Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology

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We argue in this paper that when the knowledge base of an industry is both complex and expanding and the sources of expertise are widely dispersed, the locus of innovation will be found in networks of learning, rather than in individual firms. The large-scale reliance on interorganizational collaborations in the biotechnology industry reflects a fundamental and pervasive concern with access to knowledge. We develop a network approach to organizational learning and derive firm-level, longitudinal hypotheses that link research and development alliances, experience with managing interfirm relationships, network position, rates of growth, and portfolios of collaborative activities. We test these hypotheses on a sample of dedicated biotechnology firms in the years 1990–1994. Results from pooled, within-firm, time series analyses support a learning view and have broad implications for future theoretical and empirical research on organizational networks and strategic alliances.•

In recent decades, there has been unprecedented growth in corporate partnering and reliance on various forms of external collaboration (Hergert and Morris, 1988; Mowery, 1988; Hagedoorn, 1990, 1995; Badaracco, 1991; Hagedoorn and Schakenraad, 1992; Gulati, 1995). Historically, firms organized research and development (R&D) internally and relied on outside contract research only for relatively simple functions or products (Mowery, 1983; Nelson, 1990a). Today, companies in a wide range of industries are executing nearly every step in the production process, from discovery to distribution, through some form of external collaboration. These various types of interfirm alliances take on many forms, ranging from R&D partnerships to equity joint ventures to collaborative manufacturing to complex co-marketing arrangements. The most common rationales offered for this upsurge in collaboration involve some combination of risk sharing, obtaining access to new markets and technologies, speeding products to market, and pooling complementary skills (Kogut, 1989; Kleinknecht and Reijnen, 1992; Hagedoorn, 1993; Mowery and Teece, 1993; Eisenhardt and Schoonhoven, 1996).

We do not doubt that the need to combine complementary assets has played a role in the growth of interfirm alliances. Nonetheless, we want to explore a different argument, one that we think has more explanatory power in industries in which knowledge is developing rapidly. A key finding from a diverse set of studies is that the R&D intensity or level of technological sophistication of industries is positively correlated with the intensity and number of alliances in those sectors (C. Freeman, 1991; Hagedoorn, 1995). Viewed broadly, technological change occurs in two forms. When advances build on existing know-how, established firms reap the bulk of the benefits. But when new discoveries create technological discontinuities, or radical breaks from previously dominant methods, incumbents can be robbed of many of their advantages. Moreover, new kinds of organizational practices may emerge to exploit these novel developments (Schumpeter, 1934; Abernathy and Clark,

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1985; Tushman and Anderson, 1986; Tushman and Rosenkopf, 1992). Such radical new developments have the potential to restructure a mature industry, hence Schumpeter's phrase: "gales of creative destruction." The most apt recent exemplars are the effects of first the transistor and later the integrated circuit on the electronics industry (J. Freeman, 1990) and the effects of biotechnology on the mature pharmaceutical industry. Biotechnology represents a competence-destroying innovation because it builds on a scientific basis (immunology and molecular biology) that differs significantly from the knowledge base (organic chemistry) of the more established pharmaceutical industry. Consequently, biotech provides enhanced research productivity, with less risk and with more speed and potentially higher rewards (Weisbach and Moos, 1995).

The purpose of this paper is to examine the organizational arrangements that have arisen in response to the technological ferment generated by biotechnology. We focus on forms of collaboration undertaken by dedicated biotechnology firms and assess the contribution of cooperative ventures to organizational learning. In short, we seek to map the network structure of this emerging industry and explain the purposes served by the extensive connections that typify the field.

COLLABORATION AND ORGANIZATIONAL LEARNING

When there is a regime of rapid technological development, research breakthroughs are so broadly distributed that no single firm has all the internal capabilities necessary for success. Many groups of competitors are likely to be working on the same targets; the rewards go to the swiftest. Thus, new technologies are both a stimulus to and the focus of a variety of cooperative efforts that seek to reduce the inherent uncertainties associated with novel products or markets. Running throughout the literature on partnering is an argument that collaboration enhances organizational learning (Hamel, 1991; Dodgson, 1993). We discern, however, two rather different strands of thinking about collaboration and learning.

One approach is largely strategic (Teece, 1986; Williamson, 1991). The choice to pool resources with another organization depends on calculations involving risk versus return. Obviously, reliance on external partners involves hazards (Powell, 1990; Sabel, 1993). A lack of trust between the parties, difficulties in relinquishing control, the complexity of a joint project, and differential ability to learn new skills are all barriers to effective collaboration. Moreover, in those industries in which interfirm agreements are relatively frequent, there can be competitive confusion about who is an ally and who is not. The partnering decision thus depends on each partner's size and position in the "value-chain," the level of technological sophistication, resource constraints, and prior experiences with alliances. The form of collaboration is purported to vary according to the specific types of skills and resources to be exchanged (Hennart, 1988; Pisano, 1989; Parkhe, 1993). Posed this way, the decision to collaborate is a variant of the make-or-buy decision, framed largely in terms of transaction cost

economics. Firms thus turn to collaboration to acquire resources and skills they cannot produce internally, when the hazards of cooperation can be held to a tolerable level.

According to an alternative argument, learning is a social construction process (Brown and Duguid, 1991). In this view, what is learned is profoundly linked to the conditions under which it is learned. Knowledge creation occurs in the context of a community, one that is fluid and evolving rather than tightly bound or static. The canonical formal organization, with its bureaucratic rigidities, is a poor vehicle for learning. Sources of innovation do not reside exclusively inside firms; instead, they are commonly found in the interstices between firms, universities, research laboratories, suppliers, and customers (Powell, 1990). Consequently, the degree to which firms learn about new opportunities is a function of the extent of their participation in such activities (Levinthal and March, 1994). Brown and Duguid (1991: 48) summarized this view nicely by stating that learning is about becoming a practitioner, not learning about a practice. Von Hippel (1988) has shown that the trading of know-how often requires the establishment of long-term relationships in which exchange occurs within a learned and shared code.

March (1991) captured these divergent views of learning in his discussion of the differences between exploration and exploitation in organizational learning. He argued that the "essence of exploitation is the refinement and extension of existing competencies, technologies and paradigms . . . [the] essence of exploration is experimentation with new alternatives" (March, 1991: 85). Exploitation generates predictable returns, while the returns from exploration are much more uncertain. Exploration is costly, often unfruitful, but "the only way to finish first" (Levinthal and March, 1994: 106).

Yet the messy world of practice often blurs the neat distinctions of theory. Exploitation and exploration, and calculation and community are intertwined. Organizational learning is both a function of access to knowledge and the capabilities for utilizing and building on such knowledge. We follow Nelson (1990b) and Stinchcombe (1990) in arguing that organizational arrangements that provide access to knowledge quickly and reliably produce competitive advantage. But rather than seeing such activity as calculative or strategic, we draw on a long line of research that stresses the centrality of building skills and exercising routines in organizations (Cyert and March, 1963; Nelson and Winter, 1982; Stinchcombe, 1990).

The complex reality of rapidly developing fields, in which knowledge is both sophisticated and widely dispersed, transcends the simple calculation of a make-or-buy decision. Research breakthroughs demand a range of intellectual and scientific skills that far exceed the capabilities of any single organization, as illustrated by two notable recent discoveries in biotechnology. The development of an animal model for Alzheimer's disease appeared in a report (*Nature,* Feb. 9, 1995) coauthored by 34 scientists affiliated with two new biotech companies, one established pharmaceutical firm, a leading research university, a federal research laboratory, and

a nonprofit research institute. Similarly, a publication identifying a strong candidate for the gene determining susceptibility to breast and ovarian cancer (*Science,* Oct. 7, 1994) featured 45 coauthors drawn from a biotech firm, a U.S. medical school, a Canadian medical school, an established pharmaceutical company, and a government research laboratory. More important than the number of authors are the diversity of sources of innovation and the wide range of different organizations involved in these breakthrough publications.

Learning through Networks

We argue that when knowledge is broadly distributed and brings a competitive advantage, the locus of innovation is found in a network of interorganizational relationships (Powell and Brantley, 1992). To stay current in a rapidly moving field requires that an organization have a hand in the research process. Passive recipients of new knowledge are less likely to appreciate its value or to be able to respond rapidly. In industries in which know-how is critical, companies must be expert at both in-house research and cooperative research with such external partners as university scientists, research hospitals, and skilled competitors. In examining whether research collaborations increase the subsequent likelihood of other types of cooperation, we build a network analog to Cohen and Levinthal's (1989, 1990) concept of "absorptive capacity." A firm with a greater capacity to learn is adept at both internal and external R&D, thus enabling it to contribute more to a collaboration as well as learn more extensively from such participation. Internal capability and external collaboration are not substitutes for one another, but complementary (Mowery and Rosenberg, 1989; Arora and Gambardella, 1994). Internal capability is indispensable in evaluating research done outside, while external collaboration provides access to news and resources that cannot be generated internally (Nelson, 1990b). A network serves as a locus of innovation because it provides timely access to knowledge and resources that are otherwise unavailable, while also testing internal expertise and learning capabilities.

