Network Position and Firm Performance: Organizational Returns to Collaboration in the Biotechnology Industry

Walter W. Powell

Kenneth W. Koput

Laurel Smith-Doerr

Jason Owen-Smith

University of Arizona

From Steven Andrews and David Knoke, editors, *Networks In and Around Organizations*, a special volume in the series *Research in the Sociology of Organizations*, Greenwich, CT: JAI Press. Research support provided by NSF grant #9710729, W.W. Powell and K.W. Koput, Co-PIs. We thank Steven Andrews, Charles Kadushin, and Arne Kalleberg for helpful comments on an earlier draft.

ABSTRACT

We examine the relationship between position in a network of relationships and organizational performance. Drawing on ten years of observations (1988-1997) for nearly 400 firms in the human biotechnology industry, we utilize three types of panel regressions to unravel the complex linkages between network structure, patenting, and various firm-level outcome measures. Our results highlight the critical role of collaboration in determining the competitive advantage of individual biotech firms and in driving the evolution of the industry. We also find that there are decreasing returns to network experience and diversity, suggesting that there are limits to the learning that occurs through interorganizational networks.

INTRODUCTION

We examine the effects of position within a network of interorganizational relations on organizational performance. A lacunae of the literature on organizational networks is attention to how embeddedness shapes firm-level outcomes. Building on our earlier work on the role of interfirm relations in enhancing access to knowledge in innovation-intensive fields, we analyze network position, intellectual productivity, and various firm-level performance measures in a population of firms in the human therapeutics and diagnostics sector of the biotechnology industry. We study the years 1988-1997, a key period in which the flow of new biotech medicines grew from a trickle to a steady current and firm foundings proceeded at a rapid pace. Thus, we have an opportunity to unravel the linkages between network ties, intellectual output, financial performance, and other key organizational processes such as rates of growth and the likelihood of failure or acquisition.

We begin the paper with a brief overview of the relevant network literature, reviewing both individual and organizational-level research that has attended to performance consequences. We then provide a short synopsis of the evolving structure of the biotechnology industry and summarize our previous research. In turn, we describe our data sources, which cover biotech firms, patents, outcome measures, and interfirm relations. The methods we employ include three types of panel regressions, and their utilization is detailed. The results show that research and development (R&D) alliances and network centrality matter for the performance of individual firms and the development of industry structure. We conclude with a discussion of the wide-ranging influences of network position, as well as reflect on the limits of network experience and diversity. We also identify several directions for further research, focusing on the role of patenting in interfirm relations.

EMBEDDEDNESS AND PERFORMANCE

Network research conceptualizes social structure as enduring patterns of relationships among actors--be they individuals, cliques, groups, or organizations. The structure of network linkages provides both opportunities and constraints on the actions of participants. The relational ties between parties are conduits for the flow of a broad variety of resources, in either the tangible form of money or specific skills or the intangible, but no less important, form of information, social support, or prestige. At the same time, strong social ties may pose obstacles to adaptation when task enviroments change (Uzzi 1997). Over the past decade, an impressive line of research has documented the wide-ranging effects of network ties on the behavior of both individuals and organizations (see Knoke 1990; Knoke and Guilarte 1994; Powell and Smith-Doerr 1994; Wasserman and Galaskiewicz 1994; and Podolny and Page 1998 for comprehensive reviews). The great bulk of research on the effects of networks is not, however, directly related to our central question of how embeddedness influences firm performance. Thus we review selected studies that illustrate the opportunities and resources provided by networks and draw on this research to develop arguments linking network position and organizational outcomes. We consider, in turn, the effects of networks on individuals, on intra- and inter-organizational relations, and on populations of firms, and then we discuss performance issues.

At the individual level, the pattern of personal ties influences phenomena as diverse as finding a job or catching a cold. Individuals with large, diverse social networks are less susceptible to colds because of regular exposure to viruses (Cohen et al 1997). Similarly, individuals with social ties to many friends of friends, that is, weak-tie relations with many acquaintances, are advantaged in job searches for professional employment (Granovetter 1973; 1982). There is a burgeoning literature, related to Durkheim's early insights on the importance of social ties in preventing suicide, documenting the salutary effects of social network support on the mental health of individuals. Network ties have been credited with helping people deal with stress from a variety of social and medical problems, including aging, retirement, widowhood, job burnout, depression, and cancer (Ingersoll-Dayton and Talbott 1992; Mor-Barak et al 1992; Levy et al 1993; Norris et al 1990; Haley et al 1996; Husaini and Moore 1990; Kvam and Lyons 1991; Roberts et al 1994; Eastburg et al 1994; Ali and Toner 1996).

Similarly, when we turn to corporate actors such as nonprofit organizations, business firms, and government agencies, a growing literature provides abundant evidence of the effects of network ties on various facets of organizational life, ranging from the promotion of individuals to the adoption of business strategies. At the employee level, work has focused on the positive effects of social contacts on interpersonal influence and power (Brass 1984, 1992; Brass and Burkhardt 1992; Krackhardt 1990; Krackhardt and Brass 1994), and career opportunities and benefits (Burt 1992; Ibarra 1992, 1993). Studies of the relations among organizational units have also established the primacy of network linkages in informal political squabbles (Dalton 1959; Crozier 1964) and in status disputes that influence the adoption of new technologies (Barley 1990; Burkhardt and Brass 1990). At the interorganizational level, network studies constitute a small industry. There has been ample attention paid to how the location of an organization in a pattern of external relations influences the adoption of administrative innovations and corporate strategies (Davis 1991; Burns and Wholey 1993; Palmer et al 1993; Westphal et al 1997), as well as an organization's involvement in such non-business activities as political action and philanthropy (Galaskiewicz 1985; Galaskiewicz and Wasserman 1989; Mizruchi 1992).

Closer to the concerns of our effort here has been a strand of work examining the influence of networks on financial relationships (Baker 1990; Podolny 1993; Stearns and Mizruchi 1993). This line of work demonstrates that access to elite partners may have considerable economic benefits, measured by rates of growth, profitability or survival (Baum and Oliver 1992; Podolny 1993; Koput et al 1998). Others find that elite sponsorship provides legitimacy for entire organizational populations (Baum and Oliver 1991; Aldrich and Fiol 1995; Koput et al 1997). Dyer and Singh (1997) synthesize theresearch on inter-organizational collaboration into four sources of competitive advantage that derive from such relationships: the creation of relationship-specific assets, mutual learning and knowledge exchange, combining of complementary capabilities, and lower transactions costs stemming from superior governance structures. In his work on the global auto industry, Dyer (1996) has shown a positive relationship between these interorganizational assets and performance in a sample of automakers and their suppliers.

We draw two implications from this wide-ranging literature on network effects. One, more centrally located firms will evince superior performance, to the extent that such location facilitates the accumulation of resources. Two, the evolution of industry structure will, over time, map onto the pattern of network ties, to the degree that behavioral patterns of interaction cohere into structural architectures.

At a more abstract level, much recent network research can be seen as an effort to blend arguments emphasizing constraint and agency. Network relations both provide and shape opportunities. Thus, access to benefit-rich networks can be regarded as a form of social capital that increases in value with subsequent use (Coleman 1988; Burt 1992; Smith-Doerr et al 1998). At the same time, there are clearly constraints on the formation of network ties. These constraints may be based on status, where high status participants avoid low status parties (Podolny 1994), arrival times, where existing relations may preclude other linkages (Gulati 1995; Powell et al 1996) and network configuration, where rivalry inhibits certain collaborations (Koput et al 1998). Much of the vitality of current work is animated by the drive to establish the scope conditions for network relationships, i.e., out of the welter of possible linkages, which ones are most likely, most enduring, and most consequential?

One form of advantage is legitimacy and prestige. Another is enhanced survival prospects. But network research, at the organizational rather than individual level, has been slow to measure more direct and unequivocal effects such as performance. To be sure, performance data are sometimes difficult to gain access to and often hard to interpret, given alternative accounting methods and measurement paradoxes (Meyer 1997). More generally, sociologists may have eschewed a focus on performance because it is typically the territory of economists. But in recent years, economists, management scholars, and sociologists (Cohen and Levinthal 1990; Kogut and Zander 1992; Powell et al 1996) have been developing a knowledge-based theory of the firm. In one strand of this work, patenting reflects a firm's intellectual capital (Trajtenberg 1990; Grindley and

Teece 1997; Smith-Doerr et al 1998). We extend this effort here, adding a network perspective absent from econometric studies.

Our subject is the biotechnology industry, a relatively new field that had its origins in the U.S. but has rapidly become global. Biotechnology is an ideal setting for our investigation, in part because, as we have argued, in industries where the sources of knowledge are widely dispersed and developing rapidly, network relations are used extensively to access this knowledge (Powell et al 1996).

