 1980). The occurrence dependence variable should control for the time-constant effects of unobserved factors (such as interfirm differences in internal processes and incentive structures, as well as differences in underlying innovation strategies) that produce variance in organizations' abilities, opportunities, or dispositions to patent.

Modeling the rate of sales growth

Hypotheses 2 through 4 consider how characteristics of firms' alliance partners affect their subsequent-period performance. As a measure of performance, I have chosen semiconductor sales volume rather than an accounting-based measure. There are two reasons for this choice, the first theoretical and the second pragmatic. First, the expected enhancement in reputation associated with gaining a highly regarded alliance partner should manifest in revenue increases because risk averse customers will be more willing to source from firms that have been endorsed by well-regarded organization. Therefore, the reputation arguments (Hypotheses 3 and 4) should leave a discernible trail in changes in sales volume if they operate in this sample of firms. While it is also probable that improvement in a firm's reputation will create better financial performance by lowering the organization's cost structure and increasing the prices that the market will accept for its products (Podolny, 1993), these processes

[12] Poisson regression assumes that the mean and variance of the event count are equal. Because this assumption is often violated, I have also used a fixed-effects negative binomial estimator to fit the innovation rate models, which accommodates overdispersed data (I have implemented the maximum likelihood estimator developed by Hausman, Hall, and Griliches, 1984, using Stata 5.0's built in maximum likelihood capability). Effectively, this model conditions on the event count for each unit (firm) over the observation window, so when using this model I omit the occurrence-dependence term (a one-year-lagged count of the total number of patents issued to each firm since 1975). I concentrate on the random effects Poisson models because they allow for informative estimates of the impact of time-invariant firm characteristics, such as the firm nationality dummies. However, I do report the full model using the fixed effects negative binomial to show that the results are robust to the estimator.

[13] I was unable to collect time series R&D spending data on the privately-held, diversified, and non-U.S.-based firms in the dataset. However, among all of the dedicated (non-diversified) semiconductor producers in the Compustat data base (all firms that participated only in SIC 3674), the bivariate correlation between annual sales revenue and annual R&D expenditure was 0.977. From this I infer that controlling for semiconductor sales volume is a close approximation to controlling for annual semiconductor R&D spending.

may unfold over a longer period of time. I expect increases in sales volume from gaining new customers to occur more quickly than changes in accounting-based performance measures, and therefore modeling sales growth permits a shorter lag structure in the statistical analyses. Second, because many of the firms in the data base were diversified into an array of end use products (e.g., IBM, Siemens, Hitachi) and many others were privately held, I was unable to obtain accounting measures reflecting firms' activities in the semiconductor business for the majority of the firms in the sample. However, I was able to gather sales data for the *semiconductor* operations of each of the firms in our sample, even when they were diversified or privately owned.

Following prior research (Barron, West, and Hannan, 1994; Barnett and Carroll, 1987; Podolny, Stuart, and Hannan, 1996), I have modeled the sales of the firms in the sample with the function:

$$S_{i,t+1} = S_{it}{}^{a} \exp(\pi' \mathbf{x}_{it})\varepsilon \tag{3}$$

Where S_{it} is the sales of firm i at time t and $\mathbf{x}_{it}$ is a covariate matrix. Log transforming this power function, equation (3) can be expressed as:

$$\log(S_{i,t+1}) = \alpha \log(S_{it}) + \pi' \mathrm{x}_{it} + \mathrm{e}_{i,t+1} \tag{4}$$

Equation 4 can be estimated using OLS. This approach yields unbiased and efficient estimates under the standard linearity, homoscedasticity, and independence assumptions. However, the raw data are a pooled cross-section time-series, and not surprisingly there is evidence that the disturbances in Equation 4 are autocorrelated. Because the autocorrelation appears to arise from persistent, within-firm effects (inter-temporally stable features of firms that affect the growth process), I have estimated Equation 4 using a least squares constants estimator (Tuma and Hannan, 1984). Adding fixed effects for firms assumes that the correlation structure in the disturbance term can be decomposed into a firm-specific effect and a residual term (μ) that is uncorrelated across observations and is homoscedastic. It is important to note that because of the firm dummy variables in Equation 4, the estimated coefficients represent *within*-firm effects.

