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Egocentric, sociocentric, or dyadic? Identifying the appropriate level of analysis in the study of organizational networks

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Abstract

This paper examines the use of individual, dyadic and system-level analyses in the study of relational data in organizational networks. We argue that dyadic analyses are particularly appropriate when the dependent variable is quantitative and/or involves multiple behaviors. We show that system-level analyses, by aggregating potentially significant information, provide a less grounded account of the relations across networks than do dyadic analyses. Using examples from a study of corporate political behavior, we contrast dyadic analyses with those at both the individual and system-levels. Variables measured in raw dyadic form consistently perform better in accounting for similarity of corporate political behavior than do variables measured by taking system-level properties into account. Our findings suggest that although individual and system-level analyses are useful in a number of situations, dyadic analyses are a flexible means to examine the effects of multiple networks at multiple levels.

Keywords: Network measurement; Dyads; Level of analysis

A central tenet of social network theory is the view that the structure of social relations in which actors are embedded affects their behavior. These effects are assumed to operate at the individual, organizational and even national level. To demonstrate these effects, researchers have tried to show that network ties have behavioral consequences. In the organizations field, where much of this work has appeared, a number of studies have involved showing

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that firms adopt behavior that has been previously adopted by firms with which they are in some manner connected. Two classic examples include a work by Davis (1991), who showed that firms' decisions to adopt takeover defense policies known as "poison pills" were influenced by whether firms with which they had director interlocks had previously adopted, and Haunschild (1993), who showed that firms whose officers sat on the boards of other firms that had recently engaged in acquisitions were more likely to engage in acquisitions themselves. At the individual level, Burt (1992) has shown that corporate managers whose personal networks were sparse – that is, the individuals to which they were tied tended not to be tied to one another – experienced more rapid upward mobility than did managers whose networks were dense.

Although all three of these authors focused on the effects of network ties on behavior, all of them operated at the individual level of analysis. Davis and Haunschild focused on firms while Burt focused on individuals, but in all three cases, the network effects were examined from the perspective of individual actors. Davis and Haunschild measured network ties in terms of a firm's director links to other firms. Burt measured network structures, but they were egocentric—centered around an individual actor. Although there is nothing wrong with either of these approaches, neither deals with the structure of the larger network within which the actors are embedded.[1] The question is whether the incorporation of this larger structure would have had an effect on the above analyses.

In this paper, we address the question of whether the level of analysis of an investigator's network matters. In particular, we examine the benefits that might occur for understanding social behavior were we to focus on network structures that transcend individual actors. Our focus is on questions that operate at the supra-individual level of analysis, in which our endogenous as well as exogenous variables are relational. For such situations, we argue that the most appropriate unit of analysis is neither the individual nor the entire social structure but the dyad. We draw on data from a study of firm political behavior to illustrate these points.

1. Individual behavior, or similarity of behavior?

Davis (1991) was concerned with a firm's decision to adopt a particular policy—a poison pill.[2] His hypothesis was that a firm would adopt the same behavior as a firm with which it was socially tied. In this case, the focus of interest was clearly on the individual firm's decision to adopt. One could extend the analysis, as several researchers have done, by examining the degree to which the firm is affected by firms with which it is structurally equivalent (Lorrain and White, 1971). This latter issue requires consideration of the entire social structure of firms, and thus creates an exogenous variable at a more macro level of analysis, but the unit of interest is still the individual firm. There are two alternative issues to consider, however. First, how would one handle a situation in which one was interested in a large number of behaviors? Second, how would one handle a situation in

[1] Davis does take into account the effect of actors' centrality in the larger network of firms.

[2] Poison pills were statutes invoked by firm managers in the U.S. during the 1980s as a means of warding off takeover threats.

which the concern is with the similarity of a single behavior, but the behavior is not a discrete event?

We argue that in both of these cases, our concern is a relational one—that is, a comparison between the behaviors of two or more actors. We shall illustrate this with two examples. First, we discuss a study of firms' uses of debt financing, in which our concern is the extent to which firms engage in similar levels of borrowing. Second, we discuss and analyze data from a study of firms' contributions to political candidates, in which our concern is the extent to which firms contribute to the same candidates. These examples represent two different situations that, we argue, yield the same solution.