INDUSTRY ORIGINS

The science underlying the field of biotechnology had its origins in university laboratories. The scientific discoveries that sparked the field occurred in the early 1970s. These promising discoveries were initially exploited by science-based start-ups (DBFs, or dedicated biotechnology firms, in industry parlance) founded in the mid to late 1970s. The year 1980 marked a sea-change, with the U.S. Supreme Court ruling in the Diamond vs. Chakrabaty case that genetically-engineered life forms were patentable. Congress passed the Bayh-Dole Act in the same year, which allowed universities, nonprofit research institutes, and small businesses to retain the intellectual property rights to discoveries funded by federal research grants. And Genentech, which along with Cetus was the most visible biotech company, had its initial public offering, drawing astonishing interest on Wall Street, with a single day stock price run up exceeding all previous one-day jumps. Over the next two decades, hundreds of DBFs were founded, mostly in the U.S. but more recently in Canada, Australia, Britain, and Europe.[1]

The initial breakthroughs--most notably Herbert Boyer and Stanley Cohen's discovery of recombinant DNA methods and Georges Köhler and César Milstein's cell fusion technology that creates monoclonal antibodies--drew primarily on molecular biology and immunology. The early discoveries were so path-breaking that they had a kind of natural excludability, that is, without interaction with the university scientists who were involved in the research, the knowledge was slow to transfer (Zucker et al 1994). But what was considered a radical innovation two decades ago has changed considerably as the science diffused rapidly. Genetic engineering, monoclonal antibodies, polymerase chain reaction amplification, and gene sequencing are now part of the standard toolkit of microbiology graduate students. To stay on top of the field, one has to be at the forefront of knowledge seeking and technology development. Moreover, many new areas of science have become inextricably involved in the biotech enterprise, ranging from genetics, biochemistry, cell biology, general medicine, and computer science, to even physics and optical sciences. Modern biotechnology, then, is not a discipline or an industry per se, but a set of technologies relevant to a wide range of disciplines and industries.

The commercial potential of biotechnology appealed to many scientists and entrepreneurs even in its embryonic stage. In the early years, the principal efforts were directed at making existing proteins in new ways, then new methods were developed to make new proteins, and today the race is on to design entirely new medicines. The firms that translated the science into feasible technologies and new medical products faced a host of challenges. Alongside the usual difficulties of start-up firms, such as the much-discussed liabilities of newness and smallness (Stinchcombe 1965; Hannan and Freeman 1989), the DBFs needed huge amounts of capital to fund costly research, assistance in managing themselves and conducting clinical trials, and eventually experience with the regulatory approval process, manufacturing, marketing, distribution, and sales. In time, established pharmaceutical firms were attracted to the field, initially allying with DBFs in research partnerships and in providing a set of organizational capabilities that DBFs were lacking. Eventually, the considerable promise of biotechnology led nearly every established pharmaceutical corporation to develop, to varying degrees of success, both in-house capacity in the new science and a wide portfolio of collaborations with DBFs (Arora and Gambardella 1990; Henderson 1994; Gambardella 1995).

Thus the field is not only multi-disciplinary, it is multi-institutional as well. In addition to research universities and both start-up and established firms, government agencies, nonprofit research institutes, and leading hospitals have played key roles in conducting and funding research, while venture capitalists and law firms have played essential parts as talent scouts, advisors, consultants, and financiers. Biotechnology emerged at a time, in the 1970s and 1980s, when a dense transactional infrastructure for relational contracting was being developed (Suchman 1995; Powell 1996; Koput et al, 1998). This institutional infrastructure of venture capital firms, law firms, and technology talent scouts greatly facilitates a reliance on collaboration. Small firms collaborate to obtain resources and larger organizations, such as pharmaceutical corporations or research universities, ally to access innovative activities more thoroughly than in an exclusive licensing arrangement and with less bureaucratic costs than in a merger or acquisition (Gilson and Black 1995; Lerner and Merges 1996; Powell and Owen-Smith 1998).

Taking all these elements into account, two factors are highly salient. One, all the necessary skills and organizational capabilities needed to compete in biotechnology are not readily found under a single roof (Powell and Brantley 1992). Two, in fields such as biotech, where knowledge is advancing rapidly and the sources of knowledge are widely dispersed, organizations enter into an array of alliances to gain access to different competencies and knowledge (Powell et al 1996). Progress in developing the technology goes hand-in-hand with the evolution of the industry and its supporting institutions. Following Nelson (1994), we argue that the science, the organizations, and the associated institutional practices are co-evolving. Universities are more attentive to the commercial development of research, DBFs are active participants in basic science inquiry, and pharmaceuticals are more keyed into developments at DBFs and universities.

Nevertheless, organizations vary in their ability to access knowledge and skills located beyond their boundaries. Organizations develop different profiles of collaboration, turning to partners for divergent combinations of skills, funding, experience, access, and status. Biotech firms have not supplanted pharmaceutical companies, nor have large pharmaceuticals absorbed biotechnology firms.[2] Neither has the basic science component of the industry receded in its importance. Consequently, the DBFs that are the subject of this chapter, as well as research universities, pharmaceuticals, research institutes, and leading medical centers, are continually seeking partners who can help them stay abreast of this fast-moving field. We contend that organizational and network differences matter. Put differently, some organizations reap more from the network seeds they sow than do others. Despite the efforts of nearly every DBF to strengthen its collaborative capacity, not all of them cultivate similar profiles of relationships, nor are all able to harvest their networks to comparable advantage. Our goal is to examine how position in interorganizational relationships influences a number of organizational performance metrics over a ten-year period of time. In our prior work we have added to discussions of firm capabilities the idea that firms also develop distinctive competencies in managing interfirm relations. Here we show that in a field where knowledge is developing rapidly, this network competence may be among the most consequential.

Our analytical approach in this paper is both confirmatory and exploratory. We wish to synthesize our prior studies and test our ideas with expanded data covering a much longer period of time, while, at the same time, utilizing new data sources to explore how our prior work links to key organizational outcomes, especially financial performance. Our primary proposition is straightforward: that network position matters for firm performance. Hence, we opt not to test hypotheses from rival theoretical traditions, but rather to extend an earlier model, in which we captured the dynamic interplay of network ties through a learning perspective, to include organizational outcomes and show concretely their reciprocal influences.

Adopting a learning perspective allowed us to understand the pattern and development of interorganizational collaborations as a result of a self-sustaining dynamic process in which initial research relationships triggered the development of experience at orchestrating alliances. Becoming adept at managing ties prompts firms to employ this skill to link with more diverse sources of collaboration, and in so doing, become centrally connected. Central position in the network provides access to both critical information and resource flows needed for internal growth; centrality also both sustains old and initiates new R&D alliances. We summarized this "cycles of learning" model by stating (Powell et al 1996: 138): "R&D ties…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." These results are portrayed graphically by the shadowed components in Figure 1, which appears later. While we have elsewhere presented suggestive evidence showing that well-positioned firms were also high performing, we have not yet rigorously shown that learning from collaboration accounts for their success.

We subsequently demonstrated that organizations not only learn to develop routines for collaboration, they also learn intellectually. More central firms were found to obtain more patents. We argued that this result was due in part to the social--or collaborative-- capital that occupants of prominent network positions accumulate. We concluded (Smith-Doerr et al 1998:.23): "Collaborative capital builds over time as a firm participates in research, gains experience, develops capacity, and assembles a diverse profile of activities that moves it toward the center of the network and makes it privy to knowledge spillovers. Once centrally placed, then, collaborative capital enables an organization to create opportunities with the greatest potential for timely impact and payoff." We have not, however, investigated whether patents have other influences--either on financial performance or as part of a feedback cycle that structures subsequent collaboration.

DATA SOURCES

Our data on DBFs cover 388 firms, of which as many as 313 exist in any single year and 158 are alive in all years, over the ten-year period 1988-1997. DBFs are defined as independently held, profit-seeking firms involved in human therapeutic and diagnostic applications of biotechnology. We do not include large pharmaceutical corporations, international multi-business enterprises, agricultural or veterinary biotechnology, government or private research institutes as primary units of analysis, although these organizations enter our database as partners that collaborate with DBFs. We also exclude biotech firms that are wholly-owned subsidiaries of pharmaceutical or other corporations. We do, however, include those with minority investments by large corporations. Further, we observe and study the process by which some DBFs are acquired. Our rationale for excluding subsidiaries and large, diversified firms is that biotechnology may only represent a small portion of the parent companies overall activities and the subsidiaries do not make decisions autonomously; both circumstances generate data ambiguities. The restricted nature of the population reflects our effort to assess the activities of dedicated, independent firms in the most research-intensive sector of the field.

The data on firms and their various interorganizational agreements are taken from *BioScan*, an industry publication that reports information on firms and the formal agreements in which they are involved. Firm characteristics reported in *BioScan* include age, size, public or private, and, for firms that exit, whether they were acquired or failed. The data on agreements allow us to measure network experience, diversity, and centrality, in addition to classifying ties by type of business activity. *BioScan* covers nearly the entire population of dedicated biotechnology firms in existence between 1988 and 1997. Our database draws on *BioScan's* April issue, in which new information is added for each calendar year. Hence, the firm-level and network data are measured during the first months of each year.

We match our firm-level and network data with patent data extracted from *CASSIS* for the years 1987-1996, aggregated to year-end measures. *CASSIS* is a government document, made available on CD ROM by the U.S. Patent and Trademark Office, listing patent activity in all scientific and technological areas. We sampled from the *ASSIGN* database in *CASSIS*, recording patents assigned to firms on our list of DBFs. This method captures all patents in which any DBF formally holds an interest, and allow us to develop a relational dataset that contains patent-level data for every DBF.