In addition to lagged sales volume and firm dummy variables, the sales growth models include time period effects (annual, calendar time dummy variables) and a raw count of the number of alliances formed by each of the firms in the sample. As in the innovation rate models, the effect of the characteristics of alliance partners is assessed after controlling for the number of alliances that a firm had formed during the previous five-year period. The models also include the age of the firms in the sample, defined as the number of years since founding for dedicated semiconductor producers and as the number of years since entry into the industry for diversified producers. In addition to these variables, Hypotheses 2, 3, and 4 are tested by including the combined revenues of each firm's alliance partners, the innovativeness of its alliance partners, and a series of interaction terms.

Results

Table 1 recapitulates variable definitions and, when there are hypothesized relationships, the direction of the predicted effects. Table 2 presents a correlation matrix and descriptive statistics for the variables in the innovation rate models, and Table 3 the results from the patent rate analysis.

Model 1 in Table 1 includes lagged firm sales, nationality dummy variables, annual period effects, and the lagged patent count as an unobserved heterogeneity control variable. Note that all of the models in the paper are multiplicative, so the partial effect of a variable can be understood as a multiplier rate. In Model 1, the lagged patent count has a positive and highly significant effect on the patent rate. The level of semiconductor sales is also positive. The 'Firm is European' dummy is positive although not significant, and the 'Firm is Japanese' dummy is positive and significant. Because the omitted nationality category in the patent rate models is U.S.-based firms, the coefficient on the 'Japan' dummy indicates that Japanese semiconductor producers patented at a higher rate in the U.S. than did U.S.-based companies, even after controlling for the size of the organization and a firm's proclivity to patent as indicated by the lagged patent count.[14]

[14] It is often asserted that Japanese firms apply for patents that make (relatively) narrow claims for intellectual property protection, while U.S. firms apply for fewer patents that claim broader property rights. Because 'U.S.' is the omitted nationality in the patent rate models, this difference would

Table 1. Definitions of variables appearing in patent rate and growth models

Variable name	Variable description	Expected effect
Lag of semiconductor sales	Log of firms sales in semiconductors	
Total semiconductor patents	Count of the number of semiconductor patents issued to the firm since 1976	
Firm age	Number of years since firm began operations in semiconductors	
Number of technology alliances (ΣZ_{ijt})	Count of the number of strategic alliances formed by the firm in the five previous years (*t-5* to *t-1*)	
Firm is Japanese	Dummy variable denoting that the firm is headquartered in Japan	
Firm is European	Dummy variable denoting that the firm is headquartered in Europe	
Firm is other Asia-Pacific	Dummy variable denoting that the firm is headquartered in Asia, but outside of Japan	
Sales of partners (ΣV_{it})	Sum of the semiconductor sales of the firm's strategic alliance partners	*Positive*
Age-by-sales of partners	Interaction of the firm age with the sum of the sales of the firm's alliance partners	*Negative*
Firm sales-by-sales of partners	Interaction of firm size with the sum of the sales of the firm's alliance partners	*Negative*
Innovativeness of partners (V_{it})	Sum of the patent citations received by the firm's alliance partners	*Positive*
Age-by-innov. of partners	Interaction of firm age with the number of patent citations received by the firm's alliance partners	*Negative*
Firm sales-by-innov. of partners	Interaction of firm size with the number of patent citations received by the firm's alliance partners	*Negative*

Notes: All variables are included as one-year lags. Not all variables appear in all models. For variables appearing in the patent rate and sales growth models, the expected effect pertains to both models.