Our concept of networks of learning highlights two key observations: (1) Interorganizational collaborations are not simply a means to compensate for the lack of internal skills, (2) nor should they be viewed as a series of discrete transactions. A firm's value and ability as a collaborator is related to its internal assets, but at the same time, collaboration further develops and strengthens those internal competencies. Firms deepen their ability to collaborate not just by managing relations dyadically, but by instantiating and refining routines for synergistic partnering. To illustrate, Richard DiMarchi, Vice President for Endocrine Research at Eli Lilly and Company, emphasizes that the biggest mistake his company could make in managing research alliances is to treat them as "one-offs"—independent relationships pursued separately (personal communication with the first author). The development of cooperative routines goes beyond simply learning how to maintain a large number of ties. Firms must learn how to transfer knowledge across

alliances and locate themselves in those network positions that enable them to keep pace with the most promising scientific or technological developments.

In our view, collaborations in high-tech industries typically reflect more than just a formal contractual exchange. When the first author presented the chief executive officer (CEO) of Centocor with a list of his firm's formal agreements, he observed that it was "the tip of the iceberg—it excludes dozens of handshake deals and informal collaborations, as well as probably hundreds of collaborations by our company's scientists with colleagues elsewhere." Beneath most formal ties, then, lies a sea of informal relations. Many alliances—no matter what their ostensible function—reflect a relationship that carries benefits beyond the particular exchange designated in a formal agreement. Nonetheless, R&D alliances, which are unambiguously explorative, play a critical role in allowing firms to stay abreast of rapidly changing developments. Knowledge facilitates the use of other knowledge. What can be learned is crucially affected by what is already known. A vice president for corporate research at Xerox put this point nicely: "In order for industrial research organizations to be in close contact with new advances in basic science, it is important . . . to be an active *participant* at the leading edge of world science. Effective technical interchange requires that the industrial organization have its own basic research results . . . to use as a currency of exchange" (Pake, 1986:36, *emphasis in original*).

Accumulated findings at the frontiers of research provide leverage to access, assimilate, and exploit additional ideas and information. R&D collaboration is both an admission ticket to an information network and a vehicle for the rapid communication of news about opportunities and obstacles. The CEO of Chiron remarked that his biotech firm has more than 100 short-term, small-scale (less than two years and $200,000) relationships with university scientists.[1] When such projects lead to the possibility of a new medicine, relationships become formal and contractual. Innovative activities, then, cannot be reduced to a simple process of information acquisition. Because extensive contacts typically cross-knit research communities, involvement in collaborative R&D expands the horizons of a firm's personnel and increases their awareness of additional projects that might be undertaken. Thus, R&D alliances serve as a platform for diverse network activity.

Knowledge also requires other knowledge. When the sources of expertise are disparate, collaborative R&D opens an organization's eyes to the need for accessing ideas and information from a variety of sources, to exploit the research findings in a commercial context. Both skill and experience are needed to accumulate the capability to benefit from the interdependencies across diverse collaborative behaviors. In addition, experience at collaborating is necessary to manage a diverse portfolio of ties. Hence, we argue that firms learn from exploration and experience how to recognize and

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Comments by Edward Penhoet, CEO of Chiron, on Koput, Powell, and Smith-Doerr (1995).

structure synergies across different types of alliances. Thus we posit:

Hypothesis 1: The greater the (a) number of research and development alliances and (b) experience at managing R&D and other types of collaborations a firm has at a given time, the greater the number of non-R&D collaborations it subsequently pursues; and, in turn, the more diverse its future portfolio of ties will become, controlling for prior levels.

An organization simultaneously learns which collaborations to pursue and how to function within a context of multiple cooperative ventures. The dynamics of cooperation are endogenous in high-tech fields in which scientific advances fuel new discoveries that in turn require novel forms of collaboration to develop. When collaboration stems from membership in a common technological community, as we are arguing, partnering is routinized and occurs more readily, with less effort. Collaboration becomes emergent—stemming from ongoing relationships—informal, and nonpremeditated (Von Hippel, 1988; Hakansson, 1990).

Thus, once a firm begins collaborating, it develops experience at cooperation and a reputation as a partner. Over time, firms develop capabilities for interacting with other firms. Experience with collaborative networks proves a fertile ground for both further formal partnerships and an expanding array of informal relationships. A broader range of collaborative efforts provides greater opportunity to refine organizational routines for cooperating and render them more versatile.

The information that passes through networks is influenced by each participant's position in the industry structure. Firms with access to a more diverse set of activities and those with more experience at collaborating are better able to locate themselves in information-rich positions. We contend that firms with more experience have more ties and that the ties they have provide more central connectedness. Moreover, experience with diverse research-driven networks and the connections that experience brings determine how well situated a firm becomes. Consequently, we predict:

Hypothesis 2: The greater (a) the number of R&D alliances, (b) the diversity of ties, and (c) the experience at managing R&D collaborations or other ties that a firm has at a given time, the more centrally connected the firm subsequently becomes, controlling for the total number of ties and prior connectedness.

Differential location in a network of partnerships results in firms having divergent capabilities for benefiting from collaboration. More formally, we argue that central connectedness shapes a firm's reputation and generates visibility, producing access to resources via benefit-rich networks. Such a reputation can greatly enhance a firm's ability to attract talented new employees. Network location thus shapes the nature of competition. Firms more centrally located should have more timely access to promising new ventures, while those with more collaborative experience should be better positioned to exploit them. Experience at managing ties allows a firm to move quickly in identifying new projects and funneling them inside the organization, enabling growth to occur in a fashion conversely analogous

to absorptive capacity. Put colloquially, a firm grows by being a player; it does not become a player by growing. Therefore, we contend:

Hypothesis 3: The greater a firm's (a) centrality in a network of relationships and (b) experience at managing ties at a given time, the more rapid its subsequent growth, controlling for prior growth.

Finally, we expect that these returns from experience with diverse collaborative activity should elicit positive feedback. The information that passes through networks is influenced by each participant's position in the overall network structure. Differential location in a network of partnerships results in firms having divergent capabilities for benefiting from collaboration. Firms that are located in extensive networks of collaboration are enmeshed in complex and shifting patterns of rivalry and cooperation. Moreover, a firm's experience with networks and its position within them alter the nature of competition. No longer can the goal be to vanquish your opponent, lest you eliminate your collaborator on another project. Centrality in a network facilitates common understandings and shared principles of cooperation, thus enhancing further exchange. Hence, we posit:

Hypothesis 4: The greater a firm's centrality in a network of relationships at a given time, the greater its number of subsequent R&D collaborations, controlling for prior collaborative R&D activity.

The Biotechnology Industry

We explore the hypotheses just derived in the context of the field of biotechnology, a young science-based industry. The pioneering work of Watson and Crick in the early 1950s, which described the structure of DNA as a double helix, laid the foundation for the development of the science of molecular biology. The core technologies used in biotechnology—DNA synthesizing and sequencing, cell fusion methodologies for producing hybridomas—are approximately twenty years old. Yet despite its youth, biotechnology is a burgeoning field. Commentators suggest that molecular/cellular biology has displaced physics as the most prominent of the sciences, pushing "biology beyond the descriptive stage into the development of powerful models and experimental techniques that are helping us to understand the most fundamental of life processes" (Keller, 1990: 124).

Similar to the development of physics in the first half of this century, basic research in the biosciences has been spurred by its exceptional technological potential. To a student of organizations, it is the speed and scope of commercial development in biotechnology that is remarkable. While biotech had its origins in the laboratories of universities and research institutes, it was commercially exploited by small, science-based companies, the first of which went public in 1980. In the decade and a half since, hundreds of companies were created in the U.S., and many more abroad. Investors of all kinds poured billions into biotech, by some accounts, more than $60 billion by 1993. These entrepreneurial companies face stiff obstacles; many companies stumble on the long and winding road from drug development through

regulatory approval to the medical marketplace. The process of creating new biotech drugs is research-intensive, very protracted, and extraordinarily expensive ($100–300 million per product). Nevertheless, by the close of 1994, twenty-five biotechnology-based drugs were approved by the U.S. Food and Drug Administration (FDA). At present, more than 220 medicines are in various stages of clinical testing, and some two dozen drugs await FDA approval. Drug development timelines average 7 to 11 years from discovery to launch for pharmaceuticals, while biotech firms have brought new medicines to market in a time frame of 4 to 8 years (Powell, 1996a). Biotech industry sales reached $7 billion in 1993, an impressive sum for a young field, but still two billion less than the sales of pharmaceutical giant Merck (Gupta, 1994: C4).