Data on financial measures for publicly held firms were obtained from *COMPUSTAT*, a widely-used electronic data service produced by *Standard and Poor's*, which contains information compiled from public records filed by firms listed on NYSE, AMEX or NASDAQ. We found year-end data for 164 out of 169 dedicated biotech firms that went public before the beginning of 1996.[3] We use data on sales, nonoperating income, R&D expense, and minority equity investments. We also used *COMPUSTAT* to double-check our measures of firm characteristics.

MEASURES

We utilize a variety of measures of network properties, intellectual output, and financial performance, as well as other firm characteristics. Descriptive statistics are presented in Table 1 for the measures, which we now describe. A firm's network profile consists of the number of ties it has for each of seven types of business activity--research, financing, marketing, manufacturing, clinical trials, supply/distribution, investment, or a mix of these activities. The number of research and development ties a firm has captures the extent of its involvement in the core activity of the industry, providing an admission ticket to the industry's information network, and thus we treat it separately. The range of ties that a firm is engaged in at any given time reflects a firm's portfolio of collaborative relationships. Collaborative experience at time *t* was measured as the time since inception of a firm's first alliance.[4]

INSERT TABLE 1 ABOUT HERE

Centrality is a measure of how well-connected, or active, a firm is in the overall network. In computing centrality, 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 need to define a closed set of firms to compute measures of connectivity. Yet nearly ninety percent of the ties that structure the field involve parties, such as universities, outside the scope of our definition of a DBF. Moreover, the overall universe of partners is open, highly diverse, and expanding rapidly. 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 to capture the information or skills that flow between DBFs through non-DBF partners.[5] In the measure of centrality used here, we do not distinguish among connections involving different business functions. For the purpose of our analyses, the various types of collaborative activities play comparable roles in creating a firm's overall set of relationships.[6] Centrality was computed using Bonacich's (1972; 1987) eigenvector measure, which considers not only the number of other firms connected to the focal firm (whether directly or indirectly), but also how well those others are connected.[7] Bonacich's centrality measure has been used elsewhere to assess power, prestige, and status (Burt 1982, Baker et al 1998).

Patent obtainment is measured by the number of patents granted to a DBF in each year, 1987-1996. While a simple patent count is not a perfect measure of an organization's intellectual output, it is a widely accepted proxy (Schmookler 1966; Griliches 1990; Trajtenberg 1990). The volume of patenting is an important dimension of intellectual capital in the biotechnology industry (Smith-Doerr et al 1998). By analyzing the quantity of biotech firm patenting we also capture the signaling role that patents may play in attracting potential collaborators and investors (Smith-Doerr et al 1998). Our concern, here, is to treat patents as a form of intellectual output.

For financial outcomes, we used sales, nonoperating income, R&D spending, and minority equity investments. [8] Sales represent net revenue generated from billing customers, reduced by discounts and return allowances. Sales also include equity income from R&D joint ventures when reported as operating income. Nonoperating income includes any income resulting from secondary business-related activities, such as grants, licensing or other royalties, investment income, externally-sponsored research, and any other source of income not classified as sales. R&D expense includes only company-sponsored, purchased, and other internal R&D spending, and excludes customer- or government-sponsored R&D expenses, market testing, engineering and support expenses, inventor royalties, and extra-industry activities (e.g. the acquisition of patent rights, or expenses in obtaining patents). Thus, R&D partnerships, prestigious government grants, and investments for research by outside parties are not considered R&D expenses by *COMPUSTAT*, because these forms of capital are not internally generated. Minority equity investments are the value of minority stakes purchased directly from the firm by outside parties.. Minority equity placements are a critical mechanism for young companies to finance early-stage R&D. An established firm obtains a percentage of equity in the young firm for a sizable financial investment. Minority stakes have several advantages. The established firm has a financial stake but no legal control and, hence, no legal liability. For the small firm, equity deals generate critical support from multiple partners.[9]

We also include in the models other variables that might be expected to have significant effects on centrality, patenting, and financial outcomes. These additional measures include size (number of employees), firm age, and other network properties aside from centrality. We controlled for alternative explanations that involve firm age or size as predictors of network behavior. Age routinely appears as a predictor in ecological and life-cycle theories of organization. Larger size, indicating more extensive internal integration, could be viewed as an alternative governance mode to alliances in the transaction-cost literature. On the other hand, internal growth has been seen as an outcome of learning in knowledge-based studies. We use a firm's calendar age to capture vicarious experience or advantages due to the learning of internal routines. Age is computed for each firm as the date of founding subtracted from the current date. We rely on the reported number of employees as our measure of size.[10] We also create a dummy variable that takes on a value of 1 if the firm is publicly traded and 0 otherwise. Lastly, we observe the relatively few instances when a firm exits our population, and code whether they fail or are acquired. Acquisitions come in two guises. Although both forms are infrequent in the biotech field, the most typical is the joining together of two DBFs, as when Scios and Nova merged or when Amgen acquired Synergen after the latter's lead product failed to receive FDA approval. Alternatively, and less common, is the purchase of a biotech firm by a large pharmaceutical company, such as Glaxo's acquisition of Affymax to obtain genomics capabilities.

METHODS

We extend the panel regression model developed in our earlier work. The selection of panel techniques and statistical concerns with their use were discussed in detail in that earlier work (see Powell et al 1996: 129-132). New to the effort here is the use of two-stage least squares (2SLS), and three-stage least squares (3SLS) estimators, in addition to the single-equation regressions used previously.

Guided by our prior work, in which we theorized that DBFs use collaborations as vehicles for learning, we began by performing a set of single-equation panel regressions for each performance or other downstream measure as a dependent variable. We started with network position and remaining performance or downstream measures as predictors and proceeded to remove unimportant terms by backward elimination. For this backward elimination process, we used an exclusion criteria of $p>.10$ both for the t-test of each coefficient and for the F-test of model improvement due to each term. So, for instance, when sales was the dependent variable, we included nonoperating income, minority investments, and so forth as controls in an initial model with network position as predictors. We then removed unimportant terms according to both individual component significance and model fit in an iterative process until we arrived at a final model for sales containing only the valid predictors. We then tested the robustness of the inferred relationships resulting from the backward elimination procedure by using an inclusion criteria of $p<.05$ for both the t-test of the coefficient for each term and the F-test for improvement in model fit due to each term compared with all nested models with one fewer predictors. This method for assessing fit ensured that no variable was either excluded or included due to small changes in attributed variance that might be caused by colinearity or other estimation problems.

INSERT TABLE 2 ABOUT HERE

The within-firm correlations among our variables, presented in Table 2, show two instances of severe colinearity: 1) between age and experience and 2) between size, sales and R&D expense. Hence, we were especially careful to scrutinize the effects of these variables as predictors. We also tested the robustness of our cycles of learning model in the face of financial performance measures by treating each of our network position measures as dependent variables, in turn, and following the same procedure just outlined. The results of this variable-selection process and the resulting single-equation regressions are presented in Table 3, which is described below. In regression parlance, the predictors from single-equation models are said to have a "proximate" effect on the dependent variables they explain.

INSERT TABLE 3 ABOUT HERE

We then used a series of two-stage least squares (2SLS) panel regressions to examine the key two-step links implied by the single-equation regressions and determine which variables are exogenous-- that is, which are the real drivers of our learning model. Put differently, does the prior effect of some variables explain the consequences of others? For example, in the single-equation models, R&D ties were found to predict experience and diversity of ties, but not network centrality. Experience and diversity were found to predict centrality. Hence, experience and diversity have a proximate effect of centrality, while R&D ties do not. The implied two-step link, however, is that

R&D ties influence centrality through experience and diversity. Of course, it is possible to predict that variability in experience and diversity, apart from the prior effect of R&D ties, accounts for the prediction of centrality. If so, we would say that experience and diversity are the explanators of centrality, not R&D ties. In 2SLS terminology, if the two-step link is confirmed, R&D ties would explain centrality, with experience and diversity as the "instruments" of this relationship. To confirm or disconfirm a two-step link, we conduct a t-test of a two-step coefficient in a 2SLS model, which we denote with the form "explanator>instrument" in Table 4. In this example, the 2SLS results confirmed that experience and diversity are instrumental in predicting centrality from R&D ties.

INSERT TABLE 4 ABOUT HERE

We can also assess whether the two-step instrument has a meaningful additive effect, that is, beyond its role as an instrument for a prior explanator, by comparing the R-squares from the 2SLS versus single-equation estimations. If the single-equation model explains more variance than the 2SLS model, then the proximate effect is more than just instrumental. In this example, the proximate (single-equation) effects of experience and diversity explain an additional 5% of the within-firm variance in centrality, as compared to the model (2SLS) in which they act only as instruments for prior R&D ties.

