# Social Capital, Structural Holes and the Formation of an Industry Network

Gordon Walker • Bruce Kogut • Weijian Shan
*Cox School of Business, Southern Methodist University, Dallas, Texas* 75275
*The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania* 19104
*J. P. Morgan, Hong Kong*

This paper is of interest because of its comparison of social capital theory and structural hole theory in explaining network formation. The paper demonstrates, in the case of biotechnology start-ups, that network formation and industry growth are significantly influenced by the development and nurturing of social capital. The paper raises several important implications: structural hole theory may apply more to networks of market transactions than to networks of cooperative relationships, and that the study of the structure of interfirm collaborations over time requires an analysis of the network as a whole.

*Arie Y. Lewin*

## Abstract

The formation of a network is determined by the opposition of two forces. The first is the reproduction of network structure as a general social resource for network members. The second is the alteration of network structure by entrepreneurs for their own benefit. The idea of reproduction is a conventional one in organizational sociology but has taken on increased importance due to the work of Bourdieu and Coleman. In contrast, Burt stresses the entrepreneurship of individual agents in exploiting structural holes that lie between constrained positions. Though complementary, the theories of social capital and structural holes have fundamentally different implications for network formation.

This paper investigates these theories by examining empirically the formation of the interorganizational network among biotechnology firms. We propose that network structure determines the frequency with which a new biotechnology firm (or startup) establishes new relationships. Network structure indicates both where social capital is distributed in the industry and where opportunities for entrepreneurial action are located. The reproduction of network structure depends on how startups value social capital compared to these opportunities. The critical test is, consequently, whether new relationships reproduce or alter the inherited network structure. We find strong support for the power of social capital in reproducing the network over time.

(*Social Network*; *Social Capital*; *Structural Holes*; *Network Formation*; *Biotechnology*)

## Introduction

There is a fundamental conflict in the formation of a network. On the one hand, there are powerful forces toward the reproduction of dense regions of relationships. Reproduction is powerful because it is based upon the accumulation of social capital that requires the maintenance of and reinvestment in the structure of prevailing relationships. Yet, it is exactly this principle of conservation that generates the opportunities for entrepreneurial actors to bridge these regions and alter the structure of the network.

The formation of interfirm networks is a critical point of contention between otherwise complementary views of network structure. For Pierre Bourdieu (1980) and James Coleman (1990a), a network tends toward the reproduction of an inherited pattern of relationships due to the value *to the individual* in preserving social capital. The notion of social capital implies a strategy of maintaining the structure of existing relationships. To Bourdieu, "social capital is the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu and Wacquant 1992, p. 119). Similarly, Coleman notes that an advantage of modern society is that organizations provide stability, even if people are mobile. "The

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social invention of organizations," he notes, "having positions rather than persons as elements of the structure has provided one form of social capital that can maintain stability in the face of instability of individuals" (Coleman 1990b, p. 320). Similarly, firms may tend toward the reproduction of existing interfirm relationships to maintain the value of their inherited social capital.

Ronald Burt (1992) has a different view of the conservative tendency of networks toward reproduction. To him, the emphasis should be placed on the opportunities for entrepreneurs to exploit the "structural holes" between dense pockets of relationships in the network. It is exactly the structural constraints on what people know and can control, created by the inheritance of past relationships, that presents the opportunities for brokers. These brokers seek out partners with whom they can form unique, or "nonredundant," relationships that bring new information and the possibility of negotiating between competing groups. Through forming these new and unique relationships, entrepreneurs transform network structure.

The theories of social capital and structural holes have important implications for understanding the formation of relational networks in high growth, technology-intensive industries. In these industries, the extensive innovative activities of small firms (Bound et al. 1984, Acs and Audretsch 1989) push out industry boundaries into new subfields and increase the level of competition in traditional markets. However, opportunities for cooperation are created by unintended spillovers and intended agreements. Organizations are also related through their members' professional connections, joint suppliers and customers, and industry associations. These commonalities may be sources of information about competitor behavior, new technological developments, and other industry trends. However, formal agreements are the most salient and reliable indicator of resource and information sharing between firms and the origin of information regarding a firm's cooperative strategy. This information is critical for future decisions regarding cooperation for product development and commercialization.

The emergence of the network of formal cooperative agreements influences the course of industry growth and innovation. A swelling network of cooperative agreements may provide a positive externality to which potential investors respond (Hagedoorn and Schakenraad 1992). Also, since poorly positioned firms may have access to less than adequate resources to achieve their economic goals, the network may act as a selection mechanism, culling out some firms on the basis of their partners' weakness.

Early in the history of an industry, social capital among firms is low, and yet it is critical for the identification and acquisition of new relationships. Rapid industry growth aggravates this problem of acquiring valid information on other firms. In this early period, firms enter relationships according to their differences in need and capability, and these relationships initialize the network (Kogut et al. 1994). In biotechnology, for example, small startups have extensive expertise in technological innovation but lack resources in marketing and distribution possessed by large incumbents. Cooperation between a startup and incumbent gives each access to a resource necessary for product commercialization. Variation in firm-level attributes, especially the effective management of interfirm cooperation, contributes to network growth. But this contribution is partial. As an unintended outcome of their cooperative strategies, firms build the network that serves as a map for future association.

Network formation occurs as new relationships by incumbent firms or startups exploit the opportunities inherent in the network, reinforcing the existing network structure or reshaping it (Galaskiewicz and Wasserman 1981, Marsden 1985, Kogut et al. 1994). Two types of opportunity drive the process of network formation. First, network structure is a vehicle for inducing cooperation through the development of social capital. Firms draw upon network structure as a system-level resource to facilitate the governance of their relationships. Second, however, gaps in the pattern of information flows reflect potentially profitable opportunities for establishing connections between unlinked firms (Burt 1992). These opportunities stimulate entrepreneurial action to broker different segments of the industry.

The relative advantages and risks of inducing cooperation and exploiting brokering opportunities have an important implication for network formation. The structural conditions inducing cooperation free resources for the establishment of new relationships that in turn strengthen the structure as a useful system for controlling noncooperative behavior. If the structure is reinforced by new relationships, early patterns of cooperation should persist, resulting in a path dependence analogous to the imprinting effect on an industry of the era in which it was formed (Stinchcombe 1965). However, if some firms have specific capabilities for information arbitrage, they may choose to broker relationships between organizations in different regions of the network. In this case, the existing structure is not strengthened but repeatedly reshaped. The early pattern of relationships is blurred as more organizations are linked together.

To address these issues, we examine network formation in terms of its structural development, positing network structure as a social fact interacting with firm-level behavior over time. Our theory below follows most closely recent developments in structural sociology, especially the ideas of Coleman (1990) and Burt (1992). The tests of our propositions on data from the biotechnology industry show strong support for this approach to analyzing the process of network formation.