In many respects, biotechnology is not an industry per se, but a set of technologies with the potential to transform various fields—pharmaceuticals, chemicals, agriculture, veterinary science, medicine, even waste disposal. Many researchers (e.g., Barley and Freeman, 1992; Amburgey, Shan, and Singh, 1994) treat the wide array of biotechnology companies as comparable. In contrast, we intentionally restrict our attention to only those for-profit firms engaged principally in human therapeutics and diagnostics, hereafter referred to as dedicated biotech firms, or DBFs. We are persuaded that the therapeutics sector is driven by a different research agenda and operates within a distinctive regulatory regime.[2] We intentionally omit firms engaged only in agricultural, veterinary, or bioremediation activity and exclude peripheral companies that produce only equipment, materials, or test kits for the industry.

As the human biotechnology industry developed in the 1980s, it became clear that the full range of required skills (e.g., basic research, applied research, clinical testing procedures, manufacturing, marketing and distribution, and knowledge of and experience with the regulatory process) could not be easily assembled under one roof. The basic science and applied research skills needed to create new products were based in universities, research institutes, and DBFs (Smith-Doerr, 1994; Zucker, Darby, and Brewer, 1994; Powell, 1996b). In a field in which scientific excellence is paramount, biotech companies must establish their bona fides with research scientists. They do so by investing heavily in R&D, organizing in a fashion that is, comparatively, similar to a university laboratory, allowing their scientists considerable autonomy to work on their own projects and to publish and participate in the scientific community, and by creating postdoctoral research programs. These practices help promote a common technological community between universities and DBFs. Professors take sabbaticals at biotech companies; postdoctoral fellows move back and forth between universities and firms; and top universities compete for industry scientists. The 1993 Nobel Prize in Chemistry was given to Kary Mullis for work done at a biotech firm.

Venture capitalists fueled most of the initial discoveries and guided many firms through their early years. But moving from basic research to product development required not

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Agricultural and veterinary biotechnology has encountered considerable public opposition in the U.S. to genetically altered food and animals. As a biotechnology attorney put it to the first author, "the decision to take a new cancer drug is a choice a patient makes with his or her doctor, but a new breed of strawberry is not a private decision but rather one with broad externalities."

only lots of money, it also demanded expertise in conducting extensive clinical trials and securing federal regulatory approval. Neither universities nor DBFs have been well equipped for these tasks, but large pharmaceutical firms most certainly have. Large pharmaceuticals were flush with cash and controlled marketing channels worldwide. But established pharmaceutical firms have been unable to create internally the kind of research environment that fosters constant innovation and discovery. So the various participants in biotech have turned to joint ventures, research agreements, minority equity investments, licensing, and various kinds of partnerships to make up for their lack of internal capabilities and resources (Pisano, 1989, 1991; Arora and Gambardella, 1990, 1994; Powell and Brantley, 1992). Because product development can easily last a decade, firms compete for the intellectual and financial resources that are needed to sustain the discovery and development process.

Perhaps the most profound difference between biotech firms and large pharmaceutical companies is the management and organization of the research process, with the former much closer to basic sciences than the latter. Biotechnology, however, has proven to be an unusual case of competence destruction. Scientific discoveries have profoundly reshaped the nature of the drug discovery process, but once a new medicine is developed, the key uncertainties concern the development of the technology into a safe and effective medical product that can be targeted widely, a competency at which established pharmaceutical firms are very good. Hence, the technological breakthroughs that level the playing field on the exploration front also create new opportunities for established firms in exploitation. Consequently, circumstances of mutual need develop. Small firms require large firms' financial support and regulatory savvy, while larger corporations desire access to the research prowess of smaller companies.

METHOD

Data

We sought to explain the pattern of interorganizational agreements that structure learning in the field of biotechnology. These agreements are formal ties, frequently involving very expensive investments by both parties. We built a relational database that contains separate files for (1) DBFs in human therapeutics and diagnostics, (2) the formal contractual, interorganizational agreements involving DBFs, and (3) the partners to these agreements. The information gathered for each DBF includes founding date, employment levels, sources of financing, and collaborative agreements, which we treated as ties. We coded each tie for its purpose and duration, using an implicit logic of production to classify them into categories, as described in Table 1: R&D, clinical trials, manufacturing, marketing and licensing, and so forth.[3] The "partner" datafile for all organizations that appear as partners on any tie with a DBF is large, expanding annually (numbering more than 1000 organizations active in 1994), and exceptionally diverse in both form and nationality, including multinational corporations, government agencies, hospitals, universities, and biopharmaceutical companies.

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Several readers have questioned whether learning occurs in the context of a licensing agreement, an arrangement that could be handled by the lawyers for the two parties. But we think licensing is almost always a part of a broader collaborative strategy. For instance, in 1990, out of 210 licensing ties in our sample, just three firms pursued only licensing agreements. The preponderance of licensing deals were made by firms with multiple forms of network activity. Moreover, licensing rarely occurs without prior contact between the two parties to explore the viability of the project. Other readers have wondered whether finance ties involve the transfer of knowledge. In biotech, the answer is clearly "yes." Because of their youth and academic origins, companies have been very short on experienced managers; consequently, venture capital and other sources of finance have played a vital role in providing management advice and leadership.

Table 1

Description of Biotechnology Agreements

Type of tie	Typical partners
R&D: DBF develops research program with another organization for a specific target	Other DBFs, pharmaceutical corps., research institutes, university labs
Outside investor: Partner invests funds in DBF	Venture capital firms
Clinical trials/evaluation: DBF has partner conduct trials of product on subjects for FDA approval	Research hospitals, firms specializing in clinical trials
Manufacturing: DBF contracts with partner to manufacture its product	Pharmaceutical corporations, chemical companies
Marketing/Licensing: DBF licenses idea to marketer	Pharmaceutical corporations
DBF purchases rights to partner's idea	Universities
Supply/Distribution: Agreement to receive materials or to supply products to distributors	Large chemical or pharmaceutical corporations
Investment/Joint Venture: DBF invests funds (and usually human/scientific capital) in a partner	Other biotechnology firms
Complex: DBF tie that contains more than one of the above-listed activities (i.e., R&D and marketing)	Any partner (except venture capital firms)

We began assembling the database in 1990, using *Bioscan,* an independent industry directory published six times a year that lists a great range of organizations (domestic and foreign, commercial, nonprofit, or government-owned, biotech, and diversified health care corporations). *Bioscan* lists information on a firm's ownership, its current products, and its research in progress. Thus it is reasonably easy to code firms according to our criteria. When we needed help in understanding the science, we consulted colleagues at our university's cancer center. We collected data for the five-year period 1990–1994. When information was missing from *Bioscan,* we consulted numerous other industry directories, such as various editions of *Genetic Engineering and Biotechnology Related Firms Worldwide,* Dun & Bradstreet's *Who Owns Whom?,* and listings in *Moody's* and *Standard & Poor's.* In addition, we consulted annual reports, Securities and Exchange Commission filings, and, when necessary, made phone calls to companies.

Our focus on research-driven DBFs in human therapeutics resulted in a sample of approximately 225 independently owned companies. Various industry estimates suggest there are between 500 and 1,300 companies operating in the general area of biotechnology, but this number includes all segments of the industry, public and private companies, as well as subsidiaries, joint ventures, and branches of firms in other industries. The consulting firm Ernst & Young estimates approximately 1,300 companies are involved in some aspect of biotechnology but contends that less than 20 percent of those are independent, publicly traded, dedicated biotech firms (Burrill and Lee, 1993). We did not exclude firms from the sample due to small size or non-U.S.

location. Our sample is largely U.S. based, but not exclusively so. Naturally, data availability is considerably better for publicly traded companies than privately held ones, and this is reflected in the *Bioscan* listings.

In focusing on contractual agreements, we omitted the myriad informal arrangements out of which formal relationships emerge. Consequently, our analysis is a strict test of the learning argument because the database does not include widely used less formal relationships that promote the transfer of knowledge. Moreover, in the following analyses we do not focus on year-to-year changes in the content of particular agreements; thus the many instances in which relationships are deepened with the passage of time are not analyzed. In this sense, the analyses are a conservative test of our basic argument.

Operationalizations and Measures

Dependent variables. Hypotheses 1–4 predict the subsequent number and diversity of ties, network position in terms of central connectivity, and rates of growth for firms in our sample. We take these in turn.

Number of R&D ties at time t + 1: The number of research and development ties a firm has captures the extent of its involvement in the core activities of the industry. The number of a firm's R&D alliances reflects its network profile for the purposes of exploration. As noted earlier, R&D has a unique status in theories of organizational learning, and so we treat it separately.

Number of ties of each type (other than R&D) at time t + 1: We used the disaggregated number of ties for each stage of the product life-cycle (see Table 1) to capture the non-R&D network activity in which firms are involved. We view these efforts as a way to exploit R&D discoveries and thus as a complement to R&D networks.

