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ALLIANCE-BASED COMPETITIVE DYNAMICS

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Do rivals' alliances increase or decrease the competitive pressure experienced by a firm? Linking ecological and economic research on organizations, we propose that the effects of rivals' horizontal, upstream, and downstream alliances are determined by the degree to which they (1) foreclose a focal firm's alliance opportunities and (2) increase industry carrying capacity. We also hypothesize that firms can co-opt rivals' alliances by partnering with well-linked rivals. An analysis of Canadian biotechnology firms supports these predictions.

In technology-based industries, do rivals' alliances increase or decrease the competitive pressure experienced by a firm? If rivals' alliances increase competitive pressure, what if anything can a firm do to counteract these effects? Although the last decade has witnessed an explosion of research concerning the effects of alliances on the firms that participate in them, the literature is virtually silent regarding their competitive effects on rivals. Yet these implications are crucial for scholarly understanding of the competitive dynamics of technology-based industries, as well as for managers competing in such environments.

There is by now some consensus, based on research rooted in transaction cost economics (TCE) and the resource-based view (RBV), that firms pursue collaborative arrangements to gain more efficient or timely access to scarce resources (Hennart, 1988; Kogut, 1988; Williamson, 1991). But to the extent that competitive dynamics of alliances have been considered, the literature has produced varying theoretical predictions. According to one line of reasoning, in a world of limited potential partners, a firm's alliances weaken its rivals by denying them access to desirable partners and resources (Gomes-Casseres, 1994). An alternate line of argument, stemming from ecological conceptions of environmental carrying capacity and organizational legitimation, is that links between a population's members and established organizations outside the population increase the availability of resources for the population overall; in a sense, a rising tide of alliances helps all competitors, even if the allying firms benefit more (Baum & Oliver, 1992).

We explored the varied competitive implications associated with different types of alliances. Building on evidence that incumbents' horizontal, upstream, and downstream links yield systematically different effects on the likelihood of their entry into new technology-based industry subfields (Calabrese, Baum, & Silverman, 2000), we predicted that these different types of alliances generate systematically different levels of competitive intensity among rivals. We linked these disparate effects to the degree to which an alliance (1) forecloses rivals' alliance opportunities and (2) expands the resource base available to industry participants. In particular, we distinguished among horizontal, upstream, and downstream alliances according to these conditions, hypothesizing that horizontal alliances generate the greatest competitive intensity, upstream alliances less, and downstream links less still. We also explored the degree to which a firm can mitigate competitive effects of rivals' alliances by collaborating with them, thus co-opting their alliances.

We tested our hypotheses in a study of the Canadian biotechnology industry as it existed from 1991 to 1996. We investigated the impact on focal firms' exit rates from the industry of their rivals' alliances, interpreting an increase in the exit rate as evidence of increased competitive intensity (Hannan & Carroll, 1992). In line with our predictions, we found that the competitive intensity a firm experiences generally increases with the number of alliances that its rivals form, but this effect is moderated for

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those types of alliances that are more likely to expand the industry resource base and less likely to foreclose rivals' alliance opportunities. Further, a firm benefits from the alliances of rival firms with which it collaborates. Our findings (1) highlight the multifaceted competitive impact of rivals' alliances, (2) underscore the importance of judicious partner selection in horizontal alliances to mitigate alliance-based competition, and (3) identify criteria that inform such partner selection.

Our study extends prior research by focusing on the role of alliances in shaping *competitive dynamics*. We link transaction cost economics and resource-based-view research on alliances, literatures that offer insight into sources of firm heterogeneity in capabilities but are generally silent regarding competitive implications of this heterogeneity, to recent ecological models of competition. These ecological models offer a perspective on how a firm's rivals' alliances may affect its fortunes and a general approach to studying competitive dynamics, but they lack firm-level theoretical frames within which firm heterogeneity can be studied. This linkage could foster an integrative model of alliance-based competitive dynamics in particular and theoretically informed models of interfirm competition incorporating firm heterogeneity more generally.

THEORY AND HYPOTHESES

Competitive Effects of Alliances

Interorganizational relationships provide a myriad of advantages for participating firms, primarily associated with the direct or indirect availability of complementary resources (Chung, Singh, & Lee, 2000). Transaction cost economists and resource-based theorists both propose that alliances facilitate the access of knowledge and other assets for which arm's-length contracting between parties may be hazardous (Hennart, 1988; Kogut, 1988; Williamson, 1991). Alternatively, alliances may confer upon a firm an aura of legitimacy (Baum & Oliver, 1991; Miner, Amburgey, & Stearns, 1990), which in turn enables the firm to acquire other necessary resources. Such advantages are hypothesized to be particularly important when timely access to dispersed knowledge or resources is crucial (Teece, 1992) or when ambiguous technologies lead actors to rely on indirect social indicators to assess organizational performance (Stuart, Hoang, & Hybels, 1999).

A common notion throughout this literature is that alliances enable a firm to "outcompete" its rivals in the quest for resources crucial to performance or survival. An implicit, but unexplored, corollary is that a firm's alliances not only enable it to withstand competition, but also to impose stronger competition on others. Put another way, if winning the "alliance race" increases a firm's chance to win subsequent races for partners, capital, or patents, then a firm that gains alliances today is better positioned to deny its rivals access to ancillary resources tomorrow (Amburgey, Dacin, & Singh, 1996; Walker, Kogut, & Shan, 1997). Such an outcome is exacerbated in a world of limited partners. Scarcity rewards a firm that moves quickly to secure high-quality partners by both enhancing its own reputation as a desirable partner (Gulati, 1995) and foreclosing rivals' partnering opportunities (Gomes-Casseres, 1994). Thus, much as greater size or experience makes a firm both more viable and a stronger competitor (Barnett, 1997; Barnett & Amburgey, 1990), a firm's alliances not only make it more viable, but also more competitively potent.

Scholars have made an alternate argument in the organization theory literature, proposing similarly beneficial results for participants in alliances, but also proposing benefits for rivals. In this view, a firm's alliances with established actors may benefit its rivals by increasing the carrying capacity of an industry, through increases in the capital available to industry participants, the demand for their outputs, or the legitimacy of the industry (Baum & Oliver, 1992). Alliances involving established actors thus embody a public-good element, particularly for young industries characterized by uncertainty about the fundamental viability of their technologies and organizational forms (Aldrich & Fiol, 1994). Thus, such alliances may simultaneously enhance a focal firm's organizational viability and reduce environmental competitive pressure.