Turning to the alliance variables, Model 2 includes a count of the total number of horizontal technology alliances formed by each firm during the previous five-year period, as well as the measure of the innovativeness of alliance partners. First, the addition of the two variables substantially improves upon the fit of the baseline model (chi-squared[2]=23.67, $p<0.0001$; all subsequent models are also significant against the baseline model). The findings support the first hypothesis: the effect of the alliance count variable is not significantly different from zero, but the effect of the innovativeness of alliance partners is a highly significant predictor of the patent rate. Other variables held constant, a one-standard deviation increase in the innovativeness of a firm's alliance partners produces a 40 percent increase in its innovation rate (=exp[3.400*0.098], or 1.395). Model 2 thus confirms Hypothesis 1: firms that possessed technologically advanced alliance partners innovated at a substantially greater rate than those that did not.[15]

explain the positive coefficient on the 'firm is Japanese' dummy variable in Table 2, although note that the effect persists even when the lagged patent count is included in the models. A number of supplemental analyses did suggest that this may be occurring; for example, I modeled the rate at which patents were cited by future patents as a function of the nationality of the firms that own the patents. Assuming that patents which make broad claims will be more influential, this analysis should and did show that patents held by U.S. firms are cited at a higher rate than patents assigned to Japanese firms. Although the differences in citation rates could be caused by other factors, the scope of patent claims is a plausible explanation. Regardless, differences such as these highlight the importance of controlling for firm nationality.

[15] In an influential article, Hamel, Doz, and Prahalad (1989) asserted that Japanese firms in particular have excelled at managing alliances from the standpoint of appropriating learning from their collaborators. This is readily testable with these data; I have tested for this relationship by interacting the 'Firm-is-Japanese' dummy with (a) the alliance count, and (b) the innovativeness-of-alliance-partners variables in the innovation rate models. The coefficients on the interaction variables were not significantly different from zero; in these

Not surprisingly, there is a high bivariate correlation between the total number of alliances an organization has formed during the previous five years and the summed innovativeness scores of its alliance partners computed during that same period. I have taken two additional steps to demonstrate that the innovativeness-of-partner finding is not driven by collinearity. First, in Model 3 I have included the summed innovativeness of alliance partners while omitting the variable designating total number of alliances formed. Again, I find a positive and significant coefficient on the innovativeness-of-partners variable (also note that the standard error for the innovativeness variable changes little when the alliance count is excluded from the model). Second, in Model 4 I have defined a new variable that is the average innovativeness score computed over the set of partners in each firm's alliance portfolio. This variable is not highly correlated with the total count of alliance partners but still captures differences between firms in the innovativeness of their strategic partners. Consistent with the Model 2 findings, the Model 4 results show that an increase in the mean innovativeness of alliance partners positively multiplies a focal firm's patent rate. Finally, Model 5 in Table 3 reports fixed effects negative binomial estimates using the Model 2 covariate vector (see footnote 11 above for a brief description of the estimator). Comparing the Model 2 with the Model 5 findings demonstrates that the results are not at all sensitive to the estimator. Additionally, Model 5 confirms that the results hold up when firm fixed effects are included.

Moving on to the sales growth models to test Hypotheses 2, 3, and 4, Table 4 reports within firm means, standard deviations, and correlations for the variables included in the sales growth models, and Table 5 reports the estimates from the fixed effects models of semiconductor sales.[16] The baseline Model 1 includes calendar time dummies, firm age, and firm size measured during the previous year, in addition to the fixed effects. It is not necessary to incorporate the nationality dummy variables in the sales growth models because all time-invariant attributes of the firms in the sample are captured by the firm-specific intercept adjustments. Of interest in Model 1 (and throughout Table 5) is the fact that the coefficient (denoted α in Equations 3 and 4) on the lagged sales variable is substantially less than unity. Given the log-log specification, the implication of this is that small firms have historically grown at a substantially higher *rate* than have large firms in the semiconductor industry (a coefficient of '1' would suggest that growth rates do not depend upon starting size; $\alpha>1$ would imply that large firms grow at a higher rate than small firms).