Network portfolio diversity at time t + 1: The range of ties that a firm is engaged in at any given time reflects a firm's portfolio of collaborative activities. Portfolio diversity is computed for each firm in each year as follows. For firm i in year t, denote the number of ties of type j as $n_{it,j}$ and the total number of ties aggregated over all types ($j = 1 \ldots J$; $J = 8$) as n_{it}. The proportion of firm i's ties of type j, out of the total number of ties, is denoted $p_{it,j}$ and given by $p_{it,j} = n_{it,j}/n_{it}$. Each $p_{it,j}$ is squared and then the sum is taken over all j and subtracted from 1, resulting in the index of diversity, y_{it}, so that:

$$y_{it} = 1 - \sum_{j=1}^{J} p_{it,j}^2.$$

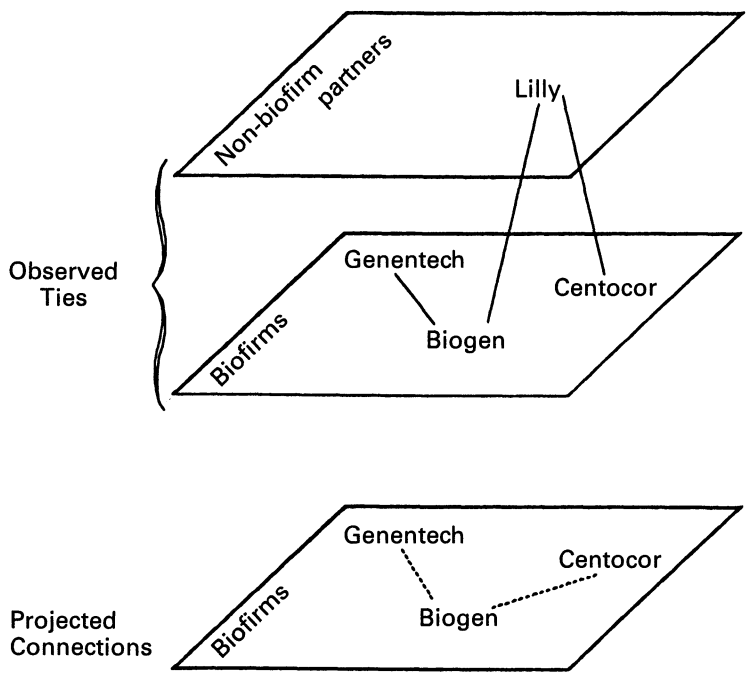
This is equivalent to Blau's index of heterogeneity (Blau, 1977). Diversity can be treated as a continuous random variable, though bounded in the interval [0, 7/8].

Central connectivity at time t + 1. Before describing the measures of network centrality that we used, a few remarks are in order. A tie is a link between organizations, i.e., between a DBF and a partner. The partner may be another DBF or, more commonly, one of many organizations in the

biopharmaceutical field. In counting ties above, we used only direct agreements between biotech firms and their partners. In computing centrality, however, we need to account for that fact that we do not have a closed network. In this respect, our measure of interfirm networks is somewhat unconventional. We wished to examine the structure of the network linking our sample of DBFs, but we had to define a closed set of firms to compute measures of connectivity. Yet many of the ties that structure the field involve parties outside the scope of our definition of a DBF—the overall universe of partners is open, diverse, and expanding. To capture the information flows that may take place between DBFs through non-DBF partners, we counted a connection between two DBFs when there was a direct tie (degree one) and when the DBFs were linked (at degree distance two) through a common partner. Graphically, Figure 1 diplays both forms of connections—direct ties and indirect linkages.

For example, in Figure 1, Biogen has two ties (to Genentech and Lilly) and two connections (one direct, to Genentech, and one indirect, to Centocor through its tie with Lilly). The direct tie to Lilly is not counted as a connection for the purposes of the DBF network measures, since Lilly is not a DBF. As we argued earlier, each tie reflects underlying, on-going relationships, and thus a common connection through an outside partner means that the DBFs share a structurally equivalent position with that partner. For similar reasons, in measuring centrality we did not discriminate among connections involving different functions. The various types of collaborative activities each play a comparable role in creating a firm's overall set of relationships. Measures of central connectivity were computed using UCINET IV (Borgatti, Everett, and Freeman, 1992).

Figure 1. Ties and connections between biotechnology firms.



Membership in the main component at time t + 1: A component is generally defined as a maximally connected subgraph, or a set of points that are connected to one another by paths of any distance (Scott, 1991: 104). We defined a component as a group of *n* firms, each of which has a connection to at least one other firm in the group. In our components, connections are either direct or degree distance two, rather than paths of any length (for an even more stringent definition of components, see L. Freeman, 1992). Components define disconnected subgroups. Such a measure captures the degree of fragmentation in an industry's network structure. In the biotech industry for each year of our sample, the field is characterized by a main component, to which the majority of firms with ties are connected. The remainder are fragmented into many very small components, typically composed of isolates. We created a dummy variable, *MainComp,* that takes the value of 1 if a firm is in the main connected component and 0 if not. A firm that is in the main component is considered much more centrally connected than an isolate.

Degree centrality at time t + 1: Centrality is a measure of how well connected, or active, a firm is in the overall network. We gauged centrality of a firm locally rather than globally, in network parlance, such that a firm's centrality is the number of other firms connected to that firm, ignoring how well those partners are connected. Degree centrality is a common measure of the centralization of power in organizational studies of interlocking directorates, where researchers using this operationalization have often noted the centrality of banks in corporate networks (Mizruchi, 1982; Useem, 1984; Mintz and Schwartz, 1985).

Closeness centrality at time t + 1: We also used a measure of centrality based on the concept of closeness (L. Freeman, 1979), which captures independence from the control of others. Closeness centrality was computed for each firm as the reciprocal of the sum of the degree distance to each other firm. In our context, a high closeness score means a firm has access to many other DBFs and, ergo, is not dependent on specific others for access to information.

Growth at time t + 1. We indexed growth in two ways. We used the reported number of *employees at time t + 1* as a measure of size. We also created a dummy variable, *public,* that takes on the value of 1 if the firm is *publicly traded at time t + 1* and 0 otherwise.

Independent variables. We based our predictions on prior measures of collaborative research activity and experience, non-R&D network experience, diversity of alliances, and network centrality. We used the number of R&D ties, network portfolio diversity, and central connectivity as defined above, but at time *t*. We also introduced measures of network experience, defined below.

Collaborative R&D experience at time t was measured as the time since inception of a firm's first R&D alliance. This was computed for each firm in each year as the current date minus the date at which the firm's initial R&D tie was formalized. *Non-R&D network experience at time t,* an

additional measure of experience at managing ties, is the time since inception of a firm's first tie for any purpose other than R&D. This was computed for each firm at time *t* as the current date minus the date at which the firm's first nonresearch alliance was formalized.

Control variables. In predicting diversity and centrality, we explicitly incorporated controls for the prior total number of ties. In addition, we controlled for the number of ties of each type (other than R&D), as well as centrality, in all of the predictions in which the number of R&D ties was used as an independent variable. We did so to demonstrate that R&D uniquely drives network behavior. Finally, we controlled for alternative explanations that involve firm age or size as predictors, rather than as outcomes, of network behavior. Age appears as a predictor in ecological and life-cycle theories of organization, while greater size, indicating a more extensive hierarchy, is seen as an alternative to alliances in the transaction-cost literature.

As an alternative to direct experience, we used a firm's calendar *age at time t* to capture vicarious experience or advantages due to the establishment of internal routines as a control in all predictions of the effects of collaborative R&D experience or non-R&D network experience. Age was computed for each firm in each year as the date of founding subtracted from the current date. We used the number of employees to incorporate firm *size at time t* as a control in all predictions of network behavior and position. *Total ties at time t* is the aggregate number of ties of all types and serves as a control in our predictions involving central connectivity.

Statistical Methods

Our data consist of five years of cross-sectional records. In each cross section, the variables were measured at the firm level. To test the predictions of our learning perspective, we used a panel regression model. The selection of this technique involves two primary theoretical considerations and the need to address a number of statistical issues that stem from these concerns. The first theoretical consideration is that learning resides within firms and occurs over time. We argue that while learning occurs through network relationships, firms are both the actors and the recipients of the skills and expertise that learning brings. This presents two related statistical concerns: unobserved heterogeneity and autocorrelation.

Unobserved heterogeneity arises due to differences among firms in omitted variables that are constant over time and may affect both independent and dependent variables (as a common cause). For example, larger firms may have more R&D ties and a more diverse portfolio because of past successes. To eliminate any spurious effects due to unobserved differences among firms, we included fixed firm effects by entering a dummy variable for each firm. Consequently, the estimated coefficients will be interpretable as the amount by which the within-firm deviation on the dependent variable shifts in response to a preceding change in the deviation of the independent

variable. This interpretation captures the dynamic and firm-centered nature of learning. Further, we essentially have the population of dedicated biotech firms over our observed time period, and not a random sample.