# Theory

## Social Capital

Social capital is a means of enforcing norms of behavior among of individual or corporate actors and thus acts as a constraint, as well as a resource. Successful cooperation cannot be achieved in interorganizational relationships without constraints on the partners to perform according to each other's expectations. These constraints allow firms to risk greater investment with a partner in a relationship that would otherwise be hindered by the threat of opportunism. Lower levels of constraint are associated with difficulties in finding information about current or potential partners and therefore impede effective cooperation. Because cooperation is less frequent, network and consequently industry growth are hindered.

The network serves an important function in the development of social constraint directing information flows in the building and maintaining of social capital. Consider two extreme examples of network structure. If all firms in an industry had relationships with each other, interfirm information flows would lead quickly to established norms of cooperation. In such a dense network, information on deviant behavior would be readily disseminated and the behavior sanctioned. Firms in this industry would benefit equally from the network as a reputation building mechanism. Coleman (1992; see also Loury 1977, Bourdieu 1980) characterizes the extreme case of a fully connected network as "closed." Members of closed networks are connected to each other. In a closed network, firms as institutional actors have access to *social capital*, a resource that helps the development of norms for acceptable behavior and the diffusion of information about behavior. As the predictability of behavior is increased in a system that is already connected, self-seeking opportunism is constrained and cooperation enabled.

At the other extreme is an "open" network. Firms in open networks have no social capital on which to rely. If firms are not connected to each other extensively, norms regarding cooperation are more difficult to achieve, and information on behavior in relationships diffuses more slowly. Without relationships that determine behavior and carry information, firms are less able to identify or control opportunism. In support of this conjecture, Raub and Weesie (1990) use a Prisoner's Dilemma framework to show that a firm embedded in a closed network is constrained to be more cooperative than a comparable firm embedded in an open network. Similarly, Granovetter (1985) argues, through extensive examples, that embeddedness in dense networks leads to effective interfirm cooperation.

However, a common result of research on interfirm network structure is that it is neither uniformly dense nor sparse (Knoke and Rogers 1978, Van de Ven et al. 1979, Nohria and Garcia-Pont 1991). The structure is uneven, composed of regions that are more or less filled with relationships. The positions firms occupy in the network are embedded in these regions. Some firms occupy positions that are embedded in regions filled with relationships, indicating a high level of available social capital, but other positions are located in regions with few relationships, suggesting a low social capital. In such a complex network, the degree of social capital available to a firm is thus determined by its position in the network structure.

A central premise of the present paper is that social capital influences how the network forms. Network formation proceeds through the establishment of new relationships, building on the base of existing interfirm ties. Managing these ties requires ongoing attention and resources, of which organizations have only limited amounts. Social capital is thus a valuable additional asset for managing interorganizational relationships since it constrains a firm's partners to be more cooperative. Firms with less social capital are more vulnerable to opportunistic behavior and less able to build an enduring history of effective cooperative behavior with their partners over time. They, therefore, are required to expend greater time and effort monitoring the relationship. In contrast, the more social capital available to a firm, the fewer resources it needs to manage existing relationships and the more resources it can use to establish new ones. Coleman explains:

> Social capital is defined by its function. It is not a single entity but a variety of different entities, with two elements in com-

mon: they all consist of some aspect of social structures, and they facilitate certain actions of actors—whether persons or corporate actors—within the structure (Coleman 1988, p. S98).

In the present study, the social structure is the interorganizational network. The amount of social capital depends on the firm's position in the network structure. The action facilitated by this structure is the formation of new relationships. These arguments lead to the central proposition that firms in network positions with higher social capital are likely to have more relationships with new partners in the following time period.

An important question follows: how do a firm's new cooperative relationships affect the social capital available to it? If social capital improves cooperation, then it seems likely that firms would seek partners that are more rather than less constrained by network structure. That is, firms should try to increase the social capital available to them through the new relationships they establish. Thus, the value of social capital motivates firms to reproduce the existing network structure, building the social capital available to them.

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on the strategic action of entrepreneurs. In Burt's view, the benefits of increasing social constraint from establishing relationships in closed regions of the network are offset by a reduction in independence. Firms with relationships in open networks have greater latitude in their cooperative strategies. These firms have higher economic gains because they are most able to parlay their superior, i.e., less redundant, information into increasing their control. Burt (1992, p. 37) argues:

The higher the proportion of relationships enhanced by structural holes, the more likely and able the entrepreneurial player, and so the more likely it is that the player's investments are in high-yield relationships. The result is a higher aggregate rate of return on investments.

Structural hole theory therefore raises the problem of free-riding on the public good of social capital. Over time, firms will seek to exploit the holes between the islands of social capital in which relationships are embedded. As a result, the social capital available to an entrepreneur should decrease as the firm forms new relationships.

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these changes as they happen, rather than all at once at the end of each year. If structural constraint represents social capital, the change in structure should determine the resources available to a firm to form new relationships. From Coleman and Bourdieu's perspective, increasing social capital in a period should enable more relationships. Alternatively, if, as Burt asserts, trust is determined only by careful partner selection, increases in social capital should have no effect on the number of new relationships. The arguments regarding network formation from both the social capital and structural hole perspectives are set out as propositions in Figure 1.

**Control Variables**

We test these propositions against the view that only organizational attributes determine interfirm cooperation. Since firms with similar attributes may occupy the same network position (Burt 1992, chapter 5), controlling for these attributes makes the analysis of network formation more robust. We identify five control variables: firm size, firm experience in cooperating with other firms, public offering of the firm's equity, the concentration of the firm's partners across global regions, and the average number of relationships of the firm's partners. The last two of these variables might be viewed more properly as partner characteristics. How-



by new relationships should be relate
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Therefore, the more social capital avai
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**Structural Holes**

Burt (1992) presents an alternative to th
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**Figure 1 List of Propositions Developed in the Theory Section and Their Tests**

| Social Capital Perspective | Tests of Propositions |
|---|---|
| 1. Firms with higher social capital are likely to have more relationships with new partners in the following time period | Regression of new relationships on social capital (for incumbent and entering partners); see Table 6 |
| 2. The more relationships a firm forms, the more likely its social capital will increase | Regression of change in social capital on new relationships (for incumbents and entering partners); see Table 7 |
| 3. The more social capital at the beginning of a time period, the lower the increase in social capital in the next time period | Regression of change in social capital on level of social capital in the previous time period; see Table 7 |
| 4. The more a firm's social capital increases over a time period, the more relationships it should have during this time period | Regression of new relationships (for incumbent and entering partners) on change in social capital; see Table 6 |
| **Structural Hole Perspective** | |
| 5. The more relationships a firm forms in a year, the more its social capital should decrease | Regression of change in social capital on new relationships (for incumbents and entering partners); see Table 7 |
| 6. Lack of empirical support for Proposition 4 above would be consistent with the Structural Hole Perspective | Regression of new relationships (for incumbent and entering partners) on change in social capital; see Table 6 |

ever, since they are aggregated by firm, they are included as firm-level controls.