Finally, based on the single-equation and 2SLS results, we constructed the system of equations presented in Figure 1. To confirm the whole model, we simultaneously estimated the coefficients in this system of equations using a three-stage least squares (3SLS) panel regression.[11]

INSERT FIGURE 1 ABOUT HERE

RESULTS

Centrality plays a substantial role in determining firm performance. The 3SLS results in the fifth row of Table 5 confirm that once firms move to a central position, they not only obtain more patents (column 5), they also bring in more nonoperating income, grow in size more rapidly, and generate greater sales revenue (columns 7-9, respectively). As seen in the "patents", "nonop. income", "employees", and "sales" columns of Table 3, centrality is proximate to these outcomes in the single-equation models. The associated column in Table 4 from the 2SLS regressions indicates that network measures of experience and diversity also have an impact on patenting, but the R-squares indicate that direct influence of centrality is greater than its role as an instrument for these prior variables--- accounting for an extra 16% of the variance in patenting. Centrality clearly enables firms to select and complete research projects that prove worthy of patent protection. The 2SLS results for the "nonop. income" column show that experience and diversity, in their roles prior to centrality, do not help to explain nonoperating income. Network position is what matters for financial results, as central firms obtain more and/or larger research grants, and more licensing royalties, as well as other non-sales sources of funds, such as externally-sponsored R&D. Nonoperating income is proximate to growth in the size of a firm's workforce, as well as increased sales revenue, in the single-equation models, as seen under the "employees" and "sales" columns of Table 3. According to the 2SLS results, however, centrality is the factor that drives growth both in terms of sales and size through its prior influence on nonoperating income. The nearly equal R-squares of the associated columns in Tables 3 and 4 (.94 versus .92 for sales and .80 versus .78 for employees) demonstrate that nonoperating income is strictly instrumental in its role between centrality, on the prior side, and growth on the outcome side. The prior effect of centrality explains these outcomes better than does the proximate effect of nonoperating income.

INSERT TABLE 5 ABOUT HERE

Centrality affects other critical outcomes as well. Being central reduces the dollar amount of equity involvement by minority investors, as shown by the negative coefficient in the sixth column ("minority equity") of Table 5. This relationship arise, we suspect, in part because well-positioned firms can generate sources of income that do not require relinquishing control. As evidenced by the negative values in the observed range of minority investments presented in Table 1, central firms also repurchase their own stock, perhaps using their financial returns to regain autonomy or to signal the investment community that the stock is undervalued. Now consider acquisitions, which are infrequent but nonetheless of interest. In the few takeovers that have occurred, the results suggest that patents are more of an attraction than centrality. Looking at the R-squares in the next to last columns in Table 3 ands 4, we see that the proximate effects of patents and minority investors explain 10% more variance in acquisitions than accounted for by the prior influence of centrality. Yet, we cannot distinguish from these results whether acquirers are buying patents per se, key process technologies that have been patented, or the network position and intellectual capital that patents reflect. The presence of other minority equity holders may dilute the value of these patents, technologies or capital to the acquirer. Not only does having multiple minority owners raise thorny legal issues in an acquisition, it reduces the possible gains because valuable lines of research may be jointly owned by competitors.

Network experience and diversity play key roles in determining organizational life course, as confirmed by the 3SLS estimates in columns 11-13 of Table 5. The network capability captured in our measures of experience and diversity affects the timing of initial public offerings, influences acquisitions, and helps explain exits from the industry. Experience and diversity act through centrality to account for nearly all the variance explained by the proximate effect of centrality on going public (.4402 of .4495 in Tables 4 and 3, respectively). Hence, it is possible for firms to leverage their network capabilities to go public. Acquisitions, in their column of Table 3, are positively predicted by experience in the single-equation model. Diversity, meanwhile, reduces the chance that a firm will leave the industry in the single-equation models, which otherwise displays a liability of oldness, as presented in the last column of Table 3. These effects of experience and diversity are not mere reflections of a prior influence of R&D ties on either acquisitions or exits, as seen in the last two columns of Table 4. Hence, the visibility of prolonged exposure in the network makes a DBF a more likely takeover target---unless it is able to make itself appear too costly or unwieldy, by attracting minority investors, as noted above. The findings regarding diversity and age on exit demonstrate that firms able to assemble a diverse range of collaborative activities in their early years are less likely to leave the industry later.

Finally, we note that R&D collaborations remain the instigators in our expanded learning model, presented in Figure 1, as they also were in our preliminary model (shadowed components of the figure). R&D alliances predict network experience and collaborative diversity, as seen in the first row of Table 5. More consequentially, R&D ties drive much of the effects of experience and diversity on centrality. As the 2SLS coefficients in the first row of Table 4 demonstrate, experience and diversity serve primarily to link collaborative R&D to centrality. The R-squares (of .4119 and .3869 in the columns labeled "centrality" in Tables 3 and 4, respectively) show that the proximate effect of experience and diversity adds less than 3% to the variance explained by prior effect of R&D partnerships. Cooperative R&D, therefore, generates centrality; nevertheless, maneuvering to a central position in the interorganizational network takes time and involves developing multiple linkages with a broad range of partners. As a result, experience and diversity are the best direct predictors of centrality in the single-equation models in Table 3.

The primacy of collaborative R&D can be seen by examining the 2SLS for the variables that have proximate impact on R&D ties in the single-equation regressions. From the first two columns of Table 3, we see that both being publicly-traded and receiving capital from minority investors have positive impact on partnered R&D. The coefficients in the second through fifth columns of Table 4, however, indicate that only the public variable has a two-stage influence on experience or diversity. The direct impact of R&D alliances, moreover, as demonstrated by the R-squares in the "experience and "diversity" columns of Tables 3 and 4, adds roughly 8% to the variance explained by the prior effect of being publicly-traded. The influence of public status and minority investments are thus part of feedback loops, and occur late in the model. The feedback nature of these influences is further evidenced by the 2SLS estimates for centrality, which acts through public on R&D ties, in the first column of Table 4, and both experience and diversity, which act through centrality in the "public" column of Table 4. The amount of variance in R&D alliances explained by centrality acting through public (.4767 in

Table 4) is virtually equal to the amount accounted for by the proximate effect of going public (.4775 in Table 3). Hence, well-positioned firms are successful at attracting attention both on Wall Street and in the laboratory. As a result, centrality appears as the source of feedback to R&D in Figure 1 and Table 5 (column 1). R&D ties, nevertheless, account for much more of the influence of experience and diversity on centrality than do other types of alliances. In sum, confirming our prior work with data covering a longer time frame, collaborative R&D drives the interorganizational network in biotechnology.

DISCUSSION

The primary question motivating this paper was whether being centrally connected in an organizational field enhances the performance of dedicated biotech firms. We analyzed this issue with network data covering the period 1988-1997 and performance data covering patents, nonoperating income, and sales. The effects of network position on performance are clear and beneficial. Centrality increases the volume of patenting, nonoperating income, and sales. In addition, centrality stimulates growth in size and internally-funded R&D, and at the same time reinforces the use of R&D alliances. These findings support our arguments that networks are the locus of opportunities for learning and innovation.

Moreover, a number of potential influences from alternative views are not borne out, and merit comment. Controlling for other explanations, age has little impact; the only significant effect of age was on exits from the industry. Previously, we showed that firms do not retreat from collaborations as they grow older (Powell et al 1996). More striking, here, we see that age also does not determine financial performance. In the results presented over a full ten-year time frame, as well as in our prior studies, growth in employees appears as an outcome. Size has no predictive influence on either alliances or performance. While more central firms are also larger, this is because access to benefit-rich networks generates growth and resources, not the reverse.

Perhaps the most interesting ancillary finding is that there are decreasing returns to network experience. The influence of experience on diversity, centrality, and acquisitions is positive, but diminishing (note the negative coefficients for experience-squared in Tables 3-5). This is a provocative result for a number of reasons. In the network literature, there is ample discussion of the benefits of embeddedness, but few scholars, aside from Burt (1992) , Granovetter (1985), and Uzzi (1997) have considered the liabilities of being too embedded in social relations and thus overly constrained in terms of choices. There is scant research on whether there are limits to the number of connections that are viable or necessary to sustain economic performance. Finally, in the burgeoning literatures on social and intellectual capital, analysts stress that these forms of capital increase rather than decrease with use, while virtually every other asset or resource depreciates with use (Putnam, 1993). But we find that there are limits to the benefits that network experience and diversity bring. To be sure, it is clear that a certain level of experience and diversity of ties are absolutely critical to providing access and generating rewards. But beyond a certain threshold, there are fewer gains to be reaped from additional network experience.

A comment is necessary with respect to a finding that, at first blush, appears controversial. A well-established relationship has been documented in the industrial economics literature between R&D spending and patenting (Pakes and Griliches 1980; Jaffe 1986; Cohen 1995; Lach 1995). But we observe the contrary result that R&D

spending does not enhance the success of obtaining patents. Does this mean that those spending more are foolish? No, instead it appears that this finding is an artifact of the disjuncture between how research is funded in biotechnology and how *COMPUSTAT* reports R&D expense data. *COMPUSTAT* only counts internally-sponsored R&D, and does not include research grants, research partnerships, joint ventures, or any of the varied ways biotech firms bring in external support to fund their R&D. These latter sources of research funding are captured by *COMPUSTAT* as income when they are received, but not when they are expensed. Our network measures are perhaps the best proxy for overall R&D spending and the impact of centrality on patenting may be due in part to the external funds that a prominent position brings. Nevertheless, it appears that internally-sponsored R&D is a by-product of successful research collaborations. Firms that develop external connections reap *more* benefits from their internal efforts.