We were interested in estimating a dynamic model, in which the independent variables are lagged one year. Firms may be "imprinted" or otherwise start on developmental trajectories before the start of our observation period. These trajectories may have naturally evolving patterns that change over time in coherent ways, but ones that we cannot foresee or measure. The omission of an important factor that changes over time within firms will result in autocorrelated errors and may bias estimates of the parameters in which we are most interested. One way of breaking the correlation over time, so as not to overestimate the effects of our hypothesized independent variables, is to include a lagged dependent variable, $y_{i,t-1}$, as a predictor. For each of the models reported, we estimated the effect of a serial correlation term in a first-order autoregressive model, as described in Hsiao (1986: 54–55). After controlling for the lagged dependent variable, we found no significant residual autocorrelation (at the .10 level). When a lagged dependent variable appears as an explanatory variable, however, the fixed effects estimator of the parameter on the lagged dependent variable may not be consistent, because our dataset involves a large number of firms observed over a short period of time. To check the robustness of our reported results to this potential problem, we obtained estimates from three other specifications of the model. First, we omitted the lagged dependent variable and included a first-order serial correlation term. Second, we ran the model with the lagged dependent variable included, but using random effects to control for unobserved firm heterogeneity. Third, we used an instrumental variables estimator (for details, see Hsiao, 1986: ch. 2). The results we report below for our hypothesized predictor variables are systematically lower than the effects from the first two alternative models and about the same magnitude as those from the instrumental variables approach. Hence, the reported estimates are conservative. Most importantly, the pattern of significance is identical across all four specifications.

The second theoretical consideration is that the dynamics of learning involve the co-evolution of firms and networks. This leads to an additional source of statistical nonindependence across our observations: For each firm we measure various properties of its position in the industry's network, but each firm's position can only be assessed in terms of the network positions of others. For instance, a particular firm might have a high centrality score, because a number of outside firms act as partners to multiple firms in the network. Hence, we need to control for effects that vary over time but are constant across firms, such as the overall number of outside partners, the density of the industry's network, government budgets for medical research, or the economic circumstances of pharmaceutical companies. To do so, we included fixed year effects: a dummy variable for each year. This gives each year its own mean on each of the measured

variables and should break the nonindependence in network measures.

In using what is termed a fixed-effects specification (Judge, 1985) for both the firm and year controls, with a lagged dependent variable as one of the predictors, the dependent variable, $y_{i,t}$, is modeled as:

$$y_{i,t} = \alpha_i + \gamma_t + \lambda(y_{i,t-1}) + \sum_{j=1}^{J} \beta_j(x_{i,t-1,j}) + \varepsilon_{i,t}.$$

In this equation, α_i is the effect of firm i: $i = 1 \ldots N$; γ_t is the effect of year t: $t = 1 \ldots T$; β_j is the within-firm slope for x_j, pooled over all firms and years; and $\varepsilon_{i,t}$ is a normally distributed error term.

The strict assumptions of the normal regression model are violated, because our primary dependent variables are skewed and only approximately continuous. Concentration and closeness are defined as continuous, though bounded. The number of ties, centrality, and size can only take on non-negative integer values. Their ranges are quite large (approximately 70, 400, 120, and 3000, respectively), however, making the continuity approximation reasonable. While the truncation and skewness are potentially problematic, these features are shared by the independent variables, allowing us to make the a priori working assumption of symmetric disturbances. We confirmed the validity of this assumption with diagnostic plots in a post-hoc residual analysis (not reported here). Nonetheless, we checked the robustness of our results in several ways. First, we applied a square-root transformation to the dependent variables and reestimated the normal regression model. Second, for those dependent variables that are integer numbers, we also estimated panel models for count data. Third, there are two dependent variables that are constrained to the values of 0 and 1: *MainComp* and *public*. For these, we also ran panel models for binary outcomes (i.e., panel logit estimators). All three of the additional models confirmed the findings of the normal regressions. We report only the results of the normal regressions for all variables, to ease interpretation and allow comparison of effects across the models.

The remaining issue in obtaining the fixed-effects estimates is that of colinearity among the predictor variables. We naturally expected some of our independent variables to be correlated within firms over time. We anticipated that as a firm ages, it would grow and gain experience. The result would be a strong correlation among age, size, and experience that could introduce bias or inefficiency into the estimation. In addition, we used a number of measures for some of our concepts, some of which were likely to be colinear. For instance, we used degree centrality, closeness centrality, and membership in the main component to operationalize the notion of central connectivity. The difficulty in operationalizing a concept such as central connectivity is obvious: The a priori restriction to just one measure would be unwise.

Table 2 shows the within-firm correlations among our explanatory variables that might cause colinearity problems

Table 2

Within-firm Correlations among Explanatory and Control Variables

Variable	1	2	3	4	5	6	7	8	9	10
1. R&D ties										
2. Total ties	.5701									
3. Diversity	.2291	.3821								
4. Collaborative R&D experience	.2702	.2390	.1835							
5. Non-R&D network experience	.2394	.2831	.3212	.7824						
6. Degree centrality	.4744	.6817	.2762	.2649	.2574					
7. Closeness	.3060	.4159	.3369	.5434	.5443	.3922				
8. MainComp	.2323	.3450	.2256	.1637	.1337	.3065	.8762			
9. Age	.2510	.3130	.3202	.7678	.8795	.2907	.6168	.2425		
10. Size	.0838	.0380	.0867	.3401	.3407	.0160	.2578	.0165	.3242	
11. Public	.2164	.3105	.3254	.3573	.3769	.2730	.3627	.2134	.4071	.0698

in the statistical estimations. We find three interrelated sets of variables. First, the time-incremental variables—age, collaborative R&D experience, and non-R&D network experience—are, as expected, intercorrelated. The second group of correlated variables are the numbers of ties, total and R&D, along with degree centrality. The third group arises from the various measures we used to locate a firm within industry networks: Closeness centrality and MainComp are highly correlated.

To deal with the problems of colinearity and operationalization, we embedded the panel regression estimator in a variable-selection procedure, programmed in MATLAB (The Mathworks, 1994). For each dependent variable, we began with a model consisting of all the hypothesized predictor and control variables for which there are no colinearity or operationalization problems. We then performed a series of estimations, each adding one of the theoretically justifiable combinations of interrelated hypothesized predictor or control variables contained in our hypotheses or important alternatives for that dependent variable. Within each of the three groups of interrelated variables, we began with each predictor variable on its own, then ran all combinations of two such predictors, and so on as needed until we arrived at a final combination consisting of all the interrelated predictor variables in that group for the dependent variable being explained. For each dependent variable, we analyzed the explanatory power of all such subsets and selected the subset providing the best model fit, adjusted for degrees of freedom. We then assessed the robustness of each selected subset using inclusion criteria of $p < .05$ for both the *t*-test of the coefficient for each term and the *F*-test for the improvement in model fit due to each term, compared with all nested models with one fewer predictors, and with exclusion criteria of $p > .10$ for both the *t*-test of the coefficient for each term and the *F*-test for the improvement in model fit due to each term, compared with all nested models with one greater predictor. This procedure for assessing fit ensures that the results are not ad-hoc: No variables are either included or excluded in the results due to small changes in attributed variance. We then repeated the steps just described across the selected subsets for all three

groups of interrelated variables, to obtain for each dependent variable a final set of predictor and control variables that is meaningful and robust.

RESULTS

We present firm demographics, by year, in Table 3. The results are broken down, within each year, for both firms with ties and those without. The table gives the number of DBFs in each category, along with means and standard deviations for age, size, *public,* and collaborative R&D experience and non-R&D network experience (in years). Firms with ties are slightly older, for most years, though the gap narrows over time and reverses in 1994. More interestingly, firms with ties are substantially larger ($p < .0001$ in all years), and the gap expands (though not significantly) over the years observed. This difference suggests that firms with ties are growing faster (in raw numbers) than those without ties. The means for the indicator variable *public* are the percentages (in decimals) of firms publicly traded. A much larger percentage of firms with ties are publicly traded ($p < .0001$), in all years, and the raw difference remains nearly constant.

Table 3

Firm Demographics by Year*

	1990		1991		1992		1993		1994	
Variable	No ties	Ties	No ties	Ties	No ties	Ties	No ties	Ties	No ties	Ties
Age	5.70	7.99	6.91	8.41	7.07	8.78	8.65	9.38	12.47	9.93
	(5.81)	(5.83)	(7.15)	(5.64)	(6.73)	(6.08)	(7.17)	(6.22)	(6.39)	(6.35)
Size	46.33	141.41	38.63†	128.63	43.36	155.58	41.18	166.70	58.46	174.83
	(52.50)	(278.27)	(49.58)	(233.79)	(44.68)	(331.59)	(44.63)	(356.08)	(81.60)	(392.50)
Public	.08	.48	.12	.49	.14	.59	.19	.62	.25	.68
Collaborative R&D	0.15	1.82	0.03	2.34	0.28	2.63	0.29	3.16	1.18	3.70
experience	(1.07)	(2.31)	(0.10)	(2.60)	(1.73)	(2.75)	(1.13)	(3.06)	(2.29)	(3.40)
Non-R&D network	.06	4.18	0.21	4.74	0.37	5.07	0.49	5.66	1.54	6.29
experience	(.42)	(3.44)	(0.91)	(3.71)	(1.43)	(3.95)	(1.59)	(4.14)	(2.87)	(4.39)
Total firms	63	179	56	184	44	190	37	192	31	195

* Means presented first, standard deviations in parentheses below.
† Mean and standard deviation trimmed of one outlier that had ties in all other years.