When are a firm's alliances likely to increase competitive intensity, and when are they likely to decrease it? We propose that alliances with different types of partners are characterized by different levels of alliance foreclosure and environmental carrying capacity enhancement and that they will yield systematically different effects on the level of competitive intensity. Calabrese, Baum, and Silverman (2000) noted that the incumbents' upstream, downstream, and horizontal alliances yielded systematically different effects on the likelihood of entry into subfields of the Canadian biotechnology industry. Below, we distinguish among these types of alliances according to the degrees to which they foreclose rivals' alliance opportunities and increase the carrying capacity of an industry. On the basis of this distinction, we then explore the effects of each type of alliance on the competitive dynamics of technology-based industries.

Downstream alliances link firms in a technology-based industry to sources of complementary assets, commercialization knowledge, and capital outside of the existing industry boundaries. For example, biotechnology firms' downstream alliances with pharmaceutical, chemical, or marketing companies provide access to distribution channels, production facilities, marketing expertise, and financing that facilitate successful development and commercialization of a product or process (Kogut, Shan, & Walker, 1992). Such alliances increase access to resources, which are likely to increase a firm's viability and make it a stronger competitor.

At the same time, such alliances directly and indirectly increase the level of resources available for industry participants. Alliances with downstream companies often involve significant infusions of capital into an industry (Lerner, 1994). Alliances between young technology-driven firms and established downstream companies also appear to increase the interest demonstrated by other sources of financing (Stuart et al., 1999), presumably because downstream firm involvement signals (or is perceived to signal) the commercial viability of the firms' technologies. Similarly, to the extent that a downstream alliance signals to other downstream firms the commercial potential of a particular area of innovation, one downstream alliance will lead other downstream firms to follow suit, thus increasing the resources available to an industry (Amburgey et al., 1996).

Finally, a firm's downstream alliances often do not pose a high foreclosure risk to its rivals. For example, large pharmaceutical firms typically maintain dozens or hundreds of simultaneous alliances with different biotech firms. Further, it is frequently the case that downstream activities, such as marketing and distribution, are the most scale- and scope-intensive aspects of a technology-based industry value chain (Calabrese et al., 2000). The scale and scope economies associated with these activities imply that it is economically feasible—and even desirable—for downstream firms to partner with multiple players in an industry. Thus, a focal firm's alliances with downstream partners are not likely to significantly foreclose rivals' access to the same partners. In sum, alliances with downstream partners typically do not prevent rivals from forming similar alliances, and these alliances simultaneously expand the resource base available to an industry.

Upstream alliances link technology-based firms to sources of research knowledge. Biotechnology firms' alliances with universities and other organizations provide them with the cutting-edge scientific and technological expertise necessary for successful discovery and patenting of new innovations (Argyres & Liebeskind, 1998). Semiconductor firms' links with universities are credited with providing similar access to key technological knowledge (Spencer & Grindley, 1993).

Such alliances increase the accessibility of scientific inputs for firms in an industry. Yet to the extent that the resulting knowledge is not subject to spillovers, it is not likely to benefit rivals of an allying firm. More important, alliances with upstream partners foreclose rivals' access to those partners to a greater degree than do downstream alliances. Zucker, Darby, and Brewer (1994) indicated that scientists, including "star" university scientists whose research efforts have a tremendous impact on biotechnology firm success, rarely transact with more than one firm at a time. The relative lack of scale and scope economies in individual research projects (as compared to, say, marketing) imposes stark limits on the number of simultaneous alliances to which an upstream research player can commit its particular scientific or technological expertise.

Finally, in contrast to downstream alliances, upstream linkages rarely directly increase the level of financing or other resources available to industry participants. In sum, as compared to downstream alliances, alliances with upstream partners are likely to foreclose rivals forming similar alliances while only modestly expanding the resource base available to an industry.

Horizontal alliances link firms to other firms in the same industry. In contrast to vertical alliances, such links between potential competitors do not tap resources outside of the focal industry. Evidence suggests that cooperative ventures with direct competitors are more difficult to manage (Doz, Hamel, & Prahalad, 1989) and more likely to spark learning races (Baum, Calabrese, & Silverman, 2000; Khanna, Gulati, & Nohria, 1998). Firms will thus likely engage in few alliances with potential rivals. Since each horizontal alliance involves two firms of the same partner type, each alliance consumes two links, further limiting the supply available. As a result, as the number of horizontal alliances increases, rivals face a rapidly shrinking pool of potential (and desirable) partners. Thus, horizontal alliances keep rivals from forming similar alliances, while having no salutary effect on the resource base available to an industry.

Effect of Rivals' Upstream, Downstream and Horizontal Alliances on Competitive Pressure

The above discussion distinguishes among rivals' upstream, downstream, and horizontal alliances in terms of their effect on the competitive pressure experienced by a focal firm. Each type of alliance is expected to make the participating rival a more potent competitor, thus raising a focal firm's exit rate (that is, the likelihood of its exit at a given time). However, vertical alliances are more likely than horizontal alliances to yield offsetting benefits in terms of expansion of the industry resource base. Further, downstream alliances are less likely than upstream alliances to foreclose a focal firm's opportunity to forge alliances of its own, thus mitigating some of the deleterious effects of rivals' alliances:

Hypothesis 1a. A firm's exit rate increases as its rivals' number of alliances increases.

Hypothesis 1b. The increase in a firm's exit rate as its rivals' number of alliances increases is lower for upstream alliances than for horizontal alliances.

Hypothesis 1c. The increase in a firm's exit rate as its rivals' number of alliances increases is lower for downstream alliances than for either upstream alliances or horizontal alliances.

Collaboration as a Response: Beneficial Effects of Rival Partners' Alliances

The foregoing hypotheses stress how a rival's alliances may increase its competitive strength. At the same time, however, these alliances may also make the rival a better partner. Powell, Koput, and Smith-Doerr (1996) noted how biotechnology firms that are more centrally positioned—crudely speaking, those with more links to other well-linked players—have greater and faster access to finer-grained information and are better able to absorb technological knowledge and other resources. As a result, well-connected rivals may represent "high quality" partners because they possess leading-edge technology, have rapid access to critical information, and have accumulated partnering experience. To the extent that access to knowledge is a primary motive for interfirm alliances, then the benefit of a firm's alliances will depend in part on its partners' alliances.

Consequently, a firm may be able to turn its rivals' alliance-based competitive strengths to its own advantage by partnering with its better-connected rivals. Alliances with well-connected rivals provide promising opportunities to learn new capabilities and acquire advanced know-how. Advantages also arise to the extent that allying with well-linked and consequently highly visible partners yields signaling benefits (Podolny, 1994; Stuart et al., 1999). Thus, we predict:

Hypothesis 2. A firm's exit rate decreases as its rival partners' number of alliances increases.