2. Studies using dyads

Organizational researchers have typically been interested in either the behavior of individual actors inside organizations or the behavior of organizations themselves. As noted above, both types of studies lend themselves to the use of individuals as units of analysis. Since the mid-1980s, organizational researchers have become increasingly interested in relations between organizations. In some cases, the questions address whether a pair of organizations forms some kind of tie. Two topics in particular have lent themselves to dyadic analysis: the study of interfirm alliances (Gulati, 1995; Gulati and Gargiulo, 1999) and the study of firms' choices of business partners (Podolny, 1994; Keister, 2001; Sorenson and Stuart, 2001). In the study of alliances, dyads are not necessary if one's concern is firms' propensity to participate in alliances. When one's concern is with which particular firms will ally with one another, however, then one is asking an explicitly dyadic question: given two firms, what is the probability that they will form an alliance? The same question holds for firm market relations. One might look, for example, at whether a venture capital firm chooses to invest in a particular startup firm (Sorenson and Stuart, 2001), whether pairs of investment banks serve together on particular bond issues (Podolny, 1994), or whether firms engage in lending or trade relations (Keister, 2001). What makes the dyadic level useful in these analyses is that researchers are often interested in the extent to which a property of the relation between organizations affects the likelihood that the firms will form another type of relation. Is there something about the prior relations between two firms, for example, that would increase the probability that they would establish a business transaction or an alliance?

There are other situations in which the use of dyads is less obvious, however, especially those involving diffusion. In the studies by Davis (1991) and Haunschild (1993), the variable of interest was a firm's decision to adopt a particular, discrete form of behavior, in these cases adoption of a poison pill or making an acquisition. These are firm-level decisions, and firm-level variables, such as the firm's size, industry, profitability and debt structure might be expected to account for these outcomes. In addition to organizational-level factors, firms may be influenced by their relations with other firms. As long as the outcome of interest is a single, discrete, firm-level decision, then the interfirm relation can be treated as an additional firm-level variable. In these studies, the variables were whether a firm's interlock partner had previously adopted a poison pill and whether the firm's CEO sat on the board of another firm that had recently engaged in an acquisition. Such variables, although reflective of an interfirm relation, can be easily modeled at the firm level of analysis.

What happens, however, when the behavior of interest is not a specific action, but rather the extent to which actors behave similarly? Although the adoption of poison pills, the use of golden parachutes, or engagement in acquisitions are variables of clear substantive interest, there are other variables that are potentially significant but do not in themselves have clear intrinsic meaning. Our substantive goal in such cases may be to know whether firms do the same (or nearly the same) thing, regardless of what the particular behavior is. Consider a firm's capital structure. For finance economists, a firm's level of debt may be an important substantive variable, something that is of theoretical interest and can be predicted by a range of firm variables. For organizational theorists, a firm's level of debt is of limited theoretical interest. Although a firm's level of capital dependence figures into some important organizational debates, the variable itself is not of central concern in the discipline. What is of interest, in both organizational analysis and economic sociology, is whether a firm's economic and financial decisions can be accounted for in part by the social structures and cultural conceptions under which the firms operate. To the extent that such behavior has a social component, it becomes a substantively and theoretically interesting issue. The question is, what exactly about it is interesting?

In an earlier study, Mizruchi and Stearns (1994) developed a model of corporate financing in which they attempted to incorporate social structural and cultural factors to account for this seemingly "economic" issue. Among their key arguments was that firms' use of debt would be affected by their embeddedness in interfirm networks. The implication was that firms would look to their peers with whom they shared social ties and would be influenced by their behavior. But the fact that firms are influenced by their peers tells us nothing about exactly how that influence manifests itself. A firm could be tied to another firm that took on a high level of debt, and the firm could then borrow heavily in response. Another firm could be tied to another firm that eschewed high levels of debt, and the firm could then refrain from borrowing in response to its peer. The upshot of these two examples is that even if a firm's use of debt is affected by its social relations, those relations would have no necessary association with how much borrowing in which the firm engaged.

