CHAPTER

13

The Make-or-Cooperate Decision in the Context of an Industry Network

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One of the most important decisions facing an organization is which activities should be carried out internally and which should be purchased. This question is frequently characterized as "make or buy," and the answers to it determine the boundaries of the firm. A fruitful line of research on this question is transaction cost economics (Williamson 1985), which has sought to determine organizational boundaries by comparing the costs of internal production to the costs of relying on the market for production. These costs are related partly to the size of the firm and to its internal capabilities, as well as to the hazards of relying on the outside market.[1]

The problem of what determines a firm's boundaries has frequently been extended to include cooperative modes of interfirm relationship that are intermediate between market and organization. Such modes include joint ventures, licensing, and other long-term cooperative agreements. "Make or buy" thus becomes "make or cooperate." It is the latter problem that we investigate here.

In the research program to which this chapter belongs, we analyze the decision to make or cooperate as influenced by the structure of relationships in a network of firms. As a way to fix ideas, it is useful to emphasize that in transaction cost studies, the influence of the external network is reduced to a summary variable measuring the degree of supplier market competition in a market; the fewer the suppliers, the greater the risk that prices may be renegotiated, especially if the buyer cannot switch easily to other sources.

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However, in our analysis, the market cannot be characterized simply by the degree of competition; rather, it is analyzed as a network with an evolving social structure. This structure has two important implications for the behavior of the firms in the network:

1. The structure of cooperative relationships influences the distribution of information available to firms about current and potential partners in the network.
2. Therefore the knowledge of a firm regarding the availability of cooperation with partners in the industry is determined by its position in the network structure.

The make-or-cooperate decision is made in the context of a concrete network as opposed to an abstract market. The network is not, however, simply given, but is itself emergent over time. The decision to cooperate is nested within the changing structure of this network as determined by the history of prior cooperation. Through the accumulation of interfirm ties a cooperative network is gradually formed, and this network defines and constrains the realm of feasible opportunities for the individual companies. Although firms make boundary decisions as individual agents and in response to the information available, the availability of information is influenced by the cumulative pattern of cooperation in the industry represented in the structure of the network.

The linking of the make-and-cooperate relationship to the distribution of information is not inconsistent with a liberal notion of what constitutes a market. Market prices are not given abstractly but are the negotiated outcomes of participating agents (Baker 1984). The discovery of buyers and sellers is influenced by the prevailing cooperative structure. Stated concretely, buyers and sellers must first find one another, and this process of search is influenced by their primary relationships with other firms as well as by the relationships of other firms to one another.

For this reason, the network approach to make or cooperate is essentially historical in nature. Information is conditioned on past decisions, or what we call the cumulative pattern, of cooperation. To understand current practice requires an analysis of the persistence of previous behavior as captured in the structure of the network.

We explore these arguments by studying the history of cooperation among new biotechnology firms (NBFs) and their partners, which are primarily large established corporations. Having suggested how the network may influence firm behavior, we turn to testing a model predicting how many new relationships NBFs establish over time. Because our dependent variable (the number of new cooperative relationships a firm establishes in a time interval) is a count measure, we test our hypotheses using negative binomial regression. This procedure is carried out in two successive periods, with a network measure of NBF information about partners and firm-level characteristics as predictors of new cooperative relationships.

The results of this analysis point in two important directions. First, we show that while the decisions of firms regarding their boundaries are related to conventional attributes (e.g., size), the network effect is consis- tently a better predictor. Second, the results provide insight into the common claim that firms are slow to change.

EMBEDDEDNESS AND NEW INDUSTRIES

The rise of new industries has generated a literature rife with disagree- ment over the characterization of new firms and their propensity to coop- erate. As White (1981) has noted, markets arise neither from a vacuum nor from yet-to-be-defined consumer preferences, but from the structural relations among existing firms. In the language of Granovetter (1985), social—and thus economic—action is "embedded" in historical structures of relationships among actors. Though changeable, these structures are persistent over time and inform individual choice.