METHODS

We tested the above hypotheses in a study of the Canadian biotechnology industry. In biotechnology, significant resource and speed demands of patent races and commercialization motivate biotechnology firms to seek out partnerships with downstream, upstream, and horizontal firms (Powell et al., 1996). Alliances with downstream partners provide access to critical complementary assets: marketing-distribution infrastructure, production facilities, and/or expertise in managing clinical trials (Pisano, 1990). This is particularly true of collaborations with pharmaceutical and chemical firms. Alliances with upstream partners, such as universities and research institutes, are a source of knowledge critical to success in patent races but too tacit to be effectively transferred through licensing (Liebeskind, Oliver, Zucker, & Brewer, 1996). Alliances with other biotechnology firms offer many of these benefits as well as access to direct experience in the industry.

Many scholars have noted the unique role of patents in biotechnology (Fligstein, 1996). Given the unusually strong appropriability regime associated with biotechnology, patents provide biotechnology firms with significant bargaining power in negotiations for other assets necessary for product commercialization (Pisano, 1990). In addition, frequent publicity surrounding a biotechnology firm's pending patents indicates that it is using publicity to signal patent race leads that are exploited in the race for additional resources. Consequently, we were careful to control for the patenting activity of a focal firm and its rivals. Although treated as control variables, the competitive dynamics of patenting are interesting in their own right, and we briefly consider these results in the discussion section.

Data

We tested our hypotheses using data describing the alliances and other organizational characteristics of biotechnology firms operating in Canada during the six-year period between January 1, 1991, and December 31, 1996. We constructed event histories for the 613 biotechnology firms that existed at any time during this period using data from *Canadian Biotechnology,* an annual directory of companies active in the biotechnology field. Published since 1991, *Canadian Biotechnology* is the most comprehensive historical listing of Canadian biotechnology firms and of their products, performance, and alliances. It tracks biotechnology firms operating in 16 sectors, which are identified in our appendixes, and compiles self-reported data on a wide range of firm characteristics, including revenues, employees, and names of alliance partners. Firms report foreign and Canadian partners; thus, we captured each firm's global alliances.[1] We cross-checked these data against the *Canadian Biotechnology Handbook,* which provides information for a more restricted set of "core" Canadian biotechnology firms (firms entirely dedicated to biotechnology) and found no significant discrepancies in information for the companies represented in both sources.

In 1991, 471 biotechnology firms were already in operation; thus, the life histories for these firms were "left-censored." With available archival information, we were able to confirm founding dates for these companies. During the study period, 142 biotechnology firms were founded, and 186 exited the industry. Exit was defined as the failure of a firm or closure of a subsidiary. As is the norm in organizational failure studies (Baum, 1996), name changes and acquisitions were not considered failures because the firms continued to operate.

We also used the Micropatent database to identify each patent issued to these biotechnology firms in the United States applied for between January 1975 and December 31, 1996.[2] We used U.S. patent data because Canadian biotechnology firms typically file patent applications in the United States first to obtain protection for one year, during which they file in Canada and elsewhere, according to a 1992 issue of the magazine *Canadian Biotech.* For biotechnology firms that were subsidiaries, we included only patents assigned to the subsidiaries. During the 1975–90 period, these biotechnology firms were granted 1,309 patents, and during 1991–96, they were granted 502 patents.

As elaborated elsewhere (Calabrese et al., 2000), several factors point to the value of studying the Canadian biotechnology industry as a "quasi-independent" population; these factors include Canadian biotechnology firms' reliance on within-Canada financing and partnering, particularly for horizontal alliances. Our inclusion of human and nonhuman biotechnology sectors (that is, sectors directly concerned with human physiology and other sectors) as part of the same industry is consistent with prior research (Amburgey et al., 1996; Walker et al., 1997), and our empirical strategy controlled for unique features of human biotechnology by allowing for sector differences in all models.

Independent Variables

To test our hypotheses, we constructed time-varying, firm-specific measures of each biotechnology firm's number of alliances by type of partner. Given the form in which alliance data appear in *Canadian Biotechnology*—as a list of partner names for each company—we counted each member of an alliance as a full-fledged partner and so, in some cases, a biotechnology firm would be assigned more than one partner for a single alliance. Thus, if firm A has a joint venture with firm B, and firm A also has a three-way alliance with firms C and D, then firm A will list firms B, C, and D as its alliance partners. Given our conception of an alliance as a potential claim on some portion of a partner's finite partnering ability, this construction seemed appropriate for our purposes. To the extent that multilateral alliances impose different demands than do bilateral alliances on partnering ability, however, this system may have introduced some noise into our analysis.[3] We aggregated alliance partners (sep-

[1] The data do not, however, distinguish among equity joint ventures, nonequity ventures, licensing agreements, and other alliance forms. Thus, although some scholars have studied differences in structure and outcomes for different types of alliances (Mowery, Oxley, & Silverman, 1996; Oxley, 1997), we could not. More generally, although our data offer a comprehensive accounting of alliance activity, they do not allow insight into the alliances' internal workings.

[2] Pending U.S. patent applications are not public information. Rather, the U.S. Patent and Trademark Office publishes patents only after they are granted. Like prior researchers using patent statistics, we thus only included information on ultimately successful patent applications. In addition, there is a time lag between a patent's filing and its granting. During the 1984–93 period, 93 percent of the patents in our sample were granted within three years of application. We used Micropatent through 1999 to search for patents granted to our sample firms that were applied for before 1996, thus identifying virtually all patents pending during our sample period.

[3] The information contained in *Canadian Biotechnology* also did not permit us to distinguish alliances intended to have short lives (such as some technology transfer alliances) from those with long-term objectives.

arately) for each biotechnology firm's rivals and partners. Below, we describe the variable construction and the aggregation procedures.