There appears to be a limit to a firm's ability to both exploit its prior work and explore new domains, as accumulated patents directly suppress subsequent patent obtainment (seen in the "patents " column both in Tables 3-5). This finding is intriguing, as is the result that patents are the one area where the effect of experience did not show decreasing returns over the time frame of our study. There may be differences between very young firms that patent aggressively and more mature firms with established portfolios of their own patents and cross-licensing arrangements. The former are actively building up a track record and generating intellectual property that can be used to attract investors and partners. Older firms, sensitive to the costs of obtaining and maintaining patents and secure in their intellectual property protection, may choose to patent only their most promising new technologies, focusing instead on product development and sales for medicines based on existing patents. To investigate the dynamics of learning how to patent, the ratio of patent filings to assignments could be traced as a function of age, or experience. Research is also needed to unpack the effects of patents on acquisitions. One promising direction is to code patents for whether they involve a process technology that can be used to develop medicines, a specific product that can be developed and marketed, or a basic scientific principle or discovery.

A number of other questions also remain to be addressed. In particular, what leads firms to embark on R&D ties? A variety of answers are plausible. We know that neither age, size, nor in-house R&D spending determine the likelihood of R&D collaborations, thus we can rule out several conventional explanations. One promising line of work stresses the linkages between star scientists in universities and early stage biotech companies (Zucker et al 1994; Audretsch and Stephan 1996; Powell and Owen-Smith 1998). In fieldwork and interviews, we have observed that social and intellectual ties, forged as early as graduate school days, link scientists across firms and universities, facilitating collaboration. Clearly, economic necessity and the need to signal legitimacy are pivotal as well. Research is enormously costly, for fledging firms as well as established ones, and research support from either a peer-reviewed government grant or a R&D partnership with a large pharmaceutical not only brings in much-needed money, it also conveys hard-won status and a greater likelihood of eventual success. In the challenging and unpredictable world of drug discovery, having many friends of friends in the right places makes for both good economics and social prestige. Additionally, initial success at collaboration has positive feedback on subsequent actions, with the catch that higher visibility also brings the possibility of acquisition, and while that may mean great wealth, it also brings a loss of independence.

Not all firms start with an R&D partnership. Firms may first engage in other types of collaboration, or may obtain patents prior to their first alliance (although our previous work suggests that research ties typically precede patents, see Smith-Doerr et al 1998). In even rarer circumstances, a firm may also generate operating or nonoperating income before their first alliance. The path to R&D ties may be highly idiosyncratic. Nevertheless, until a firm launches its first R&D alliance, for whatever reason or by whatever path, our results suggest that it will not become centrally positioned; without the benefits of being well-connected, firms do not reap the advantages of full access to the industry's network. Clearly we are not implying that firms outside the network do not grow or even perform well financially, but our results suggest both short-term and long-term returns to collaboration in biotechnology. In the short term, firms lacking in alliances will be slower to generate research discoveries, obtain patents, and turn scientific results into marketable products. In the long run, firms that learn to manage diverse portfolios of collaboration, involving multiple projects at different stages of development, are less likely to fail. Consequently, the industry is likely to continue to be organized around interorganizational networks. Moreover, both the technology and institutions are co-evolving in ways that deepen the pattern of affiliation linking DBFs, universities, research institutes and pharmaceutical companies. Competing outside this network is a daunting prospect.

Finally, is the pattern of collaboration and competition found in biotechnology unique to this life sciences field? The general story told here---that of dense collaboration in a context of intense competition---is contrary to traditional thinking in which prospects for enormous economic gain create rivalry that undermines cooperation. But, as we have shown, the fact the knowledge is advancing rapidly and technological leadership is divided means that rivalry does not occur at the level of firm-vs-firm, but network-vs-network (Powell et al 1996). Moreover, the organization of product markets rewards those who learn the fastest. Patients with debilitating and life-threatening diseases seldom wait for a second or third stage product that costs less. In this respect, competition is based on innovation, not price. The rewards for successful new medicines go to the swiftest. Thus the conditions that support this particular form of cooperative competition are strongly tied to the underlying importance of basic science discovery and novel product introduction. Nevertheless, these critical factors---the role of discovery and new product development---may also be found in other science-based fields. Add to this the growing availability of a dense transactional infrastructure of venture capital, law, and consulting firms that not only facilitate but demand collaborative ventures (Powell 1996), and biotechnology no longer appears to be such a unique industry.

---

[1] Kenney (1986), Hall (1987), Angier (1988), Orsenigo (1989), and Teitelman (1989) provide excellent discussions of the industry's origins.

[2] Even as the pharmaceutical industry consolidates and goes through a shake-out period in which excess capacity is reduced, sales forces downsized and factories closed, biotech remains thus far largely unaffected. To be sure, there are innumerable minority investments by big pharmaceuticals in DBFs, and several notable majority ownership arrangements. But the firms in which a big pharmaceutical holds a dominant equity

position, e.g., Genentech, Chiron, and Immunex, continue to be independently-traded and operated. A recent report in a leading industry journal notes that despite the calls on Wall Street for consolidation in biotech, a variety of structural, managerial, and cultural considerations preclude significant concentration (Longman 1997). Mark Edwards of Recombinant Capital, a firm that tracks venture capital in high-tech fields, puts it simply: "The scientific and entrepreneurial cultures of biotech will remain independent and should. That's how the best work will get done" (interview on CNBC, February, 1998). Many observers have noted that acquisitions only serve to chase away the best scientific talent to other firms or to universities.

[3] The five missing DBFs did not meet *COMPUSTAT's* inclusion criteria for size on the AMEX or NYSE. Note that there is no size criteria for inclusion of firms on the NASDAQ exchange, where most DBFs have been listed. Hence, our sample is not materially biased by these excluded firms. Also note that 196 DBFs went public by the end of 1997, but that only those public before the beginning of 1996 are included in the *COMPUSTAT* database beccause1997 year-end data will not be available from *COMPUSTAT* until August, 1998.

[4] Firms rarely retreat entirely from alliances for any non-negligible duration. In our database, there are only 60 firm-years, out of 2848, in which a DBF with prior collaborations listed none in a given year. Out of these, only a handful stayed unaffiliated for more than a single year; most simply reflected a reporting lag between the end of a prior alliance and the beginning of a new collaboration. Hence, we feel that duration since first tie is a more accurate measure of experience than, say, the number of years in which at least one tie is reported.

[5] We are presently re-evaluating the extent to which we can treat a degree-one tie between two DBFs as equivalent to a degree-two link in which two DBFs share a common non-DBF partner. Early on in our research, we found that only 2% of ties involving DBFs were direct connections, and treating direct connections separately provided no analytic leverage. With the subsequent growth and success of an elite cadre of DBFs, direct connections between two DBFs now account for 12.5% off all ties involving DBFs.

[6] In prior work, we separately assessed centrality for each type of relationship, but found that an overall measure was more valuable in explaining firms' network behavior, as well as in predicting outcomes such as growth and scientific visibility. To understand why, consider that, as reported in Powell et al (1996), even licensing agreements, which might be handled only by lawyers for the two firms, are typically enmeshed in a larger pattern of collaboration, often stemming from prior relationships and leading to future joint development deals.

[7] In our previous work, we used Freeman's degree centrality (Powell et al 1996, Koput et al 1997), which measures the number of connections a firm has, without regard to the network position of the firm's partners. Comments from readers of that work have prompted the change to a measure that considers how well a DBF's partners are connected. Bonacich's measure provides much better results in this paper than did earlier attempts using Freeman’s measure. We explore the reasons for this in another paper.

[8] We do not include measures of profitability because they are not yet informative for the entire biotechnology industry. In a field with such enormous R&D expenses (see Powell et al 1996, for data that show R&D spending in biotechnology far outpaces that in

any other U.S. industry), only a minority of firms consistently show profits under standard accounting rules. We also do not look at stock price as an outcome in this paper. The effect of network position on stock price is a paper of its own, for two reasons. First, prices were volatile over a large part of our observation period; and, second, there is a large literature in finance on market valuation that must be adequately addressed in such in effort.

[9] For example, two young biotech firms have raised the use of minority equity placements to the level of an art form. Myriad Genetics, a Utah-based company founded in 1991 that specializes in genetics-based diagnostics, has equity placements with Eli Lilly, Novartis, and Bayer, and each deal brought in research funds in excess of $25 million. Millenium, a DBF in Massachusetts begun in 1993 that is also involved in genomics and bio-informatics, has equity in excess of $300 million placed with Lilly, Novartis, Monsanto, and Wyeth-Ayerst.

[10] Note that there are many cases in which size data were available both from *Bioscan* and *COMPUSTAT*. We used this redundancy to check the veracity of our data and are gratified to report that, adjusting for the differences in reporting dates, the difference between the two sources were negligible.