The descriptive measures for collaborative R&D experience and non-R&D network experience point to a distinctive pattern of organizational development for firms that rely on network ties. While firms always have the option of eliminating their reliance on external collaborations, it turns out that firms that have ties for any length of time rarely do so. We estimate that roughly 15 percent of ties are terminated each year, but this does not necessarily end a relationship. An R&D alliance on a specific project may conclude, for example, and be replaced by a new research venture, a complex manufacturing and marketing agreement, or some other new arrangement. This finding is seen from the means for those firms with no ties, which are quite small. Firms with ties have significantly more competence and experience than firms without ties ($p < .0001$) in all

years. Over the five-year period, the number of firms without ties drops by exactly 50 percent, from 62 to 31. The number of firms with ties grows incrementally, both as a result of new entrants to the field and firms without ties embarking on collaborations.

Table 4 summarizes the network activity of firms, by year. We present means and standard deviations for the number of ties (total and disaggregated by types), partners, portfolio diversity, and network measures of central connectivity. The number of ties and partners, on average, are growing only slightly ($p = .33$ and .19, respectively). At the same time, the measures of centrality ($p = .0069$ for degree centrality, $p < .0001$ for closeness) are expanding substantially. Membership in the main component (MainComp) is also steadily increasing ($p = .065$). This suggests that firms are not "promiscuous" in their use of ties; rather, they are deepening their connectedness without adding substantial numbers of new ties. On average, firms have ties of each variety, save for manufacturing and clinical ties. These findings have important implications for the strategy that is apparently pursued by biotechs. In contrast to product life-cycle or transaction-cost thinking, as firms grow older and larger they do not appear to reduce the number and type of collaborations in which they are engaged. Diversity is increasing over the period ($p = .0027$), although R&D ($p = .10$) and finance ($p = .031$) ties are the only categories showing any growth in numbers.

Table 4

Network Activity for Biotechnology Firms with Ties by Year*

Variable	1990	1991	1992	1993	1994
Ties	9.56	9.68	9.31	10.04	10.02
	(11.06)	(10.15)	(9.30)	(9.73)	(8.68)
Degree centrality	18.41	20.03	18.85	22.25	24.50
	(23.76)	(23.74)	(21.52)	(24.24)	(24.00)
Closeness	1.02	1.11	1.24	1.41	1.91
	(0.24)	(0.27)	(0.34)	(0.38)	(0.44)
MainComp	.86	.86	.85	.86	.91
Partners	8.11	8.38	8.10	8.76	8.87
	(8.87)	(8.30)	(7.69)	(8.04)	(7.36)
R&D	1.48	1.47	1.56	1.77	1.74
	(1.97)	(1.96)	(2.04)	(2.25)	(2.47)
Finance	2.22	2.40	2.47	2.76	2.89
	(3.30)	(3.26)	(3.58)	(4.03)	(3.67)
Clinical trials	.05	.03	.02	.03	.03
	(0.24)	(0.19)	(0.14)	(0.17)	(0.25)
Manufacturing	.09	.09	.06	.07	.07
	(0.37)	(0.41)	(0.35)	(0.36)	(0.37)
Marketing/licensing	2.19	2.34	2.25	2.39	2.40
	(3.84)	(3.96)	(3.69)	(3.72)	(3.49)
Supply/distribution	.66	.66	.67	.66	.57
	(1.47)	(1.50)	(1.59)	(1.59)	(1.50)
Investment/joint venture	1.14	1.14	.96	.97	.95
	(2.52)	(2.33)	(2.06)	(2.05)	(1.97)
Complex	1.64	1.49	1.27	1.36	1.34
	(3.13)	(2.70)	(2.43)	(2.49)	(2.23)
Diversity	.41	.44	.44	.48	.49
	(0.30)	(0.29)	(0.26)	(0.25)	(0.25)

* Means presented first, standard deviations in parentheses below.

The results of our panel regressions are shown in Tables 5a, 5b, and 5c. All reported effects for our hypothesized predictor variables are significant at or beyond the .05 level in both coefficient *t*-tests and model-improvement *F*-tests versus nested subset or superset models, as described in the methods section. Control effects reported are also all significant, except for the effects of number of ties in predictions involving centrality, which are included whether significant or not. Each column reports the results for a dependent variable measured at time $t + 1$. Each row contains the effects of an explanatory variable measured at time t. One set of panel regressions was performed for each dependent variable (columns) in which all possible subsets of theoretically justifiable explanatory variables (rows) were entered. Where effects are not reported, the row variable was not included in the best-fitting subset for lack of significance or explanatory power (*p*-values in excess of .10). All models included fixed firm and year effects (dummy variables) that, even when significant, are not reported to conserve space and enhance the readability of the tables. These results and details on the complete variable-selection process are available from the authors. For all of the prediction equations, age was included among the explanatory variables entered but was weaker in its effect than experience when entered alone and showed no improvement in fit when added to experience. Thus, age was eliminated. Similarly, the number of ties of all types other than R&D were also eliminated.

Results in Tables 5a–5c provide support for most of our specific hypotheses and strong overall support for the

Table 5a

Determinants of Network Portfolios: Results of Panel Regressions*

	Dependent variables (at time $t + 1$)									
Predictor variables (at time t)	R&D ties	Finance	Clinical trials	Manufacturing	Marketing/ licensing	Supply/ distribution	Investment/ joint venture	Complex	Total ties	Diversity
R&D ties		.0963 (.0443)	.0069 (.0037)		.1625 (.0317)	.0249 (.0102)	.0997 (.0221)	.0589 (.0228)	.4662 (.0025)	.0133 (.0047)
Non-R&D network experience					.1148 (.0309)	.0799 (.0315)				.0186 (.0087)
Closeness centrality	.2225 (.1005)									
Control variables†										
Lagged dependent variable	.4871 (.0339)	.2535 (.0339)	.3632 (.0330)	.2977 (.0301)	.3234 (.0308)	.3755 (.0284)	.3439 (.0301)	.4009 (.0311)	.4194 (.0373)	.1818 (.0351)
Size			.0198 (.0045)							
Public								.1829 (.0933)		.0561 (.0210)
Total ties	.0307 (.1311)									
MainComp							.1429 (.0774)		.5374 (.2516)	
R-squared	.8424	.8471	.8197	.9172	.9505	.9404	.9235	.9387	.9348	.8214
Total firm-years	904	904	650	904	904	904	904	904	904	699

* Standard errors are in parentheses. All reported coefficients are significant at or beyond the .05 level, except the effect of total ties on R&D ties.

† Age and the number of ties of each non-R&D type were included as control variables in all models but were eliminated due to nonsignificance. All models included fixed firm and year effects (dummy variables), in addition to the lagged dependent variable. These estimates are not reported to conserve space.

Table 5b

Determinants of Network Centrality: Results of Panel Regressions*

Predictor variables (at time t)	Dependent variables (at time $t + 1$)		
	Degree centrality	Closeness centrality	MainComp
R&D ties	1.5073		
	(.3539)		
Collaborative R&D experience		.0578	
		(.0191)	
Non-R&D network experience	.8371	.0391	
	(.0726)	(.0188)	
Diversity	6.3366	.2202	.2509
	(2.4455)	(.0746)	(.0573)
Control variables†			
Lagged dependent variable	.2416	.2096	.0419
	(.0387)	(.0532)	(.0375)
Total ties	.3810	.0052	.0030
	(.1555)	(.0036)	(.0028)
R-squared	.8958	.7531	.6823
Total firm-years	718	707	718

* Standard errors are in parentheses. All reported coefficients are significant at or beyond the .05 level.

† Age, size and the number of ties of each non-R&D type were included as control variables in all models but were eliminated due to nonsignificance. All models included fixed firm and year effects (dummy variables), in addition to the lagged dependent variable. These estimates are not reported to conserve space.

Table 5c

Determinants of Growth: Results of Panel Regressions*

Predictor variables (at time t)	Dependent variables (at time $t + 1$)	
	Size	Public
Collaborative R&D experience		.0353
		(.0098)
Non-R&D network experience	.0618	.0429
	(.0261)	(.0183)
Degree centrality	.0108	.0018
	(.0024)	(.0008)
Control variables†		
Lagged dependent variable	.9507	.3066
	(.0277)	(.0323)
Total ties	.0076	.0031
	(.0099)	(.0033)
R-squared	.9789	.8606
Total firm-years	639	886

* Standard errors are in parentheses. All reported coefficients are significant at or beyond the .05 level.