Model 2 adds to the baseline the number of alliances formed during the previous five years and the combined size of each firm's alliance partners. An *F*-test shows that adding the two alliance variables to the baseline model significantly improves the model's fit ($p<0.01$; Models 2 through 6 are all statistically significant improvements over the baseline). Consistent with the findings in the innovation rate models, the alliance count variable, although positive, is statistically insignificant (as it is in each of the models in Table 5). In support of Hypothesis 2, the positive and significant coefficient on the size-of-partners variable establishes that semiconductor firms that had strategic alliances with large partners grew at a higher rate than did firms that did not enjoy access to large partners. Moreover, the magnitude of the effect is substantial: a one-standard deviation increase in the sales of a firm's alliance partners leads to a 2.7 percent increase in its annual growth rate (=exp[0.0172*1.52], or 1.027).[17]

Turning to the final two hypotheses, the reputation arguments expressed in the third and fourth hypotheses assert that the effect of possessing large or innovative alliance partners will be great-

data, the evidence suggests that Japanese firms were no better than companies from other nations in terms of their abilities to translate alliances into higher innovation rates. I also interacted the U.S.-firm dummy with the alliance variables as well as a dummy variable that designated all Pacific Rim firms (consisting of Japanese, Taiwanese, and South Korean firms). The interaction terms in these additional models were also not significant.

[16] In the correlation matrix reported in Table 3 a number of the interaction variables are reasonably highly inter-correlated ($p<0.70$). The high bivariate correlations are not a cause for concern because the interaction variables were not simultaneously entered into any of the estimated models.

[17] Because of the fixed effects specification, I interpret the magnitude of all of the growth model findings using within-firm standard deviation changes in a variable to compute implied changes in a firm's growth rate. A 2.7 percent annual increase would translate into a 21 percent increase in size (relative to an otherwise comparable firm) over the full time series.

Table 2. Means, standard deviations, and correlations for patent rate models

	Variable	mean	std. dev.	1)	2)	3)	4)	5)	6)	7)
1)	Firm is Japanese	0.138	0.345	–						
2)	Firm is Asia-Pacific	0.082	0.275	−0.12	–					
3)	Firm is European	0.110	0.313	−0.14	−0.11	–				
4)	Lag of semiconductor sales	0.329	0.728	0.39	−0.09	0.05	–			
5)	Total number of patents	0.179	0.424	0.17	−0.12	0.09	0.69	–		
6)	Number of technology alliances (ΣZ_{ijt})	5.479	0.891	0.14	−0.09	0.11	0.60	0.59	–	
7)	Innovativeness of alliance partners (ΣP_{it})	0.066	0.097	0.15	−0.11	0.07	0.54	0.58	0.91	–
8)	Mean innovativeness of partners ($\Sigma P_{it}/\Sigma Z_{ijt}$)	0.009	0.011	0.11	−0.13	−0.10	0.10	0.17	0.09	0.37