The present study appraises the merits of Granovetter's argument that an individual's (or firm's) actions are neither completely voluntary ("under- socialized") nor normatively prescribed ("oversocialized"). He writes:

> A fruitful analysis of human action requires us to avoid the atomization in the theoretical extremes of under- and oversocialized conceptions. Actors do not behave or decide as atoms outside a social context nor do they adhere slavishly to a script written for them by the particular intersection of social categories that they happen to occupy. Their attempts at purposive action are instead embedded in concrete, ongoing systems of social relations (1985:485).

By analyzing the influence of both individual and network variables on firm behavior, we evaluate empirically the contribution of this per- spective.

NETWORK STRUCTURE AND COOPERATION

The issue of how the structure of cooperation influences the behavior of network members is especially important in the case of new industries. Two mechanisms were emphasized by Schumpeter (1934): the willingness of banks to fund venture capital and the departure of entrepreneurs from existing organizations to join or start new firms. More recent studies have confirmed the importance of the latter mechanism; Boeker's (1989) study of founders of semiconductor firms is a good example. Other institu- tions—such as universities, research centers, and government—may also play a role in the structural evolution of new industries.

Critical for many industries are cooperative relationships between [illegible] facing new firms in the

biotechnology industry, which uniformly begin as research-and-develop- ment operations; they lack the means to distribute their products. In Stigler's view, the vertical integration decision facing these firms is equiva- lent to a theory of functions. If external firms lack the requisite specialized knowledge, forward integration (i.e., a "make" decision) should ensue.

An alternative is to build cooperative relationships with established firms that have the capability to perform these functions (i.e., a "cooper- ate" decision). At the start of the industry, new entrants face a homogeneous (and atomized) environment in the absence of cooperative relationships. Due to firm-level heterogeneity (e.g., size, product diver- sity, and unspecified factors), some firms engage in cooperative relation- ships, either intensely or moderately.

Interfirm variation of this kind has an interesting implication. Whereas economic agents act in the context of a social structure, it by no means follows that they are positioned identically in the structure. Fur- thermore, firms differ in their capability to influence the structural development of their environments. In fact, the structural heterogeneity of the network is the cumulative product of the observed strategies of individual firms. These strategies have an observable effect: cooperative relationships are either focused within a group of partners or spread across many groups.

We represent network structure by partitioning both startup firms and their established partners separately into groups in which members are structurally equivalent. Structurally equivalent startup firms share the same partners; conversely, structurally equivalent partners share the same startup firms. The intersection of a group of startups and a group of partners contains the relationships they have together. The number of these relationships may be small or large. If it is small, then we can assume the startup group knows little about the group of partners; but if there are many relationships linking the two groups, the startup group knows a great deal about the established firms in the partner group. Thus the more-or-less-dense intersections of structurally equivalent startups and structurally equivalent partners define the industry distribution of information about interfirm cooperation.

We call startup groups that have many linkages with structurally equivalent partners "highly focused." The question we address here is whether increasing focus over time is related to more new cooperative relationships. We argue that *how* potential relationships are located in the network is important for *whether* they will be realized. The distribution of information on potential partners, as represented in the structure of the network, leads startup firms to choose partners that are structurally equivalent. As a startup's focus increases over time, therefore, better information on partners is available and more new relationships should occur. The evolution of network structure thus simultaneously constrains which partners a startup is likely to choose and enables the formation of new relationships with these partners, thereby making the decision to cooperate more frequent than the decision to make.

FIRM ATTRIBUTES AS DETERMINANTS OF INTERFIRM COOPERATION

To compare the influence of changes in startup focus on cooperative frequency to the influence of firm attributes, we identify a set of firm-level variables commonly employed in the literature. Past studies of cooperative relationships in the biotechnology industry have looked at the question of whether a firm has entered into *any* cooperative relationship. Analyzing data on individual products for a sample of NBFs, Shan (1990) found that competitive position, size, and product diversity influenced the cooperative decision. Because Shan's measures for competitive position are at the product level, they cannot be directly replicated in the present study because our focus is on the firm's cooperative frequency across products. A reasonable proxy is age of the NBF, which allows the propensity of cooperative behavior to vary over its life history. Moreover, following Shan's reasoning, early entrants may have less need to cooperate due to first-mover advantages in the market.