† Age was included as a control variable in both models but was eliminated due to nonsignificance; similarly for size in the model predicting public. All models included fixed firm and year effects (dummy variables), in addition to the lagged dependent variable. These estimates are not reported to conserve space.

learning perspective. Hypothesis 1 predicted positive effects of the number of R&D ties and network experience at time t on the number of ties of each other type at time $t + 1$ and, in turn, on the diversity of ties at time $t + 1$. The row labeled R&D in Table 5a shows the effects of R&D ties on finance, marketing, clinical, complex, investment, and supply ties to be positive and significant. Further, the effects of R&D on the diversity measure are as predicted. Results in the row labeled Non-R&D network experience support the hypothesized experience effect on a firm's portfolio diversity but provide only partial support for the prediction that experience would increase the number of ties in each non-R&D category (.1148, $p < .0001$; .0799, $p = .0057$ for marketing and supply ties, respectively). Interestingly, the amount of experience with non-R&D ties is critical to a firm's ability to manage a more diverse portfolio. Collaborative R&D experience adds no explanatory power once the number of R&D ties is known. Finally, all the other tie types at t do not predict R&D ties at $t + 1$, nor do they predict each other or diversity. Hence, as hypothesized, it is collaborative R&D and network experience that drive firms' portfolios.

Hypothesis 2 predicted positive effects of the number of R&D alliances, portfolio diversity, and network experience at time t on how centrally connected a firm becomes at time $t + 1$. Central connectedness was measured variously by degree and closeness centrality and membership in the main component (MainComp). Results in Table 5b show significant positive effects of R&D ties on degree centrality, collaborative R&D experience on closeness centrality, non-R&D network experience on both degree and closeness centrality, and portfolio diversity on all three measures of central connectivity. Hence, all aspects of hypothesis 2 receive support. The amount of network R&D activity, along with skill at managing R&D alliances and other forms of collaboration (and, perhaps, the reputational benefits they may bring), help determine how quickly and deeply a firm moves into the core of the industry's network.

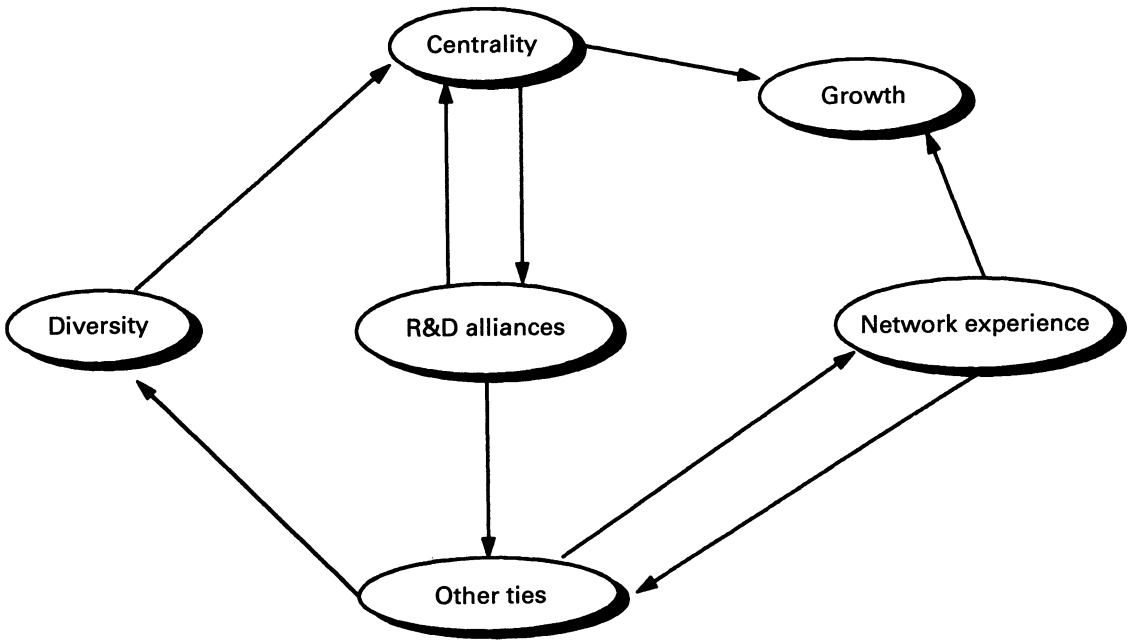
Hypothesis 3 predicted positive effects of the measures of central connectedness and network experience at time t on size and public at time $t + 1$. This prediction receives support, as shown in Table 5c. Degree centrality positively predicts increases in size and going public, though effects were not found for closeness centrality or MainComp. Size is also positively predicted by non-R&D network experience, while both measures of network experience predict going public. Our last prediction, in hypothesis 4, was that central connectivity at time t would enhance a firm's collaborative R&D activity at time $t + 1$. Returning to Table 5a, above, and looking at the first column, we see that this is where closeness centrality has its primary effect.

The overall pattern of results is quite consistent with a learning argument. We stress two general findings. First, age has no effect, while size is an outcome, not a predictor of network behavior. Growth is a process that requires time. Unlike biotic species, however, organizational growth is not programmed from age. Rather, it is the initiation of collaboration that sets the growth clock in motion, with centrality as a further stimulus. Second, network position

(central connectedness) has reciprocal influences on R&D alliances, investment ties, and total collaboration. We have argued and shown that R&D ties, experience, and diversity produce central connectedness. But the process does not stop there. Central connectedness cycles back to intensify a firm's commitment to exploring through its network.

Taken together, the effects shown in Tables 5a–5c can be summarized graphically by the learning model displayed in Figure 2, which we label cycles of learning. Firms can enter via R&D ties or by some other type of tie. Initial collaborative relationships trigger the development of experience at managing ties. R&D ties, directly and through increased experience, enable firms to access more diverse sources of collaboration. Both R&D and non-R&D ties provide experience at managing networks. The development of experience enables a firm to become more central, which in turn has two effects. First, regardless of the pathway, centrally located DBFs are connected into the main component of the industry, providing access to critical information and resource flows needed for internal growth. The second effect is a feedback process in which centrality leads to the initiation and continuance of R&D alliances, thus sustaining the dynamics of learning. R&D ties and other types of collaborations are the admission ticket, while diversity, experience, and centrality are the main drivers of a dynamic system in which disparate firms join together in efforts to keep pace in high-speed learning races.

Figure 2. Cycles of learning in the biotechnology network.



DISCUSSION

We find in our results ample support for the view that networks of collaboration provide entry to a field in which the relevant knowledge is widely distributed and not easily

produced inside the boundaries of a firm or obtained through market transactions. We argue that biotech firms grow by being connected to benefit-rich networks. What, then, are the tangible consequences of these network ties? We cannot, of course, answer this question definitively. We have stressed that this is a young industry, with many of the founding firms not quite 20 years old. We lack data on firms that were founded and subsequently failed before 1990. Thus, patterns that have emerged over a five-year period, albeit a crucial one in the industry's emergence from infancy to adolescence, do not provide the full story. Nevertheless, we think our findings are important for several reasons. First, numerous analysts have commented on the industry's very low mortality rate in its early years (Barley and Freeman, 1992; Burrill and Lee, 1993). Second, the rules of the industry have developed and become elaborated during precisely the period we are studying. The majority of the industry's initial 25 products were brought to market and met with considerable success during this period. Finally, we think there are interesting and suggestive points of commonality between our measures of network experience and centrality and various, albeit less precise rankings of success in the industry.

Two illustrations, presented in Table 6, highlight a possible linkage between networks of learning and firm performance. We list sales in 1993 for the top-ten biotech products. Four firms are responsible for developing these medicines, although for six of the cases, a larger company is responsible for sales and marketing. (This division of labor points to the different roles biotechs play in generating new knowledge and pharmaceuticals take in commercializing this knowledge.) Using our network measures as rankings, we find three of these firms on the list of the most central DBFs, and all four are among those firms most steeped in experience.

We also present a list, drawn from Ernst & Young, of biotech firms with a 1994 market value in excess of $500 million (Lee and Burrill, 1994). All of these companies appear on either our experience or centrality rankings, and four of the eight rate highly on both measures. Moreover, three of these four firms—Biogen, Chiron, and Genentech—appear on all four lists: most products to market, greatest market valuation, highest centrality, and most extensive experience.

We next look at how biotech firms compare with firms in other industries, as well as with universities and research laboratories. Again we assess how well our network measures relate to other measures of firm behavior and performance. *Business Week* publishes an annual R&D scorecard, examining the level of R&D investment by U.S. firms. In Table 7, we use this scorecard to list the top R&D spenders as a percentage of sales. The first six are all biotechs, and of this group, five of the companies appear on either our experience or centrality lists, and three companies (once again, Biogen, Chiron, and Genentech) appear on both lists.