Mizruchi and Stearns ultimately modeled their network effect by hypothesizing that firms whose boards included officers of banks would have higher levels of borrowing than would firms without such officers. This was obviously an inadequate solution, because (1) it ignored the fact that bankers might not recommend high levels of debt for all firms and (2) it failed to address the central question of whether firms' decisions were influenced by the behavior of their *peers*. The problem for Mizruchi and Stearns was that their dependent variable was a firm's level of borrowing, a firm-level phenomenon. Their interest, however, was actually in whether the firm's level of borrowing was affected by that of its network peers, regardless of what that level was. One possible response to this dilemma is to consider the Davis–Haunschild situation. Just as adoption of a poison pill or engaging in acquisitions can be affected by a firm's network partners, why not financing? The difficulty here is that a firm's level of borrowing is not a discrete event, but rather a quantitative outcome measured on a continuous scale. One cannot construct a variable equivalent to "the firm's interlock partner adopted" for the level of financing, unless one wanted to create an extremely crude qualitative indicator computed by collapsing the partners' behavior (and the outcome variable) into categories such as "high" or "low" levels of borrowing. The Davis–Haunschild solution will therefore not work.

It is possible to model this network effect at the firm level, using network autocorrelation models (Marsden and Friedkin, 1993; Leenders, 2002). In these models, the firm remains the unit of analysis, and individual-level variables remain as predictors, but the network effects are measured through the insertion of one or more square firm-by-firm matrices containing the ties between the firms. These parameters are then estimated in a way similar to the computation of the cross-sectional autocorrelation statistic in spatial autocorrelation models (Doreian, 1981).

The network autocorrelation model is a perfectly reasonable alternative to the use of dyads. The question is whether it is the most logical approach to use when one's variables of interest are relational. If the primary question is, "Does the social connection between firm A and firm B make them likely to behave more similarly than do firms C and D, which share no such connection?" then a dyadic level of analysis is logically the most feasible. When a mix of firm and network-level factors are expected to affect a firm's behavior, and that behavior is of intrinsic theoretical and substantive interest, then a network autocorrelation model might make more sense (Mizruchi et al., 2005). The key issue is the extent to which the firm-level variables are substantively important. If they are not, they can be handled as controls even within dyad-level analyses.

3. Similarity of multiple events

There are some situations in which the behavior of interest is a series of discrete events, such as a firm's contributions to charitable organizations (Galaskiewicz, 1985) or political candidates (Mizruchi, 1992). Recall that the decision to adopt a poison pill is not only discrete, but a single event. A decision to contribute to Senator McCain's re-election campaign is also a discrete event that could be modeled in the same way as Davis's analysis of poison pills. But what if one's interest was not simply in whether the firm's contribution to McCain was affected by its interfirm relations, but whether the firm's entire constellation of, say, 100 contributions was so affected? The only way to handle this problem at the firm level of analysis would be to compute a separate regression equation for each of the potential candidates to whom a firm could contribute. In recent years, that number has typically exceeded 2000.

Imagine, though, that instead of examining each individual contribution, we developed a composite measure of all of the firm's contributions. One could code the party or ideology of the candidates and develop an overall "proportion Republican" or political ideology score for each firm. Then one could predict these values using a network autocorrelation model. Substantively, however, although the firms' ideological and party preferences may be interesting (and in fact have been effectively studied; see Burris, 1987; Clawson and Neustadtl, 1989), firms' decisions to contribute to a candidate typically involve much more than ideology or party. In the political sociology literature, debates over interfirm unity have been prominent for decades. One (although not the only) possible indicator of unity is similarity of behavior. If one is interested in the level of unity, then, one is now conceiving of the issue at an interfirm level. The most basic unit of inter-actor relations is the dyad.

Once we consider interfirm unity in terms of similarity of behavior, we can devise an indicator that takes into account the firms' entire profile of contributions. Rather than examining whether if firm A's interlock partner contributes to McCain, firm A will also contribute, one can examine whether A's interlock partner has a contribution profile more similar to A than non-interlocked firms C and D have to one another. At this point, a range of measures of similarity of behavior are possible.