Firm size is a measure of a firm's capacity to cooperate and a measure of its capacity to do without cooperation. Whereas Shan (1990) found a negative relationship between size and cooperation, Boyles (1969) and Powell and Brantley (1991) found that the frequency of cooperative relationships more than proportionally rises with size. Whether this difference rises from a nonlinearity in the association between size and the frequency of cooperation is partly addressed below.

Firm experience with cooperation, represented as the number of relationships it has established, presents a similar set of issues. The more relationships a firm has, the more it should know about how to manage them and so the less costly it should be to form new relationships. On the other hand, the lower incremental learning from new relationships may attenuate their formation. Again, we address this potential nonlinearity in our analysis.

The effect of issuing public equity on interfirm cooperation also has an ambiguous interpretation. First, a public offering is one form of getting resources. As a publicly held corporation, an entrepreneurial startup

projects, thereby decreasing the need to cooperate for this purpose. However, going public may also be an indicator of the legitimacy of the firm and signal a strong position in the network. Firms with higher legitimacy are likely to attract more partners for cooperative ventures.

Regional concentration represents how a firm's partners are distributed across three major global regions: United States, Europe, and Japan. As Hofstede et al. (1990) have shown, national cultures have a significant impact on work behavior. Managing partners across different regions should therefore be a more complex and difficult task than managing partners from the same region. The higher the concentration, the more partners from a single region are represented in the firm's organization set and the less difficult its task of managing them.

The experience of an organization's partners in interfirm agreements may influence its tendency to cooperate. The more agreements a firm's partners currently have, the more likely they are to be embedded in closed regions of the network and therefore to be constrained from acting opportunistically (see Baker 1991). However, partners with more relationships may also be less dependent on the firm for its information, goods and services, releasing normative pressures for equitable behavior. Partner experience may therefore either heighten or dampen the firm's tendency to cooperate.

Finally, in studying the reproduction of network structure, it is important to differentiate between relationships with partners entering the network and relationships with partners already in the network. The first are called entering partners and the second incumbent partners. Splitting partners in this way provides a robust test of the social capital argument. In the broadest sense, social capital releases resources to firms for further cooperation whether the firm engages partners that are new to the network or already network members. A narrower view of social capital suggests that social capital theory applies to network formation only for relationships with network incumbents. If this is the case, future research must consider network incumbency as a moderator of social capital's effect.

## Data

We test these hypotheses by examining network formation in the biotechnology industry.[1] As most earlier studies have shown, the frequency of interfirm relationships in this industry is quite high, primarily between large established firms in a variety of businesses (pharmaceuticals, chemicals, agricultural products, food products) and small, entrepreneurial startup firms (Barley et al. 1992, Powell and Brantley 1992, Kogut et al. 1995). These relationships have been shown to increase the capabilities of startup firms, indicating a motivation for continuing cooperation (Shan et al. 1994). The incidence of these relationships has been explained both by network (Kogut et al. 1992) and firm-level variables (Shan 1990, Pisano 1990).

Biotechnology is typical of industries with high rates of innovation and a significant entrepreneurial sector. The motivation for interfirm cooperation in these industries is quite strong, based on the complementarity of large and small firm capabilities. Because of the tremendous potential market for new biotechnology products, established companies have sought access to this new technology both by starting up biotechnology operations in-house and by forming cooperative agreements with startup firms, typically begun by scientists. Startup firms, in turn, have been willing to enter into cooperative agreements to provide established firms with new technologies and products in exchange for funding and to breach the barriers to entry in marketing, distribution, and government certification (Shan 1987). As firms become connected through these agreements, a broad network, typically global in scope, is formed.

To analyze network formation in biotechnology, we examine new relationships by startups rather than those by established firms, for several reasons.[2] Kogut et al. (1994) showed that startups have a much greater propensity to cooperate than established firms over time and correspondingly have more relationships. Network growth is therefore determined more by the expansion of startup organization sets than by the organization sets of their established firm partners. Startups also have much higher variability than established firms in number of relationships over time and are more central in the network (Barley et al. 1992).

**Table 1** **Number of Sample Startups Founded in Each Year**

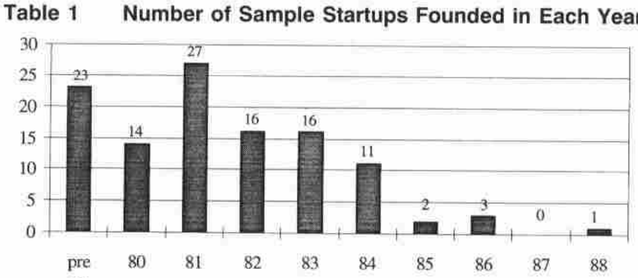
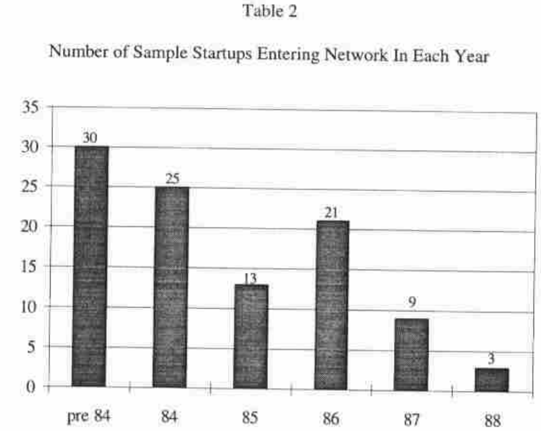



**Table 2** **Number of Sample Startups Entering Network in Each Year**




Although startups have relationships with each other, their relationships with established firms are far more prevalent. Only six percent of relationships existing in 1988 were between startups. A description of the timing of foundings of startups and the pattern of their relationships with established firms is given in Tables 1 to 4. (See Appendix A for a description of data sources and the characteristics of our sample.) The distribution of cooperative relationships is shown in Tables 1 and 2. Startup foundings (shown in Table 1) lead the formation of these relationships by three to five years (shown in Table 2). Startup foundings peak in 1981, while the number of relationships with partners peaks in 1984 with a second mode in 1986. This second (1986) mode can be partly attributed to the entry into the network of established firms (see Table 3). The modal year for all relationships, by both new and incumbent startups, is also 1986 (see Table 4).