Table 3. Determinants of the patent rate of semiconductor firms, 1986–1992

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Lag of semiconductor sales	0.206*	0.142	0.1411	0.1269	0.1457*
	(0.103)	(0.115)	(0.115)	(0.101)	(0.063)
Total number of patents	0.700*	0.651*	0.651*	0.777*	
	(0.179)	(0.202)	(0.203)	(0.162)	
Number of technology alliances (ΣZ_{ijt})		−0.005		0.0306*	−0.0017
		(0.014)		(0.008)	(0.009)
Innovativeness of alliance partners (ΣP_{it})		3.400*	3.373*		2.544*
		(1.136)	(0.996)		(0.729)
Mean innovativeness alliance partners ($\Sigma P_{it}/\Sigma Z_{ijt}$)				18.094*	
				(5.104)	
Firm is Japanese	1.060*	1.015*	1.016*	1.041*	
	(0.315)	(0.273)	(0.269)	(0.281)	
Firm is Asia-Pacific	−0.997	−0.784	−0.786	−0.936	
	(1.053)	(0.978)	(0.978)	(0.989)	
Firm is European	0.467	0.347	0.345	0.324	
	(0.446)	(0.309)	(0.311)	(0.324)	
Year is 1987	0.127*	0.072	0.047	0.041	0.107
	(0.058)	(0.052)	(0.057)	(0.060)	(0.086)
Year is 1988	0.305*	0.117	0.116	0.135	0.299*
	(0.075)	(0.076)	(0.076)	(0.084)	(0.087)
Year is 1989	0.129	0.128	−0.063	−0.084	0.249*
	(0.091)	(0.096)	(0.096)	(0.099)	(0.089)
Year is 1990	−0.054	−0.169	−0.201	−0.26	0.205*
	(0.139)	(0.134)	(0.135)	(0.142)	(0.091)
Year is 1991	−0.849	−0.983*	−1.010*	−1.043	−0.425*
	(0.187)	(0.175)	(0.173)	(0.189)	(0.110)
Constant	1.908*	1.775*	1.775*	1.605*	1.925*
	(0.196)	(0.181)	(0.181)	(0.178)	(0.138)
Pearson Chi-Square	24524.21	17298.58	17289.89	17336.63	
Number of firms	150	150	150	150	150
Number of firm years	825	825	825	825	825
Log-likelihood					−187.76
*$p<0.05$					

Notes: Models 1–4 use the random effects Poisson estimator; model 5 uses a fixed effects negative binomial estimator

est if a firm is young or small: for relatively unknown organizations, a notable strategic partner is akin to a signal of its quality. To test these hypotheses, I added a series of interaction effects to the Model 2 covariate vector. The third model includes an interaction between the age of a focal firm and the size of its alliance partners, and the fifth model contains an interaction between the age of a focal firm and the innovativeness of its alliance partners. The coefficient on the age-by-size-of-partners interaction is negative and significant, indicating that possessing large alliance partners increased the growth rate of younger firms more than it augmented the growth rate of older firms. The coefficient on the age-by-innovativeness-of-partners interaction in Model 5 is also negative, showing that having highly innovative alliance partners was a greater benefit to young than to old organizations. Both findings support the prediction that the value of coalitions with large and innovative firms is greatest for young producers, probably because important constituents are uncertain about the quality and reliability of those organizations.

To demonstrate the magnitude of the age interactions, consider the differential impact of having large or innovative alliance partners on firm growth rates assuming different levels of focal firm age. For example, consider the typical firm at two different points in its life: when it is one standard deviation below its mean age in the time series and when it is one standard deviation above its mean age (I will use the overall sample mean and the within-firm standard deviation of the age

Table 4. Within-firm means, standard deviations, and correlations for sales growth models

	Variable	mean	st. dev.	1)	2)	3)	4)	5)	6)	7)	8)
1)	Lag of semiconductor sales (logged)	4.390	0.499	–							
2)	Firm age	18.343	1.938	0.45	–						
3)	Number of technology alliances (ΣZ_{ijt})	5.479	2.337	0.18	0.30	–					
4)	Sales of alliance partners (ΣV_{it})	5.387	1.523	0.13	0.26	0.25	–				
5)	Innovativeness of alliance partners (ΣP_{it})	0.066	0.034	0.32	0.34	0.54	0.35	–			
6)	Interaction: lagged sales-by-(ΣV_{it})	27.367	8.035	0.49	0.44	0.38	0.76	0.45	–		
7)	Interaction: lagged sales-by-(ΣP_{ijt})	0.419	0.233	0.35	0.31	0.60	0.23	0.86	0.43	–	
8)	Interaction: age-by-(ΣV_{it})	118.470	40.402	0.17	0.32	0.37	0.72	0.35	0.83	0.34	
9)	Interaction: age-by-(ΣP_{ijt})	1.861	1.077	0.15	0.42	0.63	0.21	0.76	0.41	0.4	0.39