Rivals' alliances. To test Hypotheses 1a–1c, we constructed a set of firm-specific variables that separately count the aggregate number of alliances a biotechnology firm's rivals had at the start of each year with the nine following types of organizations: (1) *downstream partners:* pharmaceutical firms, chemical firms, marketing firms; (2) *upstream partners:* universities, research institutes, government labs, hospitals, industry associations; and (3) *horizontal partners:* rival biotechnology firms. For each focal firm, we defined rivals as those companies that (1) operated in one or more of the same biotechnology sectors (for instance, agriculture; human diagnostics) as the focal firm and (2) were not its partners.[4] The resulting variables are analogous to recent elaborations of the standard density-dependence model (Hannan & Carroll, 1992) that use time-varying, firm-specific characteristics to gauge the relative competitive strengths of firms and to model the dynamics of competitive heterogeneity (e.g., Barnett, 1997; Baum & Mezias, 1992; Baum & Singh, 1994; Podolny, Stuart, & Hannan, 1996). An early example is Barnett and Amburgey's (1990) use of population mass, in which they respecified organizational density as the aggregate of the sizes of competing organizations to estimate the effects of size asymmetries on competitive dynamics. Hypotheses 1a–1c predict that a firm's exit rate will increase most as a result of its rivals' horizontal alliances, will increase to a lesser degree as a result of their upstream alliances, and will increase still less as a result of their downstream alliances. We thus expected the magnitudes of the effects for these variables to exhibit the following pattern: horizontal will be greater than upstream, which will be greater than downstream.

Rival partners' alliances. To test Hypothesis 2, we constructed a set of firm-specific variables in the same manner as the rivals' alliance measures. These count the aggregate number of alliances a biotechnology firm's rival partners (firms that are simultaneously its rivals and its partners) had at the start of each year with each of the nine partner types. Hypothesis 2 predicts that a firm's exit rate should decrease as its rival partners establish more alliances, be they downstream, upstream, or horizontal. We expected the coefficients for these variables to be negative.

Control Variables

Many other factors may influence the fates of biotechnology firms. Accordingly, we developed a baseline model that included a range of biotechnology firm characteristics and environmental features. Table 1, a list of these variables, outlines how each was calculated. Each variable was included for at least one of three reasons: (1) earlier research on these data has shown the variable to affect other dependent variables (Baum et al., 2000), (2) the variable is well established in the ecological literature as influencing firm failure (Hannan & Carroll, 1992), or (3) the variable measures some aspect of environmental carrying capacity (for instance, resource availability or attractiveness) needed to obtain meaningful estimates of alliance-based competition among biotechnology firms. Additionally, each variable controlled for possible sources of time dependence that might have produced autocorrelation in the time series of exit events (Tuma & Hannan, 1984).

Descriptive statistics for the alliance variables are given in Appendix A. Correlations are generally small to moderate in magnitude (95 percent are lower than .5, indicating 25 percent of shared variance), although they are generally stronger among the rival biotechnology firms' alliance and patent variables. The largest correlation, .78 (61 percent shared variance), is between rival biotechnology firms' hospital alliances and rival biotechnology firms' university alliances. Such levels of multicollinearity among explanatory variables can result in larger standard errors for correlated variables but will not bias parameter estimates. So, although such multicollinearity does not pose a serious estimation problem, it can make it difficult to draw inferences about the effects of adding specific variables to models. Therefore, when estimating results, we followed a strategy of estimating hierarchically nested models to check that multicollinearity was not causing less precise parameter estimates (Kennedy, 1992).

Dependent Variable Model Specification

We estimated biotechnology firms' exit rate using λj, the discrete time hazard rate, as our dependent variable. The discrete time hazard rate is the con-

As a result, in some cases, we may have aggregated partnerships with quite different goals. Again, however, our conception of an alliance as, regardless of its mission, claiming a share of a firm's finite partnering ability limited any potential bias this procedure may have introduced.

[4] Only two alliances occurred between biotechnology firms operating in nonoverlapping sectors; consequently, we did not estimate nonrival biotechnology firm alliance effects.

TABLE 1
Time-Varying Control Variables[a]

Variable	Measured As
Firm characteristics	
Own alliances	Number of alliances focal firm has with each type of partner.
Own network efficiency[b]	$\{[1 - \Sigma_{ij} (PA_{ij})^2]/NA_i\}$, where PA_{ij} is the proportion of focal firm i's alliances that are with partner type j and NA_i is focal firm i's total number of alliances.
Older patents[c]	Number of patents granted to focal firm more than five years ago.
Recent patents[c]	Number of patents granted to focal firm within last five years.
Pending patents[c]	Number of patents applied for but not yet granted to focal firm.
Age	Number of years since date of focal firm's founding.
Revenue	Natural logarithm of annual revenue of focal firm, in 1991 dollars.
R&D expenditures	Natural logarithm of R&D expenditures of focal firm, in 1991 dollars.
R&D employees	Number of employees dedicated to R&D in focal firm.
Non-R&D employees	Number of non-R&D employees in focal firm.
Manufacturing facility	If focal firm owned manufacturing facility, 1; else 0.
Primary biotechnology sector	Sector in which focal firm is most active, 1; else 0.
Scope	Number of sectors in which focal firm is active.
Ownership	Set of dummy variables for private, public, initial public offering, nonprofit, government/university/hospital, subsidiary, joint venture.
Left-censored	If focal firm existed before 1991, 1; else 0.
Rival biotechnology firms' characteristics	
Older patents[c]	Number of patents granted to rivals more than five years ago.
Recent patents[c]	Number of patents granted to rivals within last five years.
Pending patents[c]	Number of patents applied for but not yet granted to rivals.
Network efficiency	$\Sigma_r ([1 - \Sigma_{rj} (P_{rj})^2]/NA_r)$, where P_{rj} is the proportion of rival r's alliances that are with partner type j and NA_r is rival r's total number of alliances.
Partner biotechnology firms' characteristics	
Older patents[c]	Number of patents granted to rival partners more than five years ago.
Recent patents[c]	Number of patents granted to rival partners within last five years.
Pending patents[c]	Number of patents applied for but not yet granted to rival partners.
Network efficiency	$\Sigma_k ([1 - \Sigma_{kj} (PA_{kj})^2]/NA_k)$, where PA_{kj} is the proportion of rival partner k's alliances that are with partner type j and NA_k is partner k's total number of alliances.
Relative scope	$S_i/(\Sigma\ S_k/NA_k)$, where k includes all of focal firm i's rival partners, S_i and S_k are the number of biotechnology sectors in which focal firm i and rival partners k are active, and NA_k is focal firm i's total number of rival partners.
Sector characteristics	
Aggregate bio financing[d]	Total financing in all sectors in which focal firm is active, in 1991 dollars.
Rival biotechnology firm density	Number of firms in all sectors in which focal firm is active.
Rival biotechnology firm mass	Sum of employees of firms in all sectors in which focal firm is active.
U.S. biotechnology industry effects	
U.S. biotechnology firm density[e]	Number of U.S. firms in all sectors in which focal firm is active.
U.S. rivals' recent patents[c]	Number of patents granted to U.S. rivals within last five years.