Product diversity can also be expected to promote cooperation by presenting more opportunity to cooperate. In addition, as many NBFs are focused in one area of technical expertise (e.g., a disease group) with many applications, greater diversity across types of application should induce cooperation to loosen resource constraints. Thus product diversity should be related to higher frequency of cooperative agreements.

Size presents a more complicated set of issues. Whereas Shan found a negative relationship between size and cooperation, Boyles (1969) found that the frequency of joint ventures more than proportionally rises with size. Whether this difference arises from a nonlinearity in the size-to-propensity relationship (i.e., large firms either have no cooperative relationships, or proportionally more) is addressed partially in the analysis that follows.

In addition to the variables of age, size, and product diversity, we also analyze the effect of firms that have been able to raise equity through secondary markets. As Schumpeter argued, a critical element in the birth of a new industry is the availability of credit. Through credit, entrepreneurs can purchase and transfer productive assets from traditional industries to themselves. Banks have performed a fundamental role in achieving this end, but recently their role has been greatly abetted by the growth of venture-capital markets that permit the raising of financing through a public offering of equity.

The effect of issuing public equity on the propensity to engage in cooperative relationships has, however, an ambiguous interpretation. From the perspective of theories such as population ecology, which see cooperative relationships as one way of providing resources to the firm, the public offering of equity provides an alternative source of funding. Hence it should decrease the need to cooperate and to acquire resources from a partner.

On the other hand, it could also be argued that the ability to issue

Table 13-1
Predicted Signs to Relationship of Covariates to Number of Agreements

	FIRST PERIOD	SECOND PERIOD
Size	+	+
Age	?	−
Diversity	+	+
Public offering	+/−	+/−
Change in density	*	+
Residual	*	−

*Variable estimated from first period data and used only in second period estimations.

public equity is an indicator of a firm's legitimacy. As Meyer and Rowan (1977) have argued, organizations vary in the extent to which they are granted institutional legitimacy. In this view, only firms with strong product-development portfolios can attract investors to purchase the equity. Public trading of an NBF may therefore signal to potential partners that its future is bright. Thus a positive association between publicly held firms and the frequency of cooperative relationships may be expected.

Table 13-1 summarizes the preceding discussion on the predicted signs of the parameter coefficients to the covariates. The predictions are presented for two periods of network evolution. Age has an ambiguous effect in the first period, as it both proxies the competitive effect (i.e., followers may attempt to leapfrog by cooperative agreements) and a cumulative bias (i.e., older firms have a longer opportunity to cooperate). This cumulative bias should be insignificant for agreements in the second period. Moreover, the possibility that the first-period relationships may have fully exhausted a firm's propensity to cooperate is addressed by incorporating directly a measure of saturation in the second-period model. This measure, labeled "Residual," is described in the section headed "Discussion" at the end of the chapter.

RESEARCH DESIGN

Sample

The commercialization of the new biotechnologies (comprising the techniques of genetic engineering—recombinant DNA—and monoclonal antibodies) in the 1970s and 1980s led to the emergence in the United States of hundreds of startup firms. Though the industry is new in terms of its technology, its techniques are used to develop products in existing industries, especially pharmaceuticals, chemicals, plant and animal agriculture, and pollution and waste control. In addition, the research and manufacturing requirements have instigated the development of new bioinstruments, thereby affecting the capital-good suppliers to biotechnology firms in these industries.

The unit of analysis in this study is the NBF, which we define as an independent firm formed for the specific purpose of commercializing the new biotechnology. The data for the analysis come from two main sources: (1) a commercial directory of biotechnology firms, *Bioscan*, published and updated quarterly by Oryx Press, Inc. and (2) telephone interviews with the sample firms. *Bioscan* provides information on firm attributes as well as a listing and description of cooperative agreements. Cooperative agreements, which are counted to form the dependent variable, include all joint ventures, licensing, and long-term contracts between NBFs and commercial firms.