Since the process of developing, testing, and commercializing biotechnology products takes many years, cooperative relationships endure for a long time. Only 18 percent of the relationships in the industry from its beginning until 1988 had a fixed duration (that is, their termination date was formally specified when they were initiated); and only 31 percent of fixed duration relationships ended before 1988. Furthermore, only 11

**Table 3 Number of Established Firms Entering Network in Each Year**

In this table, the number of established firms in 1988 does not include 24 which left the network between 1986 and 1988.

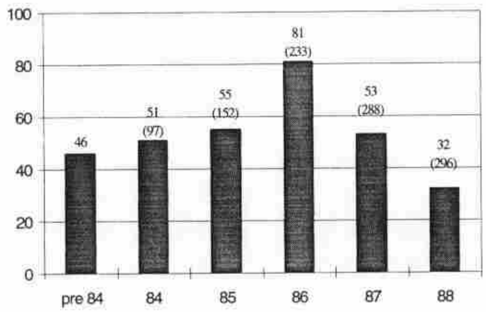
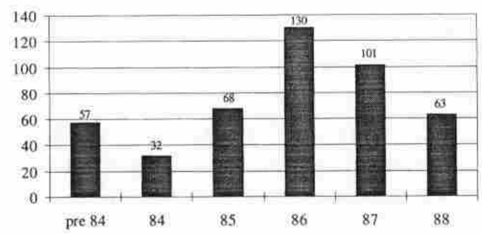



**Table 4 Number of Cooperative Relationships Formed in Each Year**




percent of the relationships with unfixed durations were terminated before 1988. Thus, in 1988 some 85 percent of all the agreements that had ever been formed were still in effect.

# Method

### Measuring Social Capital

Our measure of social capital is based on the idea of structural equivalence, which has been frequently used in the analysis of interorganizational networks (Knoke and Rogers 1978, Van de Ven et al. 1979, DiMaggio 1986, Schrum and Withnow 1988, Nohria and Garcia-Pont 1990, Oliver 1990). Determining the structural equivalence of firms is also central to network analysis in structural hole theory (Burt 1992, chapter 2). Firms that are structurally equivalent have relationships with the same other fir[illegible]

columns their established firm partners. An "X" indicates a relationship and a "0" the absence of a relationship. Note that the intersections of row and column groups are either dense with relationships or sparse.

A network where all groups of firms are densely related to each other is rare, since such it would be almost fully connected. Therefore, measuring structural equivalence in practice almost always depends on an assessment of relative partner overlap. While some groups may have firms that share almost all their partners, firms in other groups may share hardly any of their partners.

One way of measuring how much firms in a group share partners is to examine the dispersion of intergroup densities around the network average. A group of firms that share partners extensively should have dense relationships with some partner groups and sparse or no relationships with other partner groups. This pattern is found for all the groups, both row and column, in Figure 2. An equation that calculates density dispersion is:

$$G_i = n_i \sum_j m_j \left(d_{ij} - d^*\right)^2. \tag{1}$$

In this equation, $G_i$ is the measure of the dispersion of intergroup densities for the $i$th group in the network, $n_i$ is the number of firms in the $i$th group, $m_j$ is the number of partners in the $j$th partner group, $d_{ij}$ is the density of the intersection of the $i$th and $j$th groups, and $d^*$ is the overall density of the network.[4] A higher value of $G_i$ indicates greater dispersion of a group's densities and therefore more partner sharing by the firms in group $i$. Note that this measure penalizes small groups of firms with small partner groups.

To show how the structure of the biotechnology network differs from the idealized network of Figure 2, we use a method that builds on $G_i$ to analyze the biotechnology network of relationships formed before 1984. Since $G_i$ reflects the deviation of intergroup relationships from the average network density, summing $G_i$ over all groups produces a measure of network structure:[5]

$$G = \sum_i \sum_j n_i m_j \left(d_{ij} - d^*\right)^2. \tag{2}$$

The details of the methodology are presented in Appendix B, which shows how the pre-1984 network was analyzed.

structurally equivalent startups have the same estal lished firms as partners and structurally equivaler established firms have the same startups as partner The emergence of this type of structure therefo depends on the pattern of partner sharing.[3]

An idealized example of this type of network stru ture is shown in Figure 2. Rows represent startups ar

**Figure 2 An Idealized Network Structure Based on Structural Equivalence**

| | | Partners | | | |
|---|---|---|---|---|---|
| | | Group 1 | Group 2 | Group 3 | Group 4 |
| Startups | Group 1 | xxxooxxx<br>xxxxooxx<br>oxxxxoxx | oooooooooooo<br>oooooooooo<br>oooooooooooo | oooooooooooo<br>oooooooooooo<br>ooooooooo | oooooooooooo<br>oooooooooooo<br>oooooo |
| | Group 2 | oooooooooooo<br>oooooooooooo<br>ooooooooo | xxxxxxooox<br>xxxoxxxxox<br>xxoxxxoxxx | oooooooooooo<br>oooooooooooo<br>ooooooooo | xxxxxxxoox<br>xoxxoxxxox<br>xxxxxoxxox |
| | Group 3 | oooooooooooo<br>oooooooooooo<br>ooooooooo | oooooooooooo<br>oooooooooooo<br>ooooooooo | ooxxxxxxxx<br>xxxxoxxxxo<br>xoxoxxoxxxx | oooooooooooo<br>oooooooooooo<br>oooooo |
| | Group 4 | oooooooooooo<br>oooooooooooo<br>ooooooooo | oooooooooooo<br>oooooooooooo<br>ooooooooo | oooooooooooo<br>oooooooooooo<br>ooooooooo | xxxxxoxoox<br>xxoxxoxxxo<br>oxxxxoxxox |

Figure 3a shows the partitioned raw data. There are four startup groups and six partner groups. Group I has the largest number of firms, which have relationships predominantly with partner groups A, B, and C. Because the number of relationships Group I has with each of the partner groups is much smaller than the number of possible relationships, the densities of these intergroup relationships are quite low (see Figure 3b). Unlike Group I, Groups II, III and IV are densely related to their partner groups. Group II contains only one firm, the only startup to have agreements with Group E. Furthermore, this firm has only one other relationship in the network, with a partner in Group F. Finally, both Groups III and IV are composed of several startups that have established relat

with new relationships, we assume that startups have chosen partners so that social capital is increased. However, increased social capital also means increased social constraint. Following Burt's argument (Burt 1982, p. 57), if startups are searching for lower social constraint, the startup group's contribution to network structure should decline over time.

### Testing the Propositions

Although structurally equivalent startups that occupy the same position will have the same amount of social capital, they will differ in the number of relationships they establish in each year and in the control variables.