Significant investments in R&D can produce varied outcomes, ranging from a new generation of products to novel innovations. The bulk of biotech research is aimed at

Table 6

DBF Centrality, Ten Highest Rated Firms, 1990–94 (means)*

Firm name	Degree	Closeness
Centocor	110.20	1.4791
Biogen	101.40	1.4788
Cambridge Biotech	93.80	1.4796
Genentech	100.20	1.4786
Chiron	82.40	1.4781
Athena Neurosciences	78.00	1.4767
Scios Nova	71.80	1.4767
DNX	71.40	1.4773
ALZA	69.0	1.4765
Genetics Institute	80.5	1.1788

DBF Collaborative Research Experience, Top Eleven Firms, 1990–94 (means, in years)

Firm name	Collaborative R&D experience
Collaborative Research, Inc.	12.33
BioMeasure, Inc.	11.33
Chiron	9.33
Unigene Labs	8.33
PanLabs	8.33
Biogen	8.33
Applied DNA	8.33
Amgen	8.33
Genzyme	7.33
Genentech	7.33
ALZA	7.33

DBFs with Market Value in Excess of $500 Million, June 1994†

Firm name	Value
Amgen	$5,704
Genentech	5,678
ALZA	1,920
Chiron	1,802
Genetics Institute	1,093
Biogen	928
Genzyme	636
Centocor	572

Top Ten Biotechnology Drugs on the Market, 1993 Net Sales (in millions)‡

Product	Firm name	Marketer	Sales
Neupogen	Amgen	Amgen	$719
Epogen	Amgen	Amgen	587
Intron A	Biogen	Schering-Plough	572
Humulin	Genentech	Eli Lilly	560
Procrit	Amgen	Ortho Biotech	500
Engerix-B	Genentech	SmithKline Beecham	480
Recombinax HB	Chiron	Merck	245
Activase	Genentech	Genentech	236
Protropin	Genentech	Genentech	217
Roferon-A	Genentech	Roche	172
Total sales, top ten/industry			$4,288/$7,700

* Listed in order of combined rank (degree and closeness)
† Source: Lee and Burrill (1994: 14).
‡ Source: Lee and Burrill (1994: 16).

developing medicines that are fundamentally new. This focus brings biotech into close contact with basic reseach in molecular biology and genetics. We draw on citation data to emphasize biotechnology's position in the research community. In Table 7, we present a ranking of the most

Table 7

Top Ten R&D Spenders (in relation to sales) in U.S. Industry, 1993*

Firm	R&D as % of sales
	340.9%
Immunex	97.6%
Genetics Institute	58.4%
Chiron	58.1%
Biogen	48.5%
Genentech	36.0%
Genzyme	35.3%
Continuum	28.1%
MacNeal-Schwendler	26.8%
Encore Computer	25.3%
Knowledgeware	

Top Ten Most Visible Scientific Institutions in Molecular Biology and Genetics, 1988–92†

Institution	Number of papers	Cites per publication
Salk Institute	403	41.6
Cold Spring Harbor Labs	359	40.8
Whitehead Institute	392	39.7
Genentech	225	33.1
Chiron	200	32.8
Institute Chemie Biologique	261	31.8
Fred Hutchinson Cancer Center	413	27.1
MIT	1,060	25.8
Princeton	369	24.0
MRC lab Molecular Biology	430	23.7

* Source: COMPUSTAT, reported in *Business Week,* June 27, 1994, p. 79. Biotechnology firms are shown in boldface type.

† Source: Institute for Scientific Information, *Science Watch,* 4:7 (July/August, 1993). Reprinted with permission of ISI. Biotechnology firms are shown in boldface type.

significant scientific institutions in molecular biology and genetics over the period 1988–1992, measured by number of citations per paper. Two of the most central and experienced biotech firms by our measures, Genentech and Chiron, rank fourth and fifth on this prestigious and diverse list—in the company of world-class research institutes, elite private universities, and a leading cancer center. In citation data collected over a longer period of time, from 1981 to 1992, the average citations per paper for biotechs was 27.5, as compared with rates of 31.25 for independent and university labs and 10.8 for pharmaceutical companies.[4] We mention these results for two reasons. First, they illustrate the closeness of the biotech and university communities. Second, the four highest cited biotechs (Genentech, Genetics Institute, Biogen, and Chiron, with scores of 39.55, 37.54, 35.67, and 32.82, respectively) are, once more, highly rated on our experience and centrality measures.

The data in Tables 6 and 7 combine with our statistical results to suggest that being centrally connected is necessary to achieve valued organizational outcomes. Nevertheless, the use of networks is not a guarantor of success. More work is needed before we fully understand the heterogeneous pathways firms take in our cycles-of-learning model and why some lead to visible indicators of success while others do not. In addition, we underscore in the foregoing that the relationship between our measures of

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Data provided by the Institute for Scientific Information (Philadelphia, PA), as reported in *Biotechnology,* 10 (1992): 1517.

learning and the varied indicators of performance are merely suggestive. Nonetheless, we offer these signposts of organizational performance because they illustrate the critical stages in the process of developing biotechnology medicines. Highly visible publications attract scientific attention and serve as signals to investors and intellectual talent. Obtaining product approval for a new medicine and generating high-volume sales show that science-based companies can take ideas from the laboratory to successful commercialization. A market value in excess of $500 million is evidence of staying power, a robust sign that firms organized around networks of learning are capable of producing enviable results. On all these dimensions of production, our measures of learning are associated with those firms that have, thus far, been industry leaders.

CONCLUSION

We have argued that in a field of rapid technological development, such as biotechnology, the locus of innovation is found within the networks of interorganizational relationships that sustain a fluid and evolving community. Learning occurs within the context of membership in a community and may require different kinds of organizations and organizational practices to access that community. Our empirical analyses allow us to flesh out the picture of a firm under these conditions. Several standard organizational characteristics, such as age and size, appear to be ancillary in accounting for patterns of collaboration. Neither growth nor age reduced the propensity to engage in external relationships. Instead, age, per se, proved unimportant in the context of network experience, and size was an outcome rather than a determinant of partnerships.

We found a path-dependent (Arthur, 1990) cycle of learning in which an early choice of exploration elicited positive feedback. In part, this feedback involved anticipated learning with the project at hand, but many of the gains stem from consequences that are harder for firms to foresee. Knowledge is garnered from collaboration on a specific project, but this participation has unanticipated results not apparent at the outset of the relationship. Science does not follow an orderly path; it has a nasty habit of spiraling off into multiple, uncharted directions. In our view, the development of absorptive capacity (Cohen and Levinthal, 1989, 1990) and skill at managing collaborations, as well as the increased awareness of new projects and reputation as a valuable partner, are all serendipitous benefits of collaboration. Such advantages make it unlikely that firms will retreat from their overall use of alliances, although individual agreements may come and go. When the locus of innovation is found in an interorganizational network, access to that network proves critical. R&D alliances are the admission ticket, the foundation for more diverse types of collaborations, and the pivot around which firms become more centrally connected.

Equally important are changes at the network and industry levels. In our sample, firms without ties are becoming increasingly rare; the modal firm has multiple partnerships. Perhaps our most interesting descriptive result is that the

field is becoming more tightly connected not in spite of, but because of a marked increase in the number of partners involved in alliances with DBFs. Network density (based on connections) has increased 50 percent from .06 to .09, while the number of firms has dropped slightly (from 241 to 226). We take this increasing connectivity within an expanding universe as further evidence that two processes of learning are occurring simultaneously and recursively. First, firms are increasingly using ties to enhance the inflow of specific information, resources, and products. Second, firms are becoming much more adept at and reputed for the general practice of collaboration with diverse partners.

As a result of this reciprocal learning, both firm-level and industry-level practices are evolving, with boundaries becoming ever more permeable. In contrast to the much-discussed liability of newness hypothesis (Stinchcombe, 1965; Hannan and Freeman, 1989), there appears to be a liability of unconnectedness (Baum and Oliver, 1992) at work in biotechnology, and other fields in which intellectual developments are expanding rapidly. Rather than using external relations as a temporary mechanism to compensate for capabilities a firm has not yet mastered, firms use collaborations to expand all their competencies. Firms opt for sustaining the ability to learn, via interdependence, over independence by means of vertical integration. This, in turn, promotes a sense of community-level mutualism (Barnett, 1990). Competition is no longer seen as a game with a zero-sum outcome (Thurow, 1980), but as a positive-sum relationship in which new mechanisms for providing resources develop in tandem with advances in knowledge. At the core of this relationship is a vital need to access relevant knowledge: knowledge of a sort that is sophisticated and widely dispersed and not easily produced or captured inside the boundaries of a firm. These conditions are not limited to biotechnology. In fields as diverse as ceramics and software, much of the relevant know-how is neither located inside an organization nor readily available for purchase. When the sources of knowledge are disparate and the pathways of technological development uncharted, we would expect the emergence of networks of learning.

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