[11] For models that do not include financial outcomes, we report estimates fit from the entire sample of 2848 observations, whereas models that do include financial variables were fit only to a sample of 939 firm-year records on publicly-held firms. To ensure the robustness of our conclusions, we also tested the former models just on the publicly-held sample and found no material differences.

REFERENCES

Aldrich, Howard and Marlene Fiol. 1995. "Fools Rush In." *Academy of Management Review* 19, 4: 645-670.

Ali, Alisha and Brenda B. Toner. 1996. "Gender Differences in Depressive Response: The Role of Social Support." *Sex Roles* 35, 5/6: 281-294.

Angier, Natalie. 1988. *Natural Obsessions*. Boston: Houghton Mifflin.

Arora, Ashish, and Alfonso Gambardella. 1990. "Complementarity and External Linkages: The Strategies of Large Firms in Biotechnology." *Journal of Industrial Economics* 38: 361-379.

Audretsch, David B. and Paula Stephan. 1996. "Company-Scientist Locational Links: The Case of Biotechnology." *American Economic Review* 86, 3: 641-652.

Baker, Wayne E. 1990. "Market Networks and Corporate Behavior." *American Journal of Sociology* 96: 589-625.

Baker, Wayne E, Robert R. Faulkner, and Gene A. Fisher. 1998. “Hazards of the Market: Continuity and Dissolution of Interorganizational Market Relationships.” *American Sociological Review* 63: 147-177.

Barley, Stephen. 1990. "The Alignment of Technology and Structure through Roles and Networks." *Administrative Science Quarterly* 35: 61-103.

Baum, Joel and Christine Oliver. 1991. "Institutional Linkages and Organizational Mortality." *Administrative Science Quarterly* 36: 187-218.

Baum, Joel and Christine Oliver. 1992. "Institutional Embeddedness and the Dynamics of Organizational Populations." *American Sociological Review* 57: 540-59.

Bonacich, P. 1972. "Factoring and Weighting Approaches to Status Scores and Clique Identification." *Journal of Mathematical Sociology* 2: 113-120.

________. 1987. "Power and Centrality: A Family of Measures." *American Journal of Sociology* 92: 1170-1182.

Brass, Daniel. 1984. "Being in the Right Place: A Structural Analysis of Individual Influence in an Organization." *Administrative Science Quarterly* 29: 518-39.

________. 1992. "Power in Organizations: A Social Network Perspective." Pp. 295-323 in *Research in Politics and Society*, edited by G. Moore and J. Whitt. Greenwich, CT: JAI Press.

Burkhardt, Marlene and Daniel Brass. 1990. "Changing Patterns or Patterns of Change?: The Effect of a Change in Technology on Social Network Structure and Power." *Administrative Science Quarterly* 35: 104-27.

Burns, Lawton R. and Douglas R. Wholey. 1993. "Adoption and Abandonment of Matrix Management Programs: Effects of Organizational Characteristics and Interorganizational Networks." *Academy of Management Journal* 36: 106-38.

Burt, Ronald S. 1982. *Toward a Structural Theory of Action*. New York: Academic Press.

Burt, Ronald S. 1992. *Structural Holes*. Cambridge, MA: Harvard University Press.

Cohen, Sheldon, William J. Doyle, David P Skover, Bruce S. Rabin and Jack M. Gwaltney Jr. 1997. "Social Ties and Susceptibility to the Common Cold." *Journal of the American Medical Association* 277, 24: 1940-1945.

Cohen, Wesley. 1995. "Empirical Studies of Innovative Activity." Pages 182-264 in *Handbook of the Economics of Innovation and Technological Change*, Paul Stoneman, ed. Cambridge, MA: Blackwell.

Cohen, Wesley, and Daniel Levinthal. 1989. "Innovation and Learning: The Two Faces of R&D." *Economic Journal* 99: 569-596.

________. 1990. “Absorptive Capacity: A New Perspective on Learning and Innovation.” *Administrative Science Quarterly* 35: 128-152.

Coleman, James. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology* 94: 95-120.

Crozier, Michel. 1964. *The Bureaucratic Phenomenon*. Chicago: University of Chicago Press.

Dalton, Melville. 1959. *Men Who Manage*. New York: Wiley.

Davis, Gerald F. 1991. "Agents Without Principles? The Spread of the Poison Pill Takeover Defense Through the Intercorporate Network." *Administrative Science Quarterly* 36: 583-613.

Dyer, Jeffrey H. 1996. "Specialized Supplier Networks as a Source of Competitive Advantage." *Strategic Management Journal* 17, 4: 271-292.

Dyer, Jeffrey H. and Harbir Singh. 1997. "The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage." Unpublished manuscript, The Wharton School, University of Pennsylvania.

Eastburg, Mark C., Mike Williamson, Richard Gorsuch and Charles Ridley. 1994. "Social Support, Personality, and Burnout in Nurses." *Journal of Applied Social Psychology* 24, 14: 1233-1251.

Galaskiewicz, Joseph. 1985. "Professional Networks and the Institutionalization of a Single Mind Set." *American Sociological Review* 50: 639-658.

Galaskiewicz, Joseph and Stanley Wasserman. 1989. "Mimetic Processes Within an Interorganizaitonal Field." *Administrative Science Quarterly* 34: 454-79.

Gambardella, Alfonso. 1995. *Science and Innovation: The U.S. Pharmaceutical Industry During the 1980s*. Cambridge, U.K.: Cambridge University Press.

Gilson, Ronald J. and Bernard S. Black. 1996. "Venture Capital and the Structure of Capital Markets: Banks versus Stock Markets." Unpublished manuscript, Columbia University Law School.

Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78: 1360-1380.

________. 1982. "The Strength of Weak Ties Revisited: A Network Theory Revisited." Pp. 105-130 in *Social Structure and Network Analysis*, edited by P. Marsden and N. Lin. Beverly Hills, CA: Sage.

________. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91: 481-510.

Griliches, Zvi. 1990. "Patent Statistics as Economic Indicators: A Survey." Journal of Economic Literature 28: 1661-707.

Grindley, Peter C. and David J. Teece. 1997. "Managing Intellectual Capital: Licensing and Cross-licensing in Semiconductors and Electronics." *California Management Review* 39, 2: 8-41.

Gulati, Ranjay. 1995. "Social Structure and Alliance Formation Patterns." *Administrative Science Quarterly* 40: 619-52.

Haley, William E. , David L. Roth, Marci I. Coleton, Greg R. Ford, Constance A.C. West, Robert P. Collins and Teresa L. Isobe. 1996. "Appraisal, Coping, and Social Support as Mediators of Well-Being in Black and White Family Caregivers of Patients with Alzheimer's Disease." *Journal of Consulting and Clinical Psychology* 64, 1: 121-130.

Hall, Stephen. 1987. *Invisible Frontiers: The Race to Synthesize a Human Gene.* Redmond, WA: Tempus Books.

Hannan, Michael T. and John Freeman. 1989. *Organizational Ecology*. Cambridge, MA: Harvard University Press.

Henderson, Rebecca and Iain Cockburn. 1996. "Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery." *RAND Journal of Economics* 27, 1: 32-59.

Husaini, Baqar A. and Stephen T. Moore. 1990. "Arthritis Disability, Depression, and Life Satisfaction among Black Elderly People." *Health and Social Work* 15, 4: 253-261.

Ibarra, Hermina. 1992. "Homophily and Differential Returns: Sex Differences in Network Structure and Access in an Advertising Firm." *Administrative Science Quarterly* 37: 422-447.

Ibarra, Hermina. 1993. "Personal Networks of Women and Minorities in Management." *Academy of Management Review* 18: 56-87.

Ingersoll-Dayton, Berit and Maria M. Talbott. 1992. "Assessments of Social Support Exchanges: Cognitions of the Old-Old." *International Journal of Aging & Human Development* 35, 2: 125-144.

Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value." *American Economic Review* 76, 5: 984-1002.

Judge, George. 1985. *The Theory and Practice of Econometrics*, 2nd ed. New York: Wiley.

Kenney, Martin. 1986. *Biotechnology: The University-Industry Complex*. New Haven, CT: Yale University Press.

Knoke, David. 1990. *Political Networks: The Structural Perspective*. New York: Cambridge University Press.

Knoke, David and Miguel Guilarte. 1994. "Networks and Organizational Structures and Strategies." Pp. 77-115 in *Current Perspectives in Social Theory*, Supplement 1. Greenwich, CT: JAI Press.

Kogut, Bruce and Udo Zander. 1992. "Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology." *Organization Science* 3, 3: 383-397.

Koput, Kenneth W., Laurel Smith-Doerr and Walter W. Powell. 1997. "Strategies of Learning and Industry Structure: The Evolution of Networks in Biotechnology." Pp.

229-254 in *Advances in Strategic Management Research*, Vol. 14, edited by J.P. Walsh and A.S. Huff. Greenwich, CT: JAI Press.

Koput, Kenneth W., Walter W. Powell, and Laurel Smith-Doerr. 1998. "Interorganizational Relations and Elite Sponsorship: Mobilizing Resources in Biotechnology." Manuscript under review.

Krackhardt, David. 1990. "Assessing the Political Landscape: Structure, Cognition, and Power in Organizations." *Administrative Science Quarterly* 35: 342-365.