4. But what about system-level effects?

The preceding discussion of the value of dyadic analysis may come as little surprise to those who are familiar with the works cited above. There are at least three situations for which the dyadic level seems especially appropriate: those in which the concern is business transactions or alliances between organizations; cases in which researchers are interested in similarity of behavior in which the behavior being examined is measured quantitatively, rather than as a discrete event; and cases in which researchers are interested in the similarity of behavior across a large number of discrete events.

Even if one accepts the value of dyadic analysis under the above conditions, there is another issue that must be addressed: the issue of system-wide effects. Organizational research has for decades been concerned with the behavior of groups. As attention has turned to interorganizational relations, researchers have been concerned with the behavior of groups of organizations as well. The reason that this is relevant to the issue of dyads is that some of the key issues that dyads have been designed to address have originated as system-level questions.

One system-level question might be whether a group with a high degree of social cohesion is more effective in solving problems than is a less-cohesive group. In this type of case, the unit of analysis is actually the group, and as long as we can treat groups as observations, then we in effect would be conducting an individual-level analysis. Even if we were interested in group-level questions, however, a case could be made that a dyadic analysis is preferable, especially if our primary concerns are relational, which they often are in group-level studies.

An example will illustrate this. Imagine that our dependent variable is similarity of behavior and our independent variable is cohesive relations. At the system-level, our hypothesis might be that the cohesion of the group will be positively associated with its degree of similarity of behavior. Consider two 5-firm groups (each of which by definition has 10 possible relations). Group A has 6 of 10 possible social ties for a cohesion score (the network definition of density) of .6. Group B has 3 of 10 possible social ties for a score of .3. Assume for the purposes of discussion that each pair of firms can be either high or low on similarity of behavior. Group A has four similar behavior ties while Group B has two such ties. We therefore have two groups, one of which has high cohesion and a high level of similarity while the second has low cohesion and a low level of similarity. That would appear to support our hypothesis of a positive relation between cohesion and similarity.

The specific placement of the cohesive and similar behavior pairs could vary widely in both cases, however. As Fig. 1 illustrates, it is possible that the four similar behavior ties in Group A correspond to the four non-social cohesion ties. This may be unlikely but it is theoretically possible. Meanwhile, as shown in Fig. 2, it is possible that the two similar

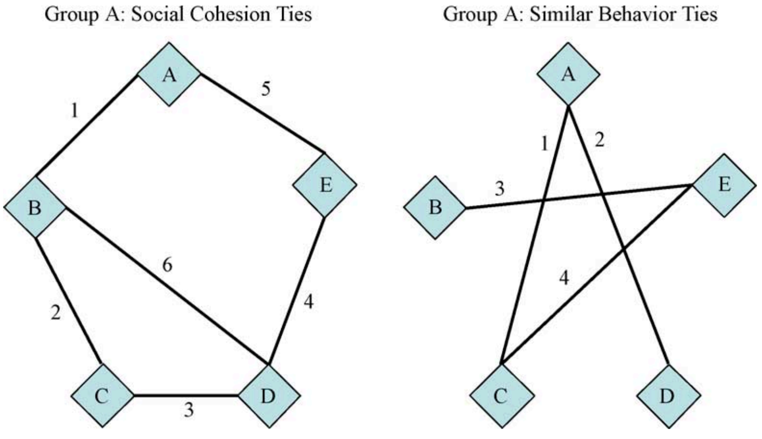

Fig. 1. Relations between social cohesion and similarity of behavior among dyads, I.

behavior ties of Group B represent two of the three social cohesion ties. For Group A (in Fig. 1), regressing similarity of behavior on cohesion among the dyads yields a correlation of −1. There is thus a perfectly negative association between a social tie and similar behavior. In Group B (Fig. 2), regressing similarity of behavior on cohesion yields a correlation of .764. There is thus a very high positive association between the two.

It can easily be shown that any number of combinations is possible in either of the two groups. The problem with analyzing networks at an aggregate level is that all of this variation is missed. If one is concerned about identifying as closely as possible the direct relation between social ties and similarity of behavior, each dyad must be investigated individually.