**Figure 3A** **Partitioned Raw Data for 1983 Network**

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                                   Partner Groups

                              A               B    C       D       E          F
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Startup            XOOOOOOOOOOOOOOOOOO •OO •OOOOO •OOOOO •OOOOOO•OOOOOOOOO
Groups             OOOOOOOOOOOOOOOOOOO •OX •OOOOO •OOOOO •OOOOOO•OOOOOOOOO
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                   OOOOOOOOOOOOOOOOOOO •OO •OOOOO •OOOOO •OOOOOO•OOOXOXOXO
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**Figure 3B** **Density Matrix of 1983 Network**

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| I | .05 | .09 | .05 | 0 | 0 | .01 |
| II | 0 | 0 | 0 | 0 | 1 | .11 |
| III | 0 | 0 | 0 | .6 | 0 | 0 |
| IV | 0 | 0 | 0 | 0 | 0 | .33 |

dependent variable is not a count but continuous and use two-stage least squares. Generalized least squares permits corrections for serial correlation in the error term and unobserved firm-level effects. Figure 1 shows how these regressions test the propositions based on the theories of social capital and structural holes.

## Results

Table 5 shows the means, standard deviations and correlations among the variables, and Table 6 presents the findings for the regressions. Five of the explanatory variables have consistent results: the social capital and change in social capital, startup experience, partner experience, and public offering (IPO). Both network variables explain the frequency of new relationships strongly, as social capital theory predicts. Interestingly, neither startup nor partner experience has an effect on new relationships, controlling for the network variables.[8] This finding shows that new relationships are not explained by how many relationships a startup or its partner has, but how the relationships are distributed across partner groups. Public offering has a positive, significant effect on establishing relationships with entering partners but no influence on relationships with incumbents.

The results for startup size and regional concentration are not as clear. Neither has an effect for incumbent partners. However, for entering partners, the results for the two techniques differ in significance but not in sign.

Table 7 reports the results of testing whether social capital and the number of new startup relationships

**Table 5 Means, Standard Deviations and Correlations**

| Variables | MN | STD | Correlations | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Social Capital | 0.039 | 0.036 | 1.00 | | | | | | | | | |
| 2. Change in Social Capital | −0.001 | 0.027 | −0.52 | 1.00 | | | | | | | | |
| 3. Number of Relationships with Entering Partners in Each Period | 0.73 | 1.16 | 0.25 | 0.17 | 1.00 | | | | | | | |
| 4. Number of Relationships with Incumbent Partners in Each Period | 0.52 | 0.95 | 0.17 | 0.14 | 0.27 | 1.00 | | | | | | |
| 5. Size | 170.08 | 245.99 | 0.38 | 0.01 | 0.27 | 0.07 | 1.00 | | | | | |
| 6. IPO | 0.74 | 0.44 | 0.12 | 0.01 | 0.19 | 0.12 | 0.16 | 1.00 | | | | |
| 7. Regional Concentration | 1.79 | 0.61 | 0.03 | −0.001 | 0.04 | 0.03 | 0.41 | 0.10 | 1.00 | | | |
| 8. Startup Experience | 3.94 | 4.64 | 0.55 | −0.08 | 0.14 | 0.18 | 0.41 | 0.26 | 0.05 | 1.00 | | |
| 9. Partner Experience | 2.45 | 1.52 | −0.09 | 0.04 | −0.14 | −0.11 | −0.12 | 0.12 | 0.06 | 0.03 | 1.00 | |
| 10. Number of Startups in Group | 40.16 | 28.09 | −0.65 | 0.37 | −0.19 | −0.13 | −0.20 | −0.06 | −0.07 | −0.32 | 0.14 | 1.00 |

influence change in social capital. Included in the model are dummy variables for each year and a variable indicating the number of firms in a startup's group. Controlling for this variable is necessary since $G$ (in Equation (1)) is linearly related to it. The two-stage least squares regression shows that more new relationships increase social capital. Also, the increase in social capital is lower when a startup has more social capital in the beginning period.

Startup propensities to cooperate may vary to some extent. There may be unobserved firm-level factors that influence how frequently cooperation occurs. The $a$ term in the negative binomial regression captures these unobserved variables to a degree.

To explore this problem further, we regressed the frequency of new startup relationships on the explanatory variables including firm-specific dummy variables to account for unobservable effects. Since our sample draws from a larger population of startup firms, a random effects specification is appropriate. The hypotheses are therefore tested, without simultaneity, using Generalized Least Squares. The results of this GLS regression are stronger than those of the negative binomial and two-stage least squares regressions.[9] Consequently, we can be reasonably confident that unobserved firm-level variation in the propensity to cooperate does not confound our findings.

## Discussion

We have posed two theories to explain the incidence of new relationships. One theory emphasizes the positive effect of social capital, as structural constraint, on new cooperation. The other argues that highly constrained cooperation has lower rewards and is therefore avoided. Our analysis of biotechnology startups shows that social capital theory is the better predictor of cooperation over time. More constrained firms cooperate with partners that can be firmly embedded in the historical network structure. The network is thus increasingly structured over time. Network formation, and industry growth, are therefore significantly influenced by the development and maintenance of social capital.

Why have biotechnology startups chosen to increase social capital rather than exploit structural holes? First, relationships in the biotechnology network last a long time. Long durations entail extensive, ongoing interaction over a broad range of technical and commercial problems. Were partners to behave in a self-interested way during the course of such a long relationship, a substantial investment in time and effort would be jeopardized. Structural stability is therefore desirable. In a network where relationships are of shorter duration, the structure would undoubtedly be less stable and less available as a resource for action. Enduring interfirm ties sustain the structure that facilitates new cooperation. Second, structural hole theory may apply more to networks of market transactions than to networks of cooperative relationships. Lacking the requirement to cooperate over time, firms may not ... onship

Third, interfirm relationships in biotechnology a[re] based on a kind of mutual dependence that may pr[e]vent either startups or established firms from gainin[g]