variable for this illustration). Now, assume that this firm has large alliance partners at both stages of its life—suppose that the combined sizes of its alliance partners rank at the 75th percentile of the size-of-partners distribution at both life stages. When the firm is young (one standard deviation below its mean age in the time series), the partial effect of having large alliance partners leads to a predicted increase in the annual growth rate of 15.7 percent; when it is one standard deviation above its mean age, however, having the same alliance partners leads to a predicted annual growth rate increase of only 9.6 percent.[18] Assuming the same age conditions but substituting the size-of-partners results (Model 3) with the innovativeness-of-partners results (Model 5), the predictions are for a 9 percent increase in growth rate when the firm is younger and a 6 percent increase when it is older.

The results for the interactions between the size of a focal firm and the characteristics of its alliance partners appear in Models 4 and 6 in Table 5. The coefficient on the focal-firm-size-by-size-of-alliance-partners interaction in Model 4 is negative and significant, demonstrating that large alliance partners had the greatest effect on the growth rates of firms when they were small. In Model 6, the coefficient on the size of a focal firm interacted with the innovativeness of its alliance partners is also negative, demonstrating that having large alliance partners was a greater advantage for firms when they were small. Therefore, the identical patterns appear in the age and the size interactions: the Model 4 and 6 findings offer evidence that the value of having well-known strategic partners was greatest for small firms, just as the Model 3 and 5 findings showed that it was greatest for young firms. Calculations similar to those reported above for the age interactions suggest even larger disparities in the advantage of possessing large and innovative alliance partners across different levels of focal firm size: the benefit of large alliance part-

[18] The partial effect of the size-of-alliance-partners (V_{it}) in Table 5, Model 3 is: $\exp[V_{it}(0.054–0.002AGE_{it})]$. Replacing the variables with their assumed values, the young firm experiences a growth rate increase of 15.7 percent (=exp[6.88(0.054–0.002*16.4)]) from having relatively large strategic alliance partners. Without altering the value of the size-of-partners variable and changing only firm age, the older firm has a predicted growth rate increase of 9.6 percent (=exp[6.88(0.054–0.002*20.3)]) from having relatively large alliance partners.

Table 5. Fixed effects (OLS) estimates of growth rate of semiconductor firms, 1986–1992

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Lag of semiconductor sales (lagged)	0.669*	0.683*	0.664*	0.752*	0.659*	0.692*
	(0.025)	(0.025)	(0.025)	(0.033)	(0.026)	(0.025)
Firm age	0.033*	0.030*	0.039*	0.029*	0.037*	0.033*
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Number of technology alliances		−0.007	−0.002	−0.002	0.002	−0.001
(ΣZ_{ijt})		(0.006)	(0.006)	(0.005)	(0.007)	(0.006)
Sales of partners (ΣV_{it})		0.0172*	0.054*	0.063*		
		(0.007)	(0.012)	(0.017)		
Age-by-sales of partners			−0.002*			
			(0.001)			
Lag sales-by-sales of partners				−0.012*		
				(0.004)		
Innovativeness of alliance partners					2.186*	3.666*
(ΣP_{it})					(0.713)	(1.199)
Age-by-innov. of partners					0.081*	
					(0.02)	
Lagged sales-by-innov. of partners						−0.557*
						(0.17)
Year is 1987	−0.042	−0.018	−0.022	−0.022	−0.019	−0.021
	(0.03)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Year is 1988	0.083*	0.106*	0.104*	0.101*	0.107*	0.107*
	(0.03)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Year is 1989	−0.039	−0.037	−0.036	−0.036	−0.037	−0.037
	(0.03)	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)
Year is 1990	0.029	0.015	0.021	0.021	0.018	0.018
	(0.03)	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)
Year is 1991	0.035	0.003	0.002	0.005	−0.003	−0.001
	(0.03)	(0.034)	(0.034)	(0.034)	(0.035)	(0.035)
Constant	1.272*	0.966*	0.834*	0.684*	0.926*	0.869*
	(0.092)	(0.126)	(0.128)	(0.152)	(0.130)	(0.132)
R-squared (within)	0.6283	0.6367	0.6444	0.6414	0.6407	0.6434
Number of firms	150	150	150	150	150	150
Number of firm years	825	825	825	825	825	825

*P<0.05

Notes: models 1–4 use the random effects Poisson estimator; Model 5 uses a fixed effects negative binomial estimator

ners was much greater for small firms.