All firms in the final sample must be *independent* business entities specializing in the commercialization of biotechnology products. In order to select a homogeneous industry, all firms in the sample must have at least one pharmaceutical product in either the therapeutic or the diagnostic area, or both. Excluded from this initial sample are established companies, their subsidiaries and divisions, and joint venture entities. Since only firms that have engaged in at least one agreement can contribute to network structure, NBFs with no agreements are also excluded.[2]

Application of the preceding criteria results in a sample of 114 NBFs. Of the 114, 22 have agreements only with universities and research institutes. Many of these agreements are licensing of the original patents stemming from university research. We dropped these NBFs from the sample in order to retain a homogeneous group engaging only in clearly commercial and ongoing agreements. Although university ties are important—albeit often only for the initial licensing and subsequent consulting service—our focus is on the structuring of relationships among commercial

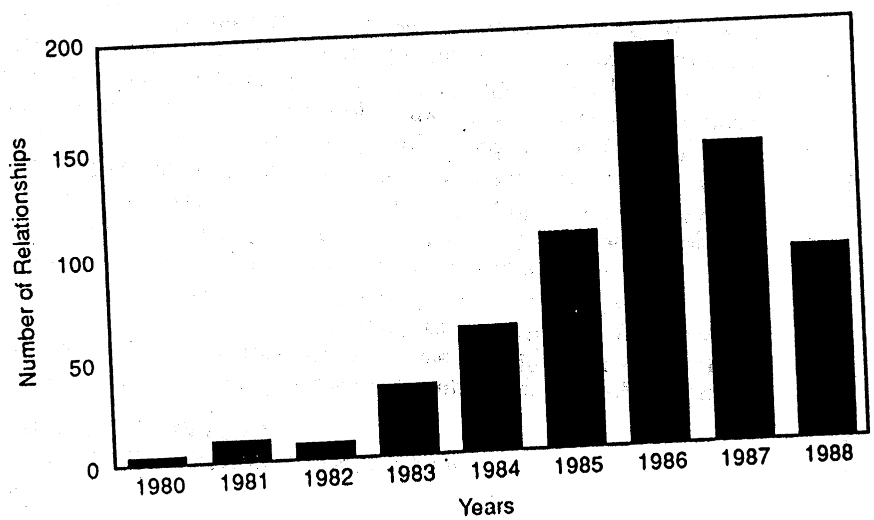


Figure 13-1
Formation of Cooperative Ventures by Sample Firms

Table 13-2
Descriptive Statistics of Number of Agreements

PERIOD FROM 1976 TO	MEAN	STANDARD DEVIATION	MAXIMUM
January 1, 1986	1.84	2.71	15
January 1, 1987	3.47	3.77	20
January 1, 1988	4.68	4.50	25
January 1, 1989	5.38	5.00	26

competitors.[3] Of the remaining 92 NBFs, 5 were missing data. Thus 87 NBFs were used in the sample.

From the beginning of the biotechnology industry, cooperative agree- ments have played a significant role. In Figure 13-1, the number of relationships is tracked for the 87 firms between the years of 1983 and 1988. Clearly, 1986 represents a watershed year, with the number o agreements falling in 1987 and 1988. This ebb in frequency may reflec structural shifts, but it also raises the possibility of the saturation of th propensity to cooperate, a possibility that we model directly.

The peak in 1986 presents a reasonable cut point in comparing th evolution of network structure. In Table 13-2, means and standard devia tions are given for relationships cumulative to 1986, 1987, 1988, and 198 (the latter representing the total number of relationships up to January 1 1989). Relationships up to 1986 represent under one-half the total, bu those up to 1987 over one-half. For this reason, we divide our sample into two periods. For the purposes of sensitivity analysis, we run th estimates for both January 1, 1986 and January 1, 1987 as the cut points.