[a] All variables were measured at the beginning of each year. All data were from *Canadian Biotechnology,* unless otherwise is noted.
[b] Efficient alliance networks provide access to more diverse partners with minimum redundancy. The variable "left-censored" is not time-varying.
[c] Source: MicroPatent database of U.S. patents.
[d] Source: National Research Council of Canada.
[e] We thank Terry Amburgey for providing us the U.S. biotechnology firm data. See Amburgey et al. (1996) for additional details.

ditional probability of a biotechnology firm's exiting at time t_j. Formally:

$$\lambda j_j = \Pr(T = t_j | T \geq t_j),$$

where T is a random variable that takes values at distinct times, $t_1 < t_2 < \ldots < t_j$ (Guo, 1993: 233).

The left-censored cases in our data created an estimation problem. Since firms founded before 1991 overrepresent low-risk cases by having survived long enough to appear in our sample, standard event history models would have produced underestimates of exit rates for younger firms. We corrected for this sample selection bias by using a conditional likelihood approach, which addresses the problem by conditioning estimates for left-censored firms on their having survived to t_0, the amount of time a firm had survived in the *preobservation* period. We estimated the conditional form of the above discrete time model using logistic regression analysis following the procedure outlined by Guo (1993: 239).

To estimate the conditional discrete time model, we used year as a discrete unit of time, viewing each time unit as an independent trial. A biotechnology firm that exited in its *k*th year was treated as having experienced *k* trials. Corresponding to these trials are *k* success indicators, which were coded 1 if an exit occurred during a trial and 0 otherwise. Accompanying each trial is a vector of annually updated independent and control variables. To obtain conditional discrete time estimates for left-censored biotechnology firms (those already operating at the start of 1991), all trials prior to the start of the observation period (that is, t_0 = 1991) must be dropped from the analysis (Guo, 1993). We used TDA 5.7 (Transition Data Analysis) to obtain parameter estimates using logistic regression procedures.

RESULTS AND DISCUSSION

Table 2 reports estimates for our analysis of biotechnology firm exit rates. Model 1 provides a baseline consisting of basic environmental and firm-

TABLE 2
Conditional Discrete Time Models of Biotechnology Firms' Industry Exit, 1991–96[a]

Variable	Model 1	Model 2	Model 3	Model 4	Effect-Size Multipliers[b]
Own alliances					
Biotechnology		0.16	0.16	0.35*	
University		−0.21*	−0.22*	−0.21*	
Research institute		−0.09	−0.13	−0.13	
Government lab		0.20	0.24	0.33	
Hospital		−0.15	−0.17	−0.15	
Industry association		−0.61	−0.64	−0.63	
Pharmaceutical		−0.26*	−0.29*	−0.28*	
Chemical		−0.27	−0.27	−0.27	
Marketing		−0.03	−0.04	−0.03	
Rival biotechnology firms' alliances					
Biotechnology—Horizontal			0.04*	0.04*	16.86
University—Upstream			−0.04*	−0.03*	0.10
Research institute—Upstream			0.13*	0.13*	3.35
Government lab—Upstream			0.06*	0.06*	6.08
Hospital—Upstream			0.09	0.10	
Industry association—Upstream			0.13	0.13	
Pharmaceutical—Downstream			−0.03	−0.02	
Chemical—Downstream			−0.03	−0.02	
Marketing—Downstream			0.01*	0.01*	1.72
Rival partner biotechnology firms' alliances					
Biotechnology × 10				0.09*	1.33
University × 10				−0.18*	0.86
Research institute × 10				−0.14*	0.97
Government lab × 10				−0.14	
Hospital × 10				−0.08	
Industry association × 10				−0.36*	0.96
Pharmaceutical × 10				−0.16*	0.87
Chemical × 10				−0.22*	0.91
Marketing × 10				0.03*	1.05
Constant	−2.28*	−2.15*	−3.12*	−3.31*	
Log-likelihood	−587.14	−574.46	−559.04	−541.86	
Likelihood ratio test		25.34*	30.84*	34.36*	
Degrees of freedom[c]		13	13*	14	

[a] Values for all variables are computed for the start of each yearly spell. n = 2,163 yearly spells; there are 186 industry exits.
[b] Evaluated at each variable's mean based on model 4 coefficients.
[c] As compared to previous model.
* $p < .05$

level controls. Coefficients for these controls are reported in Appendix B. Model 2 adds controls for a focal firm's own alliances and patents. Model 3 adds rival biotechnology firms' alliances to test Hypotheses 1a–1c and controls for rivals' alliance network efficiency and patenting activity. Finally, model 4 adds rival partners' alliances, to test Hypothesis 2, and controls for rival partners' patenting and focal biotechnology firms' relative scope vis-à-vis their rival partners. As indicated by the likelihood ratio tests reported in the table, each nested model yields a significant improvement in fit, and thus, model 4 is our best-fitting model. Coefficients are robust across models and show no evidence of multicollinearity problems. We report interpretation of model 4.

Effects of Rival Biotechnology Firms' Alliances (Hypotheses 1a–1c)

Rivals' alliances with five of the nine partner types are positively associated with a focal firm's likelihood of exit. Of greater interest, these results vary systematically across alliance category. Rivals' alliances with other biotechnology firms unambiguously raise a focal firm's exit rate. Rivals' alliances with upstream partners offer mixed results. University alliances are significantly, negatively associated with exit, and the coefficients for hospital and industry association links are positive but insignificant, but research institute and government lab alliances are positively associated with exit. Finally, rivals' alliances with downstream partners generally are unrelated to a focal firm's likelihood of exit. The coefficients for pharmaceutical and chemical firm alliances are negative and not significant. Although rivals' marketing firm alliances are positively associated with a focal firm's exit rate, the coefficient is an order of magnitude smaller than that for rivals' horizontal alliances.

To further explore these effects, we considered the effect size multipliers at the mean number of alliances formed.[5] Multipliers were computed as $e^{\beta X_\mu}$, where β is the variable's estimated coefficient and μ is its mean value. At the mean, the multiplier for alliances with other biotechnology firms is nearly three times larger than that for any other type of alliance. The multipliers for upstream alliances are smaller than those for horizontal alliances and, with the exception of university alliances, are larger than multipliers for downstream alliances. Thus, the effects of rivals' alliances on a focal biotechnology firm's exit rate generally conform to the predictions in Hypotheses 1a–1c: horizontal alliances generate the greatest competitive intensity, followed by upstream alliances, and downstream alliances generate the least.