Krackhardt, David and Daniel Brass. 1994. "Intraorganizational Networks: The Micro Side." Pp. 207-29 in *Advances in Social Network Analysis*, edited by S. Wasserman and J. Galaskiewicz. Thousand Oaks, CA: Sage.

Kvam, Sharon Hancher and John S. Lyons. 1991. "Assessment of Coping Strategies, Social Support, and General Health Status in Individuals with Diabetes Mellitus." *Psychological Reports* 68, 2: 623-633.

Lach, Saul. 1995. "Patents and Productivity Growth at the Industry Level: A First Look." *Economics Letters* 49: 101-108.

Lanjouw, Jean Olson, Ariel Pakes and Jonathan Putnam. 1996. *How to Count Patents and Value Intellectual Property: Uses of Patent Renewal and Application Data*. NBER Working Paper #5741.

Lerner, Joshua and Robert P. Merges. 1996. "The Control of Strategic Alliances: An Empirical Analysis of Biotechnology Collaborations." Unpublished manuscript, Harvard Business School.

Levy, Leon H. , Joyce F. Derby and Karen S. Martinkowski. 1993. "Effects of Membership in Bereavement Support Groups on Adaptation to Conjugal Bereavement." *American Journal of Community Psychology* 21, 3: 361-382.

Longman, Roger. 1997. "Biotech Sidesteps Consolidation." *In Vivo* 15, 11: 41-48.

Meyer, Marshall. 1997. "Dilemmas of Performance Measurement." Unpublished manuscript, The Wharton School, University of Pennsylvania.

Mizruchi, Mark. 1992. *The Structure of Corporate Political Action*. Cambridge, MA: Harvard University Press.

Mor-Barak, Michal E. , Andrew E. Scharlach, Lourdes Birba and Jacque Sokolov. 1992. "Employment, Social Networks, and Health in the Retirement Years." *International Journal of Aging & Human Development* 35, 2: 145-160.

Nelson, Richard. 1994. "The Co-Evolution of Technology, Industrial Structure, and Supporting Institutions." *Industrial and Corporate Change* 3: 47-63.

Norris, Virginia K. , Mary Ann Parris Stephens and Jennifer M. Kinney. 1990. "The Impact of Family Interactions on Recovery from Stroke: Help or Hindrance?" *The Gerontologist* 30, 4: 535-543.

Orsenigo, Luigi. 1989. *The Emergence of Biotechnology*. London: Pinter.

Pakes, Ariel and Zvi Griliches (1980). "Patents and R&D at the Firm Level: A First Look." *Economics Letters* 5: 377-381.

Palmer, Donald P., Devereaux Jennings, and Xueguang Zhou. 1993. "Late Adoption of the Multidivisional Form by Large U.S. Corporations: Institutional, Political, and Economic Accounts." *Administrative Science Quarterly* 38: 100-131.

Podolny, Joel M. 1993. "A Status-Based Model of Market Competition." *American Journal of Sociology* 98: 829-872.

________. 1994. "Market Uncertainty and the Social Character of Economic Exchange." *Administrative Science Quarterly* 39: 458-83.

Podolny, Joel M. and Karen L. Page. 1998. "Network Forms of Organization." *Annual Review of Sociology*, forthcoming.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr. 1996. "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology." Administrative Science Quarterly 41: 116-45.

Powell, Walter W. and Jason Owen-Smith. 1998. "Commercialism in Universities : Life Sciences Research and its Linkage with Industry." *Journal of Policy Analysis and Management* 17, 2: 253-277.

Powell, Walter W. and Laurel Smith-Doerr. 1994. "Networks and Economic Life." Pp. 368-402 in *Handbook of Economic Sociology*, edited by N. Smelser and R. Swedberg. Princeton, NJ: Princeton University Press.

Roberts, Cleora S., Charles E. Cox, Vicki J. Shannon and Nancy L. Wells. 1994. "A Closer Look at Social Support as a Moderator of Stress in Breast Cancer." *Health and Social Work* 19, 3: 157-165.

Schmookler, Jacob. 1972. *Invention and Economic Growth*. Cambridge, MA: Harvard University Press.

Schmookler, Jacob. 1972. *Patents, Invention and Economic Change: Data and Selected Essays*. Cambridge, MA: Harvard University Press.

Smith-Doerr, Laurel, Jason Owen-Smith, Kenneth W. Koput, and Walter W. Powell. 1998. "Networks and Knowledge Production: Collaboration and Patenting in Biotechnology." Forthcoming in *Corporate Social Capital*, edited by R.T.A.J. Leenders and S. Gabbay. Addison Wesley.

Stearns, Linda and Mark Mizruchi. 1993. "Board Composition and Corporate Financing." *Academy of Management Journal* 36: 603-618.

Stinchcombe, Arthur. 1965. "Social Structure and Organizations." Pages 142-193 in *Handbook of Organizations*, edited by James G. March. Chicago: Rand McNally.

Suchman, Mark. 1994. "On Advice of Counsel: Law Firms and Venture Capital Firms in the Structuration of Silicon Valley." Ph.D. dissertation, Department of Sociology, Stanford University.

Teitelman, Robert. 1989. *Gene Dreams*. New York: Basic Books.

Trajtenberg, Manuel. 1990. "A Penny for Your Quotes: Patent Citations and the Value of Information." *Bell Journal of Economics* 21: 172-187.

Uzzi, Brian. 1997. "Social Structure and Competition in Interfirm Networks: The Problem of Embeddedness." *Administrative Science Quarterly* 42: 35-67.

Wasserman, Stanley and Joseph Galaskiewicz, editors. 1994. *Advances in Social Network Analysis*. Thousand Oaks, CA: Sage.

Westphal, James D., Ranjay Gulati, and Stephen Shortell. 1997. "Customization or Conformity: An Institutional and Network Perspective on the Content and Consequences of TQM Adoption." *Administrative Science Quarterly* 42, 2: 366-94.

Zucker, Lynne G., Michael R. Darby and Marilynn B. Brewer. 1994. "Intellectual Capital and the Birth of U.S. Biotechnology Enterprises." Cambridge, MA: National Bureau of Economic Research Working Paper #4653.

Table 1
Descriptive Statistics

	Mean	Standard deviation	Min	Max	N DBF-years
Firm Characteristics					
Age	8.1694	6.4500	1	49	2848
Size	156.64	418.81	1	7467	1971
Held	.4594	.4984	0	1	2848
Firm Survival					
Acquired	.0105	.1021	0	1	2848
Exited	.0197	.1389	0	1	2848
Network Position					
R&D ties	1.4396	2.6687	0	26	2848
Experience	4.2686	4.2365	0	28	2848
Diversity	1.8532	1.6132	0	7	2848
Centrality	.0341	.0485	0	.3209	2848
Intellectual Output					
Patents-current	.6345	1.9657	0	25	2848
Patents-accumulated	4.6808	14.7528	0	216	2848
Financial Measures					
Minority equity	14.3532	86.2666	-330.69	672.34	944
R&D expense	18.4095	45.7816	0	528.30	944
Nonoperating income	2.7950	9.8948	-32.82	110.168	944
Sales	35.4336	153.50	0	2239.80	944
Retained earnings	-41.1693	109.9874	-1055.70	879.40	944

Table 2
Within-firm Correlations among variables

	Age	Size	Held	Acquired	Exited	R&D ties	Experience	Diversity	Centrality	Patents-current	Patents-accum.	Minority equity	R&D expense	Nonop. income
Age														
Size	.2655													
Held	.4861	.0508												
Acquired	.0962	.0095	.0650											
Exited	.1027	.0008	.0070	--										
R&D ties	.2644	.1073	.2663	.0067	.0032									
Experience	.9361	.2728	.4672	.1001	.0880	.2565								
Diversity	.4261	.0319	.4388	-.0027	-.0096	.3247	.3772							
Centrality	.2026	-.0858	.3833	-.0200	.0036	.4713	.1782	.4867						
Patents-current	.0863	-.0130	.0975	.0411	-.0059	.0590	.0740	.0868	.0891					
Patents-accumulated	.3974	.3857	.0958	.0636	.0195	.0767	.4169	.0476	-.0851	.0718				
Minority equity	.1008	.2236	.0018	-.0502	-.0125	.0222	.1016	-.0297	-.0757	-.2403	.1642			
R&D expense	.3548	.7569	.0665	.0203	.0010	.1599	.3578	.0298	-.1442	.0621	.4474	.1677		
Nonoperating income	.1805	.5555	.0350	.0209	.0010	.0942	.1821	.0559	-.0278	.0035	.3557	.3037	.3870	
Sales	.2732	.8307	.0114	.0004	.0005	.1585	.2761	.0033	-.1566	-.0660	.4083	.2814	.8370	.3411