Measurement

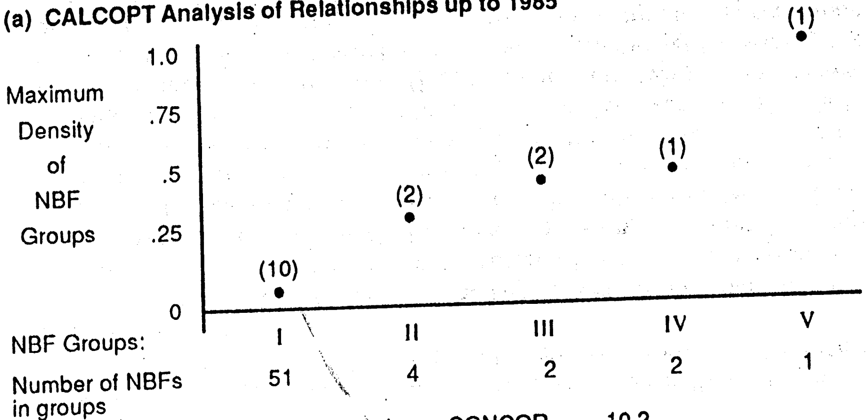
Bioscan and the telephone survey also provide data to be used as measur of the firm-level attributes. Age is measured as the time from foundin of the firm. Product diversity is a count of how many of the following sectors a fir participated in: therapeutic drugs, diagnostic drugs, agricultural applic tions, veterinary drugs, and food and brewery. Size is measured as t number of employees. Both age and size are measured at the end of t period; missing size data for each year were corrected either by interpo tion or by regression estimates, depending on the availability of inform tion for other years.

OPERATIONALIZATION OF NETWORK STRUCTURE

We identified the structure of the network of cooperative relationshi and thereby the extent to which NBFs were focused or unfocused, w blockmodeling techniques (White, Boorman, and Breiger 1976; Arab Boorman, and Levitt 1978). First we analyzed the asymmetric matrix

In the graphs below, points on scale represent maximum densities. The numbers of partner group affiliations (i.e., nonzero blocks) are in parentheses above maximum density.

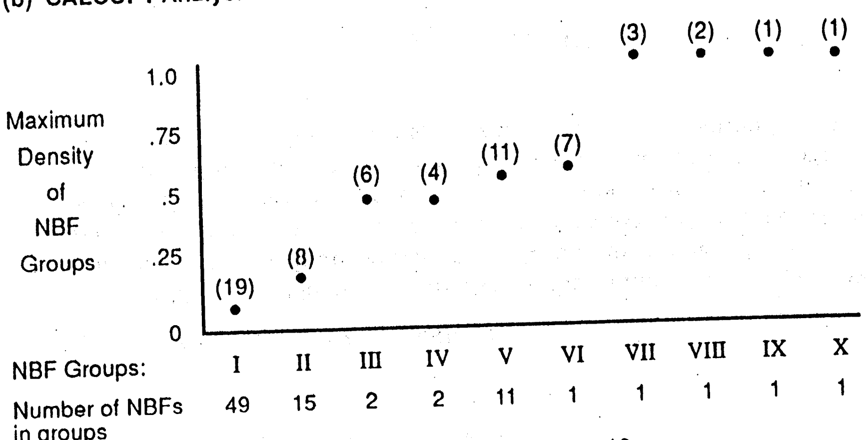
(a) CALCOPT Analysis of Relationships up to 1985



Target function values: CONCOR – 10.2
CALCOPT – 31.55

Total number of partner groups: 11.

(b) CALCOPT Analysis of Relationships up to 1986

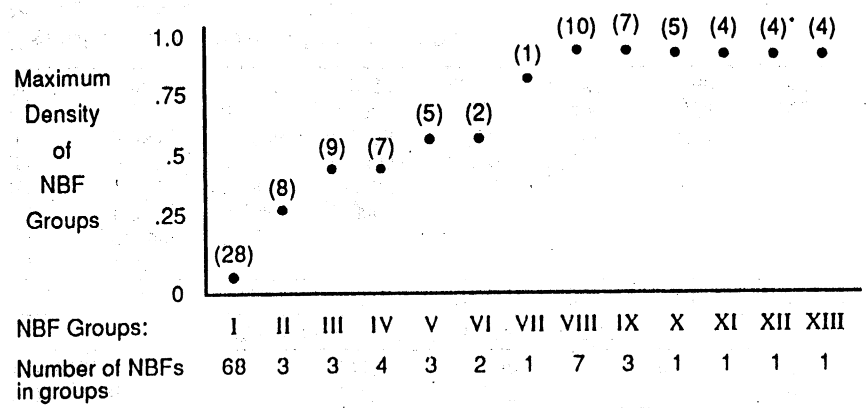


Target function values: CONCOR – 18
CALCOPT – 76.5

Total number of partner groups: 24.