Note finally that although young and small firms may be expected to grow at high rates (in fact, the baseline model in Table 5 demonstrates this to have been the case in the chip industry), the strong support for Hypotheses 3 and 4 cannot be attributed to the fact that young and small semiconductor producers grow at a higher rate than larger and older producers. Although true, the differences in growth rates attributed to initial sizes and ages are already captured in all of the Table 5 models by the inclusion of the main effects of age and size. Thus, the results from the models that include the partner characteristics variables interacted with focal firm attributes (Models 3–6) convey consistent and convincing support for the hypothesized relationships.

Discussion and conclusions

This study has offered additional evidence to confirm the prevalent assumption that strategic alliances can improve performance. However, in both the patent rate and the sales growth rate analyses, the results demonstrated that the important determinants of the strength of the alliance-performance link are the attribute profiles of the firms that an organization is affiliated with—not the mere fact that it is affiliated. In fact, in the analyses reported in this paper, the count of the number of alliances formed proved to be an insignificant predictor in the models that also included measures of the size or innovativeness of a firm's alliance partners (see also Hagedoorn and Schakenraad, 1994). In short, technology alliances with large and innovative partners improved baseline innovation and growth rates, but collaborations with small and technologically unsophisticated partners had an immaterial effect on performance.

The results also at least suggest that alliances are more than pathways for the exchange of resources and know-how; they also can be signals that convey social status and recognition. The Table 5 results suggest that alliances with well-known partners may fortify producers' reputations, in addition to providing access to resources such as technological know-how and new customers. Although I have been unable to directly measure customer and investor perceptions of the firms in the sample, the consistent performance effects of the interactions between the size and age of an organization and the prominence of its partners are in full accordance with sociological arguments about the effects of affiliations on actors' reputations. Particularly when one of the firms in an alliance is a young or small organization or, more generally, an organization of ambiguous quality, I believe that alliances convey endorsements: they build public confidence in the value of an organization's products and services and facilitate the firm's efforts to attract risk averse customers. In this sense, gaining an alliance partner signals a firm's quality. Not surprisingly, however, the value of an alliance as an endorsement is also highly contingent upon the regard accorded to the partner firm: because large and innovative organizations are recognized for their reliability and a track record of prior accomplishments, the imprimatur implicit in an alliance with a large and innovative firm may be a particularly valuable signal of the associate's quality. In contrast, alliances with small and insignificant firms apparently do little to promote a focal organization's social standing. Thus, both from a resource access and reputation standpoint, large and innovative firms are likely to be the most valuable associates.

Another implication of this study that merits emphasis, particularly as it relates to the existing literature on alliances, is that endorsements are perhaps the easiest to obtain of the potential benefits of intercorporate partnerships. The empirical work investigating the performance of alliances has concluded that most partnerships fail to achieve hoped-for goals (e.g., Harrigan, 1985). We know from a large body of research that interorganizational collaboration is fraught with the potential for opportunistic behavior and is inherently difficult to manage. However, the findings of this study suggest that alliances can be highly advantageous *even when they fail to achieve the strategic objectives that led to their formation*. The reason for this is that a focal organization's reputation may be upgraded simply because it has survived the due diligence of a prominent strategic partner, particularly if the focal organization is young or small. This advantage occurs regardless of whether or not the resource access benefits of an alliance materialize.