**Table 6 Results for Regression Explaining New Startup Relationships**

**Table 6A**

| Explanatory Variables: | Entering Partners Negative Binomial | Entering Partners 2SLS[1] | Incumbent Partners Negative Binomial | Incumbent Partners 2SLS |
|---|---|---|---|---|
| Constant | −1.35*** | −0.15 | −1.97*** | −0.13 |
| | (0.42)[2] | (0.28) | (0.67) | (0.23) |
| Social Capital | 8.08* | 17.94*** | 13.08** | 11.82*** |
| | (4.27) | (5.39) | (5.32) | (4.26) |
| Change in Social Capital | 13.06*** | 27.52*** | 18.84*** | 16.95*** |
| | (3.12) | (8.26) | (5.74) | (6.28) |
| Startup Experience | 0.002 | −0.03 | 0.023 | 0.0042 |
| | (0.031) | (0.024) | (0.038) | (0.02) |
| Partner Experience | −0.057 | −0.035 | 0.089 | −0.59 |
| | (0.057) | (0.043) | (0.27) | (0.38) |
| Size | 0.0004 | 0.0004 | −0.001 | −0.0004* |
| | (0.0003) | (0.0003) | (0.0006) | (0.0003) |
| IPO | 0.79*** | 0.39*** | 0.39 | 0.12 |
| | (0.23) | (0.15) | (0.27) | (0.13) |
| Regional Concentration | 0.09 | 0.0004 | 0.089 | 0.0001 |
| | (0.15) | (0.0001) | (0.27) | (0.0009) |
| D86 | 0.52** | 0.73** | 1.04*** | 0.64*** |
| | (0.26) | (0.25) | (0.39) | (0.21) |
| D87 | −0.30 | −0.056 | 0.77* | 0.39** |
| | (0.29) | (0.24) | (0.44) | (0.20) |
| D88 | −0.99*** | −0.34 | 0.26 | 0.16 |
| | (0.35) | (0.26) | (0.48) | (0.22) |
| $\alpha$ | 0.081 | | 0.59* | |
| | (0.13) | | (0.32) | |
| $F$-value | | 12.49 | | 5.27 |
| df | | 10,262 | | 10,261 |
| $R^2$ | | 0.32 | | 0.16 |
| Adj. $R^2$ | | 0.29 | | 0.13 |

[1]2SLS coefficients are adjusted for serial correlation in the error term. $R^2$ terms pertain to unadjusted estimates.
[2]Standard errors are reported in parentheses.
$*p < 0.10$
$**p < 0.05$
$***p < 0.01$

**Table 6B**

| Explanatory Variables: | Entering Partners Negative Binomial | Entering Partners OLS[1] | Incumbent Partners Negative Binomial | Incumbent Partners OLS |
|---|---|---|---|---|
| Constant | −1.08*** | 0.51*** | −1.50** | −0.32* |
| | (0.40)[2] | (0.19) | (0.69) | (0.17) |
| Social Capital | | | | |
| Change in Social Capital | | | | |
| Startup Experience | 0.029 | 0.026* | 0.056 | 0.042*** |
| | (0.020) | (0.016) | (0.037) | (0.014) |
| Partner Experience | −0.057 | −0.037 | −0.12 | −0.057 |
| | (0.066) | (0.044) | (0.084) | (0.039) |
| Size | 0.0008*** | 0.0009*** | −0.0002 | −0.0001 |
| | (0.0003) | (0.0003) | (0.0006) | (0.0003) |
| IPO | 0.87*** | 0.47*** | 0.47* | 0.16 |
| | (0.24) | (0.15) | (0.27) | (0.13) |
| Regional Concentration | 0.17 | 0.0004 | 0.18 | 0.0003 |
| | (0.16) | (0.001) | (0.28) | (0.0009) |
| D86 | 0.15 | 0.26 | 0.63 | 0.35* |
| | (0.23) | (0.19) | (0.42) | (0.18) |
| D87 | −0.67*** | −0.45** | 0.31 | 0.13 |
| | (0.26) | (0.19) | (0.42) | (0.17) |
| D88 | −1.43*** | −0.79*** | −0.26 | −0.14 |
| | (0.29) | (0.19) | (0.48) | (0.18) |
| $\alpha$ | −0.27 | | 0.99** | |
| | (0.17) | | (0.40) | |
| $F$-value | | 9.94 | | 3.15 |
| df | | 8,263 | | 8,263 |
| $R^2$ | | 0.22 | | 0.087 |
| Adj. $R^2$ | | 0.19 | | 0.059 |

[1]The OLS regression results reported are adjusted for autocorrelated error. The $F$-statistic reported is not adjusted for this error.

control over the other. Biotechnology startups and their established firm partners have complementary resources that are jointly necessary for product development and commercialization.

Such mutuality may not be present to such an extent in other technology-intensive industries. For example, Kogut et al. (1992) argue that cooperative agreements between startups and established firms in the semiconductor industry are based on the technical standards which large firms own. Large firms dominate the network structure of the semiconductor industry as they compete for technological dominance through their alliances with startups. In such a structure, embeddedness clearly has a different meaning than in the biotechnology network (compare, e.g., Marsden 1983).

Our results lead to the conclusion that some firms continuously improve their already strong social endowments, although at a decreasing rate, while other firms have less social capital to draw upon in forming new relationships. This conclusion holds for relation-

**Table 6C**

| Explanatory Variables: | Entering Partners: Negative Binomial | Entering Partners: 2SLS[1] | Incumbent Partners: Negative Binomial | Incumbent Partners: 2SLS |
|---|---|---|---|---|
| Constant | −0.94*** | 0.15 | −1.87*** | −0.13 |
| | (0.26) | (0.18) | (0.39) | (0.16) |
| Social Capital | 11.91*** | 14.75*** | 12.17*** | 9.62*** |
| | (2.34) | (1.97) | (3.73) | (1.77) |
| Change in Social Capital | 17.22*** | 21.14*** | 18.16*** | 13.09*** |
| | (3.41) | (2.66) | (5.003) | (2.38) |
| D86 | 0.72*** | 0.69*** | 1.12*** | 0.60*** |
| | (0.25) | (0.19) | (0.38) | (0.17) |
| D87 | −0.1 | −0.095 | 0.75* | 0.36** |
| | (0.28) | (0.19) | (0.38) | (0.17) |
| D88 | −0.80** | −0.42** | 0.27 | 0.10 |
| | (0.32) | (0.19) | (0.41) | (0.17) |
| $\alpha$ | −0.24 | | 0.75** | |
| | (0.16) | | (0.34) | |
| $F$-value | | 22.93 | | 9.82 |
| df | | 5,266 | | 5,266 |
| $R^2$ | | 0.30 | | 0.16 |
| Adj. $R^2$ | | 0.29 | | 0.14 |

[1]The 2SLS regression results reported are adjusted for autocorrelated error. The $F$-statistic reported is not adjusted for this error.