Figure 13-2
Maximum Densities of NBF Groups

(c) CALCOPT Analysis of Relationships up to 1988



Target function values: CONCOR – 43.89
CALCOPT – 132.15

Total number of partner groups: 35.

Figure 13-2 ***(Continued)***

cooperative relationships between NBFs and their partners with CONCOR, a well-known network analysis algorithm (Breiger, Boorman, and Arabie 1975) that has been used frequently in interorganizational research. Second, we applied an algorithm called CALCOPT[4] to reallocate network members from group to group in the partition if the shift in group membership improved a target function based on the dispersion of densities between structurally equivalent groups of firms. The CALCOPT target function is thus based on the principle underlying our concept of focus as a predictor of increased cooperation in the network. CALCOPT evaluates the CONCOR partition sequentially for possible changes in group membership sequentially until no change improves in the target function. CALCOPT was applied to the CONCOR partitions of both NBFs and partners separately.

The results of applying CALCOPT to the CONCOR partitions for relationships up to 1985, to 1986, and to 1988 are shown in Figure 13-2. For each year, the figure shows (1) the CALCOPT and CONCOR target function values, (2) maximum densities of each group of NBFs, and (3) the number of NBFs in each group. For all three years, the CALCOPT target function values show strong increases over the CONCOR values, indicating that the reallocation of network members among groups substantially improves the dispersion of densities in the blockmodel.

Because blocks with one or a few members are distinct in each density matrix, the density matrices across years share a strikingly similar pattern that corresponds to our theoretical distinction between focused and unfocused firms. In each network there is a rapid progression in a group's maximum density from a very large group of NBFs with very low maximum density to groups of NBFs with maximum densities of about .5, to a set of groups with maximum density of 1.0. It should be clear that high maximum density is associated quite strongly with a small number of NBF group members and a small number of partner groups. Thus, as maximum density increases, so does (in our terminology) the focus of the NBF. We therefore use the change in the maximum density of an NBF group as our measure of change in focus.

NEGATIVE BINOMIAL REGRESSION

The dependent variable in our model is the number of cooperative relationships into which an NBF enters within a given year. Because the variable is a count measure (i.e., an integer truncated at 0), we model the probability that the number of relationships will occur n times within an interval. A natural choice of a discrete model is a regression with a

RESULTS

Table 13-3 presents descriptive statistics for the covariates. (The last two variables are explained under the Discussion heading that follows the subsequent tables.) The correlations show some association between the dummy variable for public offering and several of the other variables, but the magnitudes do not suggest problems of multicollinearity. The collinearity between the density variables is not a problem, since they are never used in the same regression.

In the estimates that follow, we run the regression for two different cut points: January 1, 1986 and January 1, 1987. The cut point affects the magnitude but never the signs of the parameters and only infrequently their significance levels. We use two-tail significance tests.

As we noted earlier, the negative binomial regression accounts for heterogeneity and generates an estimate (labeled α) of the degree of overdispersion of the variance. It also can be interpreted as representing either

Table 13-4

Poisson and Negative Binomial Regression Estimates of Effects of Covariates on the Number of a Firm's Relationships (First-Period Result)

	1986 CUTOFF	1987 CUTOFF
Intercept	−1.356***	−0.060
	(−3.05)	(−0.17)
Size	0.001*	0.001**
	(1.835)	(2.01)
Age	0.124**	0.025
	(2.40)	(0.62)
Diversity	0.396***	0.361**
	(2.50)	(2.82)
Public offering	0.087	0.236
	(0.33)	(1.19)
α	0.570**	0.365**
	(2.54)	(2.85)
Log-likelihood	−142.08	−188.68

(Two-tail test) (Student T in parentheses)
***$p < .01$
**$p < .05$
*$p < .10$

tive choices, this specification reduces an omitted variable bias, while at the same time provides an estimate of the significance of firm variation.[6]

Table 13-4 presents the negative binomial regression estimates of the firm-level covariates on the count measure of the number of agreements in the first period. Sensitivity analysis around the cut points is included, with the 1987 cut-point results also shown. The estimates show that product diversity and size are significant at .05 level. Omitted firm-level heterogeneity, represented by α, indicates substantial overdispersion of the variance.