Effects of Rival Partner Biotechnology Firms' Alliances (Hypothesis 2)

Consistent with Hypothesis 2, rival partner biotechnology firms' alliances generally decreased a focal firm's exit rate. Rival partners' alliances with five of the nine alliance types are negatively associated with a focal firm's exit rate, and the coefficients for two other types are negative, although they are not statistically significant. The two types of partners' alliances that are positively associated with a focal firm's exit rate are those with marketing firms and other biotechnology firms. This latter finding may reflect, in part, the hazards a biotechnology firm faces when its partners go on to form relationships with firms that are also the focal firm's rivals (Singh & Mitchell, 1996). In such cases, the partner may reduce its dependence on the focal biotechnology firm, thus altering the parties' bargaining power in a way that harms the focal company (Burt, 1992). Although we made no predictions concerning the relative sizes of partner alliance effects across types, Table 2 presents the effect sizes at the means for partners' alliances. These are clustered much more tightly than were rivals' alliance effects. No distinctions between partners' upstream and downstream alliances are evident.

Other Effects on Exit Rates

We note four results related to the control variables (see Appendix B). First, a biotechnology firm's own alliances with pharmaceutical firms, chemical firms, and universities lower its exit rate significantly. However, alliances with other biotechnology firms and government labs do not. The first of these results is consistent with evidence that cooperating with direct competitors is difficult (Doz et al., 1989; Mowery, Oxley, & Silverman, 1996). Not all alliances with other biotechnology firms are harmful, however. The significant, negative coefficients for rival partners' recent and older patents and for relative scope indicate that judicious partnering with skilled innovators; with firms that have a narrower scope and so are less

[5] Computed in this way, the multipliers indicate differences in *effect size,* that is, the relative magnitudes of the *competitive* effects of different kinds of rivals' alliances, rather than the *incremental* effect of rivals' adding alliances, which can be gauged by comparing *coefficient size.*

likely to initiate learning races; and with well-connected biotechnology firms can attenuate or reverse the hazardous "main effect" (Baum et al., 2000; Khanna et al., 1998). The apparently harmful effect of government lab alliances may reflect the greater commercial uncertainty associated with endeavors in which government facilities become involved (Powell & Brantley, 1992).

Second, a biotechnology firm's patenting activity is generally negatively associated with its exit rate. The more pending patents a company had, the lower its exit rate. Similarly, the more older patents it has, the lower is its exit rate. Recently issued patents do not significantly affect the exit rate, however. Thus, biotechnology firms that successfully commercialize past patent race victories and those that currently hold current patent race leads gain survival advantages. We suspect that the insignificance of recent patent race victories may reflect the uncertainty and market risks associated with development and commercialization of biotechnology patents. The patent activity of a firm's rival partners, as we noted above, is also generally negatively associated with its exit rate.

Third, rival biotechnology firms' recent and pending patents are positively associated with a focal firm's exit, while rivals older patents are negatively associated with it. The increased exit rate associated with rivals' recent and pending patents likely reflects the ability of rivals to use their patent race wins (or leads) to keep a focal company from making technological progress or to attract the lion's share of other assets necessary for survival. The negative association between rivals' older patents and a focal firm's exit rate is consistent with Amburgey and colleagues' (1996) finding that although one firm's patenting success in an area often gives it a short-run advantage, such success signals the technological and commercial potential of the entire area, leading to growth in the longer term.

Fourth, coefficients for alliance network efficiency indicate that the exit rate for biotechnology firms whose alliances, taken as a whole, provide access to a wide range of partner types while limiting redundancy, is significantly lower than the exit rate for firms whose alliance networks are comprised of redundant ties to one or a few partner types. Notably, this "configuration effect" holds even when the main effects of each type of alliance are controlled. It is consistent with this finding that Baum and colleagues (2000) found that start-ups that configured more efficient alliance networks at the times of their foundings outperformed those that did not on several dimensions (including growth in R&D expenditures, patenting rate, and others). Rivals' alliance network efficiency is, in contrast, positively associated with a firm's likelihood of exit. Thus, as well as benefiting themselves, rivals with more efficient networks also generate more intense competition than those with less efficient networks.

CONCLUSION

Despite the recent explosion of research on alliances in technology-based industries, the competitive dynamics of these phenomena remain poorly understood. We were therefore motivated to explore the effects of a focal firm's *rivals'* alliances, and its *rival partners'* alliances, on patterns of firm survival in the Canadian biotechnology industry.

We found, as hypothesized, that rivals' alliances are often, but not always, harmful to a focal biotechnology firm. Notably, these effects vary systematically with type of alliance. Rivals' downstream alliances increase a focal firm's exit rate less than their upstream alliances. In turn, rivals' upstream alliances increase a biotechnology firm's exit rate less than their horizontal alliances. We also found, as hypothesized, that a biotechnology firm benefits from the alliances of rivals with which it collaborates. The two exceptions to this result are that survival chances are harmed as rival partners form more alliances with other biotechnology firms and marketing firms. As noted, this finding may reflect dependence of a biotechnology firm's fate on its partners' striking up new alliances with its rivals or shifting strategic focus after initiating these partnerships. More generally, these findings reinforce the precariousness of collaborating with potential rivals who collaborate, in turn, with other potential rivals (Singh & Mitchell, 1996).

Before noting directions for future research, we comment on the potential generalizability of our empirical strategy for examining asymmetric competitive dynamics. Our approach was grounded in the growing ecological literature on the dynamics of competitive heterogeneity, which uses time-varying, firm-specific characteristics to gauge the relative competitive strengths of and potential for interfirm competition (e.g., Barnett, 1997; Baum & Mezias, 1992). Although strategic management scholars have long noted the importance of firm heterogeneity for behavior and performance, they have had less to say about the competitive implications of this heterogeneity. Ecological research, in contrast, has demonstrated competitive effects of firm heterogeneity and provided a general modeling apparatus for gauging how firm heterogeneity influences interfirm competition, but it lacks refined theoretical understanding of firm-level competitive advantages. Thus, strategic management theories (notably, transaction cost economics and the resource-based view) offer a great deal of insight into sources of firm heterogeneity in organization and capabilities, and organizational ecology offers an approach to exploring the dynamic, competitive implications of key features of firm heterogeneity. We believe the approach used here, linking insights from strategic management research on alliances and ecological research on the dynamics of competitive heterogeneity, can eventually yield a general, integrative approach to studying strategic and competitive dynamics and a greater understanding of the dynamics of competitive advantage.