**Table 7 Results of Two-stage Least Squares Regression on Change in Social Capital**

| Explanatory Variables: | Dependent Variable: Change in Social Capital | |
|---|---|---|
| Constant | 0.0043 | 0.0049 |
| | (0.0054) | (0.0077) |
| Number of Startup Relationships with Entering Partners | 0.018*** | |
| | (0.0038) | |
| Number of Startup Relationships with Incumbent Partners | | 0.036*** |
| | | (0.017) |
| Existing Social Capital | −0.44*** | −0.41*** |
| | (0.056) | (0.086) |
| Number of Startups in Group | 0.0001* | 0.0003** |
| | (0.00007) | (0.0001) |
| D86 | −0.025*** | −0.037*** |
| | (0.0054) | (0.010) |
| D87 | −0.0047 | −0.023*** |
| | (0.0051) | (0.009) |
| D88 | 0.0018 | −0.014* |
| | (0.0054) | (0.0075) |

*$p < 0.10$
**$p < 0.05$
***$p < 0.01$

ships with both incumbent and newly-entering partners, indicating that the effect of network structure on forming new relationships is not moderated by partner incumbency. Although the results for network formation are similar for both incumbent and entering partners, these partner types differ in two important ways. First, entering partners tend to establish relationships with startups whose equity is publicly trad[illegible] choice of incumbents does not depend on the characteristics of individual startups. *IPO* (Initial Public Offering) appears to signal organizational legitimacy to entering firms rather than represent a source of potential startup capital substituting for a partner's financial resources. A second difference between incumbent and entering partners is in the time trends. For relationships with entering firms, the signs on the year dummy variables turn from negative to positive to negative over the four years. Relationships with entering partners decline in the later years simply because there are fewer firms coming into the network. But, as shown in Table 4, the trend for incumbent partners remains positive, though declining in the later years. When

## Path Dependence in Network Formation

The firms in the industry recreate a stable network structure whose foundation was laid at an early point in the industry's history. Firms' early partner choices thus have a significant impact on the course of future [illegible] we analyze and compare the network structures from 1984 to 1988. Examining structural equivalence over time indicates how much network structure is altered by network growth through entry and new relationships among incumbents.

Table 8 presents cross-tabulations showing whether pairs of firms remained structurally equivalent or nonequivalent from one year to the next. Entries on the main diagonal in each table indicate persistence. To assess whether these entries are larger than the off-diagonal entries, we calculated the cross-product ratio for each table. The cross-product ratio is a commonly used statistic for estimating the degree of association [illegible]

**Table 8 Structural Equivalence of Organizations over Time**

1. Startups

| 1983 \ 1984 | Str. eq. | Not Str. eq. |
|---|---|---|
| Str. eq. | 52* | 190 |
| Not. Str. eq. | 4 | 189 |

Log cross product ratio = 2.56
Std. error = 0.53

| 1984 \ 1985 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 189 | 99 |
| Not. Str. eq. | 605 | 592 |

Log cross product ratio = 0.62
Std. error = 0.14

| 1985 \ 1986 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 917 | 528 |
| Not. Str. eq. | 270 | 631 |

Log cross product ratio = 1.40
Std. error = 0.09

| 1986 \ 1987 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 1162 | 1067 |
| Not. Str. eq. | 426 | 1261 |

Log cross product ratio = 1.17
Std. error = 0.07

| 1987 \ 1988 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 1609 | 519 |
| Not. Str. eq. | 903 | 1722 |

Log cross product ratio = 1.78
Std. error = 0.07

2. Established Firms

| 1983 \ 1984 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 56 | 187 |
| Not. Str. eq. | 15 | 777 |

Log cross product ratio = 2.74
Std. error = 0.03

| 1984 \ 1985 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 141 | 270 |
| Not. Str. eq. | 187 | 4058 |

Log cross product ratio = 2.43
Std. error = 0.13

| 1985 \ 1986 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 257 | 651 |
| Not. Str. eq. | 377 | 10190 |

Log cross product ratio = 2.47
Std. error = 0.09

| 1986 \ 1987 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 339 | 1097 |
| Not. Str. eq. | 784 | 24808 |

Log cross product ratio = 2.28
Std. error = 0.03

| 1987 \ 1988 | Str. eq. | Not. Str. eq. |
|---|---|---|
| Str. eq. | 368 | 1561 |
| Not. Str. eq. | 971 | 37855 |

Log cross product ratio = 2.22
Std. error = 0.07

*Entries in cells are pairs of organizations

greater than one imply a positive relationship. Because the logarithm of the cross-product ratio is less skewed than the ratio itself, we use the log of the ratio to test for structural persistence (Wickens 1989, pp. 218–222). These log ratios are all positive and strongly significantly different from zero for both startups and partners. Except for the 1983–1984 period, the tables show that once a pair of startups are structurally equivalent, the odds are significant that they will continue to be so. Furthermore, the reverse is also generally true: if a pair of startups are not structurally equivalent, they are likely to remain this way.

Predicting partner groups over time depends mostly on the persistence of structural dissimilarity, however. Between 1987 and 1988, for example, the odds that a pair of partners will continue to be structurally equivalent are roughly one to five (368/1561), while the odds that they will remain structurally nonequivalent are roughly forty to one (37855/971). The reason for this pattern is the large number of entering partners relative to partners already in the network.

The structural development of the industry, based on the building and reinforcement of social capital, offers a simple insight into the rigidity of organizational forms. Since an organization depends on the resources available in its network, organizational inertia may be less an inherent property of organizations than a product of the organization's position in a rigid network. The persistence of these positions, as shown in Table 8, suggests that a startup's characteristics may endure because of structural conditions (see Shan et al. 1994).

## Conclusion

Social capital, as outlined by Coleman and Bourdieu, is a powerful concept for understanding how interfirm networks in emerging industries are formed. It is important to note that network formation need not lead towards an optimal structure for innovation or product commercialization.[10] Although there is evidence that interfirm cooperation and startup patent activity are related (Shan et al. 1994), the local benefits of partner sharing may not be distributed so that the most productive and useful technological advances are commercialized successfully.

The importance of network formation for interfirm cooperation has important consequences for organization theory. Taking the transaction as the unit of analysis is inadequate to capture the structural effects we have identified. The study of interfirm cooperative agreements over time requires an analysis of the network as a whole.

The persistence of network structure has subtle implications for entrepreneurial behavior. Structural persistence does not imply that firms are equally situated to exploit profitable opportunities for cooperation. Because the structure is relatively inert, brokering positions are established early in the history of the network. In fact, if structure did not persist, all firms would be potential brokers but with few enduring opportunities. Given the relative fixity of brokering positions, the kind of entrepreneurship Burt proposes, as the exploitation of structural holes, should be especially profitable. An intriguing hypothesis is that the pursuit of these rewards explains the current wave of mergers and acquisitions among biotechnology firms.

The persistence of the past is welcomed if alternative futures look less promising, especially scenarios with free-rider or prisoner-dilemma problems. But social capital can also be associated with encumbering commitments that impede competition and change. If biotechnology firms could rewrite their histories of cooperation, few would be surprised that an alternative path of network formation would eme[...] desired and the actual that expresses m[...] clearly the idea that structure both enables and c[...]strains entrepreneurial ambitions.