Table 13-5 gives the second-period estimates, which contain the same covariates (though the values may have changed for the time-varying variables). In addition, the variable—Change in Focus—is included. The results confirm our central hypothesis that an increase in focus is related to an increase in cooperative agreements. This result is significant at the .001 level.

Public offering is positively signed, indicating that firms that have issued equity on secondary markets also tend to engage in more cooperative agreements. Causality, however, cannot be inferred, as cooperative agreements can provide the legitimacy required for public offering of equity. However, the low significance level discourages any interpretation. Diversity is positively signed and significant in most of the regressions. Size is not significant.

Table 13-5

Poisson and Negative Binomial Regression Estimates of Effects of Covariates of the Number of a Firm's Relationships (Second-Period Result)

	1986 CUTOFF	1987 CUTOFF	1986 CUTOFF	1987 CUTOFF
Intercept	.467	−.194	0.385	−0.360
	(1.27)	(−.421)	(1.12)	(−0.86)
Size	.0004	.0004	0.0003	0.001
	(1.01)	(.646)	(1.00)	(1.12)
Age	−.0567	−.0421	−0.035	−0.022
	(−1.29)	(−.696)	(−0.84)	(−0.39)
Diversity	.279***	.265*	0.228**	0.203
	(2.42)	(1.75)	(2.25)	(1.45)
Public offering	.591*	.549	0.348	0.326
	(1.82)	(1.40)	(1.10)	(0.83)
Change in focus	—	—	0.815***	1.016***
	—	—	(3.15)	(2.64)
α	.288***	.4540**	0.228**	0.370**
	(2.68)	(2.44)	(2.30)	(2.11)
Log-likelihood	−191.32	−154.85	−186.69	−151.30

(Two-tail test)
***$p < .01$
**$p < .05$
*$p < .10$

DISCUSSION

The results confirm that the number of new cooperative agreements is positively related to shifts in a firm's focus in the network structure. As relationships accumulate over time, previous industry decisions increasingly constrain a firm to cooperate. The relationship between change in a firm's focus and the number of new agreements suggests that movement in the network is possible, but only through extensive relational contracting.

This result is not an artifact of the scaling or of a potential tautology between the densities measuring NBF focus and the number of NBF relationships. A firm could as easily disperse its cooperative efforts across many partner groups as concentrate its relationships within a few. Thus there is no definitional bias toward a correlation between change in focus and cooperation. Also, it is important to underscore that the density measures that form the basis of the variable "Change in focus" are derived from the *cumulative* pattern of relationships in the industry.

It would be interesting and important to have greater insight into the underlying determinants of focused and unfocused firms. Why firms should differ in this dimension is largely unknown. The significance of the heterogeneity measure suggests that there is a considerable way to go before pinning down individual firm variations in the decision to cooperate, regardless whether this cooperation leads to a focused or unfocused position in the network.

To initiate an inquiry into this unknown variation, two avenues of reasoning seem appropriate. One is to posit simply that firms differ in their inherent propensities to cooperate, and leave unsettled for the time

Table 13-7

Poisson and Negative Binomial Regression Estimates of Effects of Covariates of the Number of a Firm's Relationships (Second-Period Result)

	1986 CUTOFF	1987 CUTOFF
Intercept	0.402	−0.346
	(1.11)	(−0.84)
Size	.0004	.0001
	(1.01)	(1.11)

... firm attributes over time is

Mapping Techniques Based on Combinatorial Optimization for Analyzing ... Over Time." *Economics Letters*