That said, two specific directions for further research appear particularly promising. Empirically, more nuanced measures of alliances and intellectual property could incorporate insights from recent research on the structure of interorganizational networks (Burt, 1992; Gulati, 1995; Podolny et al., 1996). Development of measures that reflect structural holes, cumulative alliance experience, network centrality, and technology network position would likely enhance the predictive power of our current model and support more extensive integration of sociological and economic models of competitive dynamics. Of course, a major obstacle to this is the detailed data required. Nevertheless, pursuit of these connections may yield important insights into sources of firms' competitive advantages from alliances yielding intellectual property. Theoretically, the results of this study indicate that competitive dynamics occur at a group-versus-group level as well as a firm-versus-firm level. To the extent that alliance networks increase members' interdependence as well as their capabilities, members' success depends increasingly on the competitive strength that groups of organizations build collectively, and competition surfaces among alliance groups (Barnett & Carroll, 1987; Gomes-Casseres, 1994). Such group-versus-group competition does not lessen the importance of firm-level competition, but it does alter the nature of competition in a way that increases the competitive significance of a firm's alliances. This observation suggests the importance of recasting our analysis at the alliance-group level and of developing additional measures designed to capture the collective competitive strength of alliance groups. Notably, it is possible to draw on organization ecology (Barnett & Carroll, 1987) and the resource-based view (Dyer & Singh, 1998) to develop theoretical implications regarding group-versus-group dynamics, just as we drew on these theories for firm-level insights in this study.

In sum, this study, the first to investigate the competitive dynamics of alliances, moves strategic management and organization theory scholarship forward in their understanding of the influence of rivals' and partners' alliances on focal firm survival and interfirm competition.

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APPENDIX A
Descriptive Statistics

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Own alliance and patent variables																			
1. Biotechnology	0.51	1.19																	
2. Pharmaceutical	0.30	0.84	.29																
3. Chemical	0.15	0.52	.19	.05															
4. University	0.62	1.38	.14	.16	.02														
5. Institute	0.32	0.69	.04	.04	.08	.21													
6. Government	0.11	0.39	.03	−.01	.07	.08	.24												
7. Hospital	0.07	0.38	.04	.02	−.03	.19	.10	.02											
8. Industry association	0.05	0.34	−.01	−.01	−.05	.02	.03	.04	−.02										
9. Marketing	0.81	2.62	−.03	.01	−.02	−.02	.00	−.02	.03	−.03									
10. Alliance network efficiency	0.08	0.39	.11	.09	.08	.12	.21	.17	.07	.03	−.07								
11. Older patents	0.36	4.43	.01	.02	.02	.00	−.03	.00	−.01	.00	.00	.00							
12. Patent applications	0.22	1.48	.05	.13	−.02	.05	.06	.03	−.01	.01	.01	.05	.09						
13. Recent patents	0.56	2.71	.05	.11	.02	.01	.04	.03	−.02	.02	.00	.08	.30	.46					
14. Relative scope	0.54	2.14	.15	.15	.17	−.01	.02	−.02	.00	−.02	.00	.03	−.01	.00	.00				
Partner biotechnology firms' alliance and patent variables																			
15. Older patents	0.24	3.78	.17	.16	.02	.06	.03	.00	−.01	.00	.02	.00	.01	.02	.01	.10			
16. Patent applications	0.21	3.99	.17	.25	.01	.07	.01	.03	.00	.00	−.01	.02	−.01	.01	.01	.13	.11		
17. Recent patents	0.37	4.49	.31	.32	.03	.11	.03	.04	.02	.01	−.01	.01	.00	.02	.02	.14	.36	.66	
18. Biotechnology	0.31	1.23	.23	.13	.05	.04	.06	.00	.00	.00	.05	.13	.00	.08	.07	.08	.13	.26	.27
19. Pharmaceutical	0.09	0.51	.16	.11	.01	.02	.02	.02	.01	−.01	.02	.27	.10	.09	.06	.02	.08	.46	.41
20. Chemical	0.04	0.30	.10	.02	.06	.01	.06	−.02	−.02	.01	−.02	.10	.00	.02	.02	.03	−.04	.02	.04
21. University	0.08	0.48	.20	.12	.02	.04	.07	.00	−.01	.02	.03	.08	.00	.11	.16	.11	.18	.35	.30
22. Institute	0.02	0.13	.12	.00	.00	−.02	.01	.02	−.01	.00	−.01	.05	.00	.05	.04	.07	.12	.03	.02
23. Government	0.06	0.30	.17	.07	.04	.03	.05	−.01	.02	−.01	.00	.10	−.01	.03	.03	.11	.14	.26	.20
24. Hospital	0.02	0.14	.12	.08	−.01	.00	.05	−.02	.00	.00	.04	.08	.00	.05	.07	.16	.16	.22	.12
25. Industry association	0.01	0.05	.10	.02	.01	.00	.01	.02	−.01	.01	.02	.02	.00	.04	.07	.02	.07	.15	.10
26. Marketing	0.16	1.75	.07	.05	.00	−.01	.03	−.02	.02	−.01	.01	.07	.00	.00	.00	.03	.03	.07	.06
27. Alliance network efficiency	2.20	2.30	.06	.04	.07	.03	.02	.04	.02	.03	−.02	−.01	.02	.03	.03	.04	.02	.02	.09
Rival biotechnology firms' alliance and patent variables																			
28. Biotechnology	68.90	31.20	.00	−.01	.10	.01	.01	−.01	−.03	.04	−.08	.04	.00	.01	.08	−.01	−.02	−.01	−.05
29. Pharmaceutical	34.30	25.60	.08	.13	.06	.13	.04	−.04	.06	−.01	−.06	.08	−.01	−.02	.06	.02	−.01	.02	.05
30. Chemical	25.90	19.10	−.02	−.07	.10	−.03	.01	.02	−.07	.05	−.08	.01	.00	.00	.07	−.01	.00	−.02	−.02
31. University	67.20	35.70	.03	.03	.10	.04	.04	.00	−.01	.01	−.07	.06	.00	.00	.10	.01	.00	.01	.02
32. Institute	9.30	4.00	−.01	−.06	.11	−.01	.03	.01	−.06	.04	−.10	.01	.00	−.01	.07	−.01	.01	−.02	−.02
33. Government	29.10	11.30	.00	−.04	.11	.00	.02	.02	−.05	.04	−.10	.01	.00	.00	.08	−.01	−.01	−.01	−.01
34. Hospital	7.60	7.20	.09	.19	−.04	.15	.01	−.06	.09	−.05	.00	.10	−.01	.04	.06	.03	.04	.06	.09
35. Industry associations	5.10	2.90	−.02	−.05	.09	−.02	.01	.02	−.05	.01	−.08	.02	.00	.02	.10	−.01	.00	−.02	−.01
36. Marketing	90.40	72.10	.04	.01	.04	.03	−.04	−.04	.00	.02	.02	.03	.01	.02	.06	.00	.00	.00	.01
37. Alliance network efficiency	4.10	2.20	.04	.07	−.11	.04	−.09	−.08	.13	−.03	.20	.06	.03	.06	.00	.02	.02	.05	.03
38. Older patents	14.80	11.90	.00	.04	−.10	.03	−.06	−.05	.11	.00	.07	.04	−.34	.02	−.07	.00	.01	.00	−.02
39. Patent applications	13.20	16.50	.00	.08	−.10	.07	−.07	−.08	.15	−.06	.09	−.03	.06	.06	−.01	.02	−.03	−.04	−.06
40. Recent patents	29.70	22.10	−.01	.13	−.13	.08	−.07	−.09	.21	−.02	.10	.05	−.02	.03	−.02	−.01	−.01	−.04	−.06