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## Appendix A

### Data Sources

The primary source of data is BIOSCAN (1988, 1989), a commercial directory of biotechnology firms, published and updated quarterly by ORYX Press, Inc. Because it has generally been considered the most comprehensive compendium of information on relationships in the industry, any relationship listed in BIOSCAN is included in our sample. However, because BIOSCAN may have omitted some relationships terminated before 1988, we collected data from the three other sources: (1) a proprietary database obtained from a leading biotechnology firm (called the "black volumes") in 1986; (2) a database developed by the North Carolina Biotechnology Center, based on published announcements of cooperative agreements; and (3) a direct mail survey of and telephone interviews with startups.

Because these latter three sources had neither BIOSCAN's history of direct contact with startups and their partners nor its depth of information about agreements, we relied less on their data. We added an agreement if it appeared in at least two of these sources. We found 46 relationships in this category. As they do not appear in the 1988 BIOSCAN directory, we assumed that these relationships had been terminated before 1988; the network analysis for 1988 therefore excluded them.

All startups in the final sample were independent businesses specializing in the commercialization of biotechnology products. Their portfolio of products must include diagnostic or therapeutic pharmaceuticals. The agreements consisted of joint ventures, licensing, and long term contracts between startups and their partners. Powell and Brantley (1992) found that different types of relationships—e.g., licensing, joint venture, research and development limited partnership—were not statistically related to how much firms engaged in cooperative agreements. Consequently, the network we analyze contains these types of relationship together. Since only firms that have engaged in at least one agreement can contribute to network structure, startups without relationships are excluded from the sample.

Application of these criteria produced a sample of 114 startups that had cooperative agreements before 1989. These startups dif[...] time of entry into the network, as Table [...] 2 shows. Thirteen have agreements only with universities, governm[...]ent agencies and research institutes. (Many of these relationships represent licenses of the original patents stemming from university research.) We dropped these startups from the sample in order to retain a group of partners whose interests were clearly commercial. Whereas university ties are important for the initial licensing and subsequent consulting services, our focus is on the structuring of relationships among commercial partners.[11]

## Appendix B

### Operationalization of Measures of Network Structure

We analyzed the asymmetric matrix of cooperative relationships with CONCOR, a network analysis algorithm (Breiger et al. 1975) that has been used frequently in interorganizational research (Knoke and Rogers 1978, Van de Ven et al. 1979, DiMaggio 1986, Schrum and Withnow 1988). The usual practice of applying CONCOR (see

Arabie et al. 1978) is to dichotomize the full set of network members; then to split these two groups separately; then to split these results; and so on until either (1) a desired number of groups are obtained or (2) groups are obtained with a specific number of members. We used the following rules for applying CONCOR to both startups and their partners: (1) groups with fewer than 10 members were not split; and (2) when splitting a group produced a singleton subgroup, the group was kept whole. We followed this practice separately for both the startups (rows) and their partners (columns) of the matrix of relationships. The purpose of these rules is to avoid groups with small sizes that are inappropriate relative to the size of the network (see Walker 1985).

Although CONCOR's results at the two-group level have been benchmarked against an optimality criterion (Noma and Smith 1985), the results of subsequent splitting have not been evaluated. Because of potential variation in decision rules for subsequent splits of the data, different results may be achieved for the same data set. To address this problem, we applied a second algorithm to the partition of network members produced by CONCOR. This algorithm, called CALCOPT, reallocates network members from group to group in the partition if the shift in group membership improves a target function consistent with Lorrain and White's (1971) original definition of structural equivalence. This target function is Equation (2). Thus CALCOPT reallocates network members from one group to another if the move increases the dispersion of densities in the density matrix. CALCOPT evaluates the CONCOR row partition and then the column partition iteratively until no reassignment improves the target function.

CONCOR and CALCOPT were applied to each year of data from 1984 to 1988. The data for each year are all cooperative relationships that were established between the startups and their partners up to that year minus any relationships that were terminated during that year. For example, the 1985 network includes the 1984 network plus all agreements begun between 1984 and 1985 minus terminated relationships. Thus five separate networks, one for each year, were analyzed to identify (1) groups of structurally equivalent startups and groups of structurally equivalent partners and (2) the pattern of intergroup densities used to measure social capital.

## Endnotes

[1]Biotechnology includes all techniques for manipulating microorganisms. In 1973 Cohen and Boyer perfected genetic engineering methods, an advance that enabled the reproduction of a gene in bacteria. In 1975, Cesar Millstein and Georges Kohler produced monoclonal antibodies using hybridoma technology; and in 1976 DNA sequencing was discovered and the first working synthetic gene developed. These discoveries laid the technological base for the "new biotechnology."

[2]Our definition of interfirm cooperative relationships is inclusive. For our purposes a cooperative relationship may be organized as equity or nonequity joint ventures, licensing, marketing or distribution agreements, or research and development limited partnerships (see Appendix A). Further, we define a relationship between firms rather than between projects so that new relationships entail new partners rather than old partners attached to new projects. This definition coincides with our focus on network formation, rather than the evolution of a single interfirm relationship.

[3]We do not observe the actual communication of information regarding partner behavior among startups. However, conversations with board members of startup firms confirm that such communication is quite common (Hamilton 1992).

[4]Density is defined as: $k/mn$, where $k$ is the number of actual relationships a group of $n$ structurally equivalent startups and a group of $m$ structurally equivalent partners. The densities of each intersection can be calculated to form a density matrix. This matrix is the basis for the construction of a blockmodel, a binary matrix representing relations among groups of structurally equivalent firms in the network (White et al. 1976, Arabie et al. 1978). Blockmodels typically are constructed only for symmetric networks—i.e., networks that are formed by relationships between only one type of firm, say, startups. Consequently, we do not develop a conventional blockmodel for our data.

[5]This function has been used to analyze sparse networks in a number of studies (Boorman and Levitt 1983, Walker 1985, 1988) which found it to have strong construct and predictive validity.

[6]See endnote 3.

[7]This measure of social capital is structural, consistent with Coleman's (1990) usage and arguments. Alternative measures based on attributes of specific interfirm relationships may be useful when global network data are not available (see Baker 1990).

[8]To test whether the effect of startup experience on new startup relationships might be quadratic, we included experience$^2$ in the equation, without significant results. We made the same test for startup size, also without significant results.

[9]The GLS results are not shown and are available from the authors on request.

[10]For different perspectives on this topic see Baker (1987) and Delany (1988).

[11]See Barley et al. (1992) on the sparseness of the university/NBF density matrix, as well as a breakdown of agreements by type (e.g., licensing, joint venture).

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