Table 3
Results of Single-equation Panel Regressions

Predictor variables at t-1	Dependent variables at time t R&D ties	R&D ties	Experience	Diversity	Centrality	Patents	Minority Equity	Nonop. Income	Employees	Sales	Internal R&D	Public	Acquisition	Exit
R&D ties	.6196***	.6775***	.1228***	.1582***										
	(.0249)	(.0164)	(.0089)	(.0385)										
Experience			.8668***	.0992***	.0083**								.0057**	
			(.0035)	(.0224)	(.0036)								(.0016)	
Experience-squared				-.0213***	-.0029**								-.0003*	
				(.0043)	(.0007)								(.0001)	
Diversity			.0068*	.5267***	.0377***									-.0520***
			(.0032)	(.0247)	(.0066)									(.0026)
Centrality					.5191***	7.6805***	-1.5856***	.0871***				.7252**		
					(.0195)	(1.8646)	(.2683)	(.0052)				(.1857)		
Patents-current						.3494***								
						(.0314)								
Patents-accumulated						-.1110***		.0753***					.0013**	
						(.0079)		(.0186)					(.0004)	
Minority Equity	.0030***					.0018**	1.0047***				.1657***		-.0426*	
	(.0005)					(.0006)	(.0185)				(.0111)		(.0236)	
Public		.2158*										.5817***		
		(.0604)										(.0175)		
Nonop. Income								.6441***	.0767***	1.7754***				
								(.0252)	(.0111)	(.1519)				
Sales										1.0543***				
										(.0103)				
Employees									1.0215***		1.6499***			
									(.0228)		(.3704)			
Internal R&D											.2277***			
											(.0374)			
Age														.0135***
														(.0015)
Within R-square	.4697	.4775	.9702	.5008	.4119	.5046	.7923	.6094	.8077	.9389	.6788	.4495	.2300	.3230
Full R-square	.8526	.8470	.9977	.9210	.8357	.8500	.9600	.8969	.9473	.9840	.9064	.8612	.4013	.6311
Total N firm-years	937	2460	2460	2460	2460	939	791	782	705	783	706	2460	943	2460

Notes--1.) All models include fixed firm and year effects (dummy variables). 2.) Significance levels: *p<.05, **p<.005, ***p<.0005

Table 4
Results of 2SLS Panel Regressions

Predictor variables at t-1	R&D ties	Exper-ience	Diversity	Exper-ience	Diversity	Centrality	Patents	Nonop. Income	Employees	Sales	Internal R&D	Public	Acquisition	Exit
	Dependent variables at time t													
R&D ties>exp,div						.0120** (.0033)							n.s.	n.s.
Experience>centrality							.3503*** (.0705)	n.s.				.0283*** (.0054)		
Experience-squared>centrality							n.s.	n.s.				-.0016*** (.0003)		
Diversity>centrality							.1701* (.0628)	n.s.				.0268*** (.0052)		
Centrality>public	1.7108* (.8592)													
Centrality>patents, minority equity											-6.4652* (2.6454)		.2303** (.0814)	
Centrality>nonop.									4.4478** (2.1536)	6.9181** (3.3100)				
Public>r&d ties		.0679** (.0184)	.2693*** (.0556)											
Min. Inv>r&d ties				n.s.	n.s.									
Age														.0129*** (.0015)
Experience			.0921*** (.0178)		.1134** (.0301)								.0080** (.0022)	
Experience-squared			-.0051*** (.0011)		-.0066** (.0018)								-.0003* (.0001)	
Diversity		.1138*** (.0053)		.0409*** (.0050)										
Patents-accumulated							-.1322*** (.0080)	.0750** (.0212)						
Lagged DV	.6758*** (.0164)	.8649*** (.0036)	.5296*** (.0160)	.8936*** (.0034)	.4970*** (.0275)	.5694*** (.0180)	.3856*** (.0289)	.6426*** (.0252)	1.0936*** (.0209)	1.0853*** (.0109)	.2897*** (.0339)	.5996*** (.0171)		
Within R-square	.4767	.8903	.4371	.8109	.3713	.3869	.3470	.5091	.7845	.9182	.6098	.4402	.1304	.1310
Full R-square	.8468	.9077	.8487	.8770	.8132	.8259	.7653	.8468	.9456	.9825	.8941	.8588	.3390	.4303
Total N firm-years	2460	2460	2460	939	939	2460	939	783	705	783	706	2460	943	2460

Notes--1.) All models include fixed firm and year effects (dummy variables). 2.) Significance levels: *p<.05, **p<.005, ***p<.0005

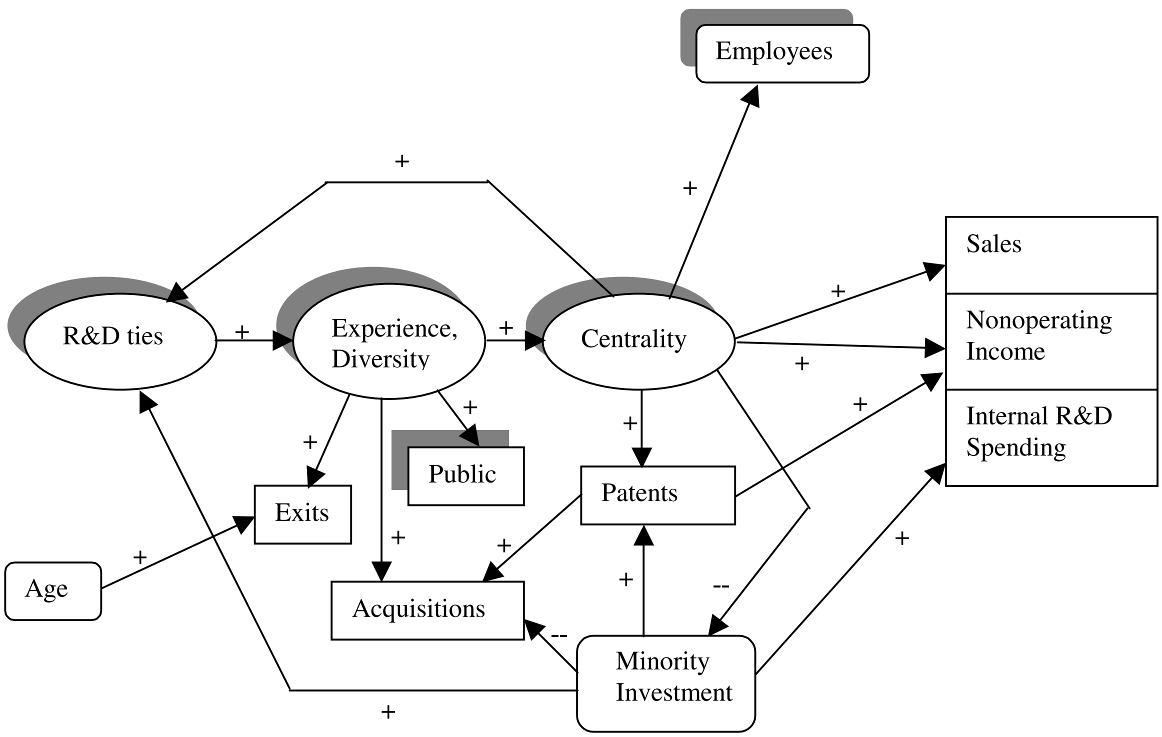
Table 5

Results of 3SLS Panel Regressions

Predictor variables at t-1	1 R&D ties	2 Experience	3 Diversity	4 Centrality	5 Patents	6 Minority Equity	7 Nonop. Income	8 Employees	9 Sales	10 Internal R&D	11 Public	12 Acquisition	13 Exit
	Dependent variables at time t												
R&D ties		.1228***	.1853***										
		(.0089)	(.0338)										
Experience			.1019***	.0095***							.0316***	.0055***	
			(.0216)	(.0029)							(.0045)	(.0010)	
Experience-squared			-.0211***	-.0029***							-.0015***	-.0003**	
			(.0037)	(.0005)							(.0003)	(.0001)	
Diversity		.0069**		.0412***							.0255***		-.0661***
		(.0028)		(.0060)							(.0032)		(.0020)
Centrality	1.6502***				7.5569***	-1.5995***	.1497***	4.4475***	7.0320***				
	(.8313)				(1.6192)	(.2618)	(.0049)	(2.0019)	(3.1972)				
Patents-current													
Patents-accumulated					-.1109***		.0875***					.0018***	
					(.0074)		(.0166)					(.0003)	
Minority Equity	.0031***				.0020***					.2121***		-.0403**	
	(.0005)				(.0005)					(.0111)		(.0217)	
Nonop. Income													
Age													.0133***
													(.0011)
Lagged DV	.5395***	.8069***	.5057***	.4981***	.3341***	.9969***	.6224***	1.0023***	1.0103***	.2192***	.5766***		
	(.0144)	(.0027)	(.0299)	(.0166)	(.0287)	(.0144)	(.0197)	(.0191)	(.0095)	(.0304)	(.0170)		
Overall within R-square	.6194												
Overall full R-square	.8946												
Total N firm-years	705												

Notes--1.) All models include fixed firm and year effects (dummy variables). 2.) Significance levels: *p<.05, **p<.005, ***p<.0005

Figure 1: Cycles of Learning and Organizational Returns



Notes:

1. Model consisting of shadowed components is taken from our earlier work, especially Powell et al 1996.
2. Legend: Ovals represent network properties, rectangles are performance and outcome measures, while rounded rectangles can be treated as either firm characteristics or outcomes.