APPENDIX A (continued)

18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
.57																						
.41	.22																					
.38	.29	.23																				
.21	.09	.20	.19																			
.45	.33	.38	.42	.33																		
.25	.21	.02	.22	.22	.36																	
.14	.07	.01	.11	.03	.04	.09																
.10	.09	.02	.06	.09	.11	.19	.02															
.13	.04	.05	.07	.05	.04	.02	.05	−.04														
−.03	−.03	−.01	−.02	.01	−.03	−.01	.00	.00	.03													
.05	.02	.01	.04	.04	.01	.04	.03	.00	.07	.66												
−.04	−.04	−.01	−.03	.00	−.03	−.03	−.02	.00	−.01	.29	−.29											
.02	.00	.01	.00	.03	.00	.00	.01	.01	−.03	.73	.73	−.08										
−.03	−.05	−.01	−.03	−.01	−.04	−.03	−.01	−.01	.01	.42	.12	.50	.35									
−.02	−.03	.00	−.02	.01	−.03	−.03	.00	.00	.01	.45	.42	.51	.62	.71								
.09	.08	.00	.06	.04	.03	.05	.05	−.01	.06	.56	.75	−.44	.78	.00	.40							
−.03	−.03	−.01	−.02	.00	−.03	−.02	−.02	.01	−.02	.37	.05	.61	.22	.54	.57	−.06						
−.02	−.02	−.04	−.02	.01	−.02	.03	.01	−.03	.03	.40	.43	−.26	.37	−.26	−.07	.48	−.21					
.05	.09	−.05	.02	.00	.02	.08	.01	.06	−.01	.65	.61	−.14	.59	−.10	.23	.55	−.02	.69				
.01	.02	−.03	.01	.01	.01	.05	−.01	.03	.04	.37	.44	−.18	.41	−.05	.15	.45	.02	.35	.42			
.02	.06	−.04	.00	−.02	−.01	.03	−.01	.03	.02	.50	.63	−.39	.58	−.17	.20	.65	−.18	.47	.69	.33		
.04	.04	−.03	.01	.01	.01	.06	.01	.03	.04	.66	.66	−.29	.68	.02	.41	.68	.15	.53	.68	.55	.65	

APPENDIX B
Control Variable Coefficients for Table 2

Characteristics	Model 1	Model 2	Model 3	Model 4
Firm				
Firm age	−0.01	−0.01	−0.01	−0.01
Left-censored	0.55*	0.56*	0.57*	0.57*
Biotechnology employees	−0.04*	−0.05*	−0.06*	−0.05*
Biotechnology R&D employees	−0.04*	−0.04*	−0.03*	−0.03*
Manufacturing facility	−0.23	−0.21	−0.24	−0.23
Revenues[a]	0.07	0.06	0.07	0.07
R&D expenditures[a]	0.09	0.16*	0.17*	0.17*
Scope[b]	−0.19*	−0.16*	−0.09	−0.08
Private[c]				
Initial public offering 1991–96	−1.01*	−0.87*	−0.83*	−0.80*
Public[d]	−0.03	−0.03	−0.08	−0.10
Nonprofit	−0.34	−0.53	−0.54	−0.53
Government/university/hospital	−1.16*	−1.09*	−1.30*	−1.26*
Subsidiary	0.40*	0.43*	0.43*	0.44*
Joint venture	−0.94	−0.75	−0.80	−0.79
Agriculture	−0.48*	−0.59*	−0.65	−0.62
Aquaculture	−0.12	−0.17	−0.53	−0.49
Engineering	−1.35*	−1.56*	−1.87*	−0.95
Environment	−0.56*	−0.71*	−1.29*	−1.24*
Food/beverage/fermentation	0.12	−0.03	−0.24	−0.08
Forestry	0.73*	0.65*	0.93*	1.26*
Human diagnostics	0.09	0.09	0.32	0.31
Human therapeutics[c]				
Human vaccines	−0.62	−0.69	−0.71	−0.52
Horticulture	−1.16*	−1.35*	−1.37*	−1.29*
Contract research organization	−1.48*	−1.58*	−1.67*	−1.60*
Veterinary	−0.83	−0.76	−0.77	−0.62
Energy	−0.24	−0.34	−0.34	−0.28
Biomaterials/cosmetics/mining	0.11	0.20	0.18	0.74
Alliance network efficiency		−0.02*	−0.03*	−0.03*
Pending patents		−0.34*	−0.39*	−0.37*
Recent patents		−0.02	−0.02	−0.01
Older patents		−0.08*	−0.04	−0.03
Rivals' characteristics				
Alliance network efficiency			0.24*	0.24*
Pending patents			0.03*	0.03*
Recent patents			0.02*	0.02*
Older patents			−0.02*	−0.02*
Rival partners' characteristics				
Alliance network efficiency				−0.14
Pending patents				−0.03
Recent patents				−0.06*
Older patents				−0.07*
Relative scope				−0.33*
Sector characteristics				
Aggregate biotechnology financing[a]	−0.004*	−0.003*	−0.004*	−0.003*
Aggregate biotechnology financing × biotechnology firm's pending patents	−0.001*	−0.001*	−0.001*	−0.001*
Number Canadian biotechnology firms	−0.001	−0.000	−0.008	−0.007
Mass Canadian biotechnology firms	0.204*	0.211*	0.253*	0.261*
Number of U.S. biotechnology firms	0.000	0.000	0.000	0.000
Number of U.S. biotechnology firms' recent patents	0.009*	0.009*	0.006*	0.006*

[a] In millions of Canadian dollars.
[b] Number of sectors.
[c] Omitted dummy.
[d] Initial public offering before 1991.
* $p < .05$