In conclusion, I would like to suggest a few avenues for future research. First, the demonstration that characteristics of an organization's strategic partners affect the benefits that it derives from strategic coalitions has relevance for the large and active research on the antecedents of alliance formation. The contingent value of alliance partners suggests that it would be informative to have studies of the alliance formation process that also consider the characteristics of strategic partners, rather than simply viewing the formation of an alliance as a binary event (and therefore implicitly treating all partners as being of equal value). Thus, research on the organization and industry-level conditions that predict firms' propensities to enter alliances could begin to explore two-stage models, in which the occurrence of the alliance is modeled and, conditioning on the occurrence, the attributes of strategic partners are then explored in a second-stage model. For instance, using the data in this paper, one could first estimate the rate at which a firm enters alliances as a function of firms' attributes, firms' positions in the alliance network, or time-varying industry conditions, and then, in a second model, explore the size and innovativeness of the firm's strategic partners. If it is true that the performance consequences of alliances are tightly connected to the characteristics of a firm's strategic partners, it is important that the alliance antecedent literature begin to attend to the factors that promote the more valuable kinds of collaborations.

Second, we know little about the multifaceted relationships between the characteristics of alliance partners and the advantages of a cooperative strategy. For instance, at least from a learning standpoint, Burt's (1992) structural holes argument suggests that the addition of a nonredundant strategic partner, because it purveys access to new information, is likely to be more valuable than the acquisition of a new partner that is similar in kind to an existing one. This suggests that a portfolio of alliances consisting of ties to organizations in a variety of different market niches may be more valuable than an otherwise similar portfolio of alliances with firms in the same or similar market niches. In addition to research on the returns to particular kind of alliance network structures, it is also important to understand how a focal firm's characteristics, such as its level of absorptive capacity, conditions the returns it garners from occupying particular positions in an industry's alliance network. More generally, a large number of partner attributes as well as characteristics of the structural configuration of firms' alliance networks are likely to determine the magnitude of the advantage of a cooperative strategy, both on their own and when interacted with focal-firm characteristics.

In a related vein, researchers have recently become attentive to the dyadic conditions that must be present for interoganizational learning to occur in the context of strategic alliances (e.g., Lane and Lubatkin, 1998; Dyer and Singh, 1998; Stuart, 1998). One interesting question is the extent of dependence of the returns to technology-based alliancing on the absorptive capacity of the firms in the partnership. This question could be explored with many existing datasets and a research design that investigates the interaction effects between partner characteristics, properties of the collaborating dyad, and proxies for focal firm absorptive capacity on the firm-level innovation rate. For example, it would be informative to know whether the level of focal firm R&D spending interacts with the innovativeness of the firm's strategic partners in a model of patenting rates. It would be very valuable to have evidence that informs the necessary conditions for inter-organizational learning to occur and the contingencies that bear upon the intercorporate knowledge transfer process.

Because technology alliances are access relationships, it is also likely that the partnership quality of the relationship between two firms affects the gain in ex post performance. Much of the work on alliance antecedents that has grown out of network theory has been keenly interested in how prior relationships between firms affects the likelihood that they will collaborate in the future (Gulati, 1998, provides a comprehensive review of this literature). For instance, network theorists have argued that existing alliance ties dictate the selection of collaborators. Because prior alliances convey first-hand information on the reliability and trustworthiness of potential partners, an established relationship with a particular partner reduces the risk and transaction costs of a future partnership with that organization (Granovetter, 1985; Podolny, 1994; Gulati, 1995; Dyer, 1996). These ideas, which have been shown to influence the alliance formation process, may also have implications for the degree to which access is actually achieved in alliance contexts: if an intercorporate relationship is rooted in a high degree of trust, mutual access is a much more likely alliance outcome. In other words, relationship-level variables such as the degree of trust between alliance partners are another set of factors that influence the link between alliances and firm performance.

ACKNOWLEDGEMENTS

I would like to thank the Graduate School of Business at the University of Chicago for financial support for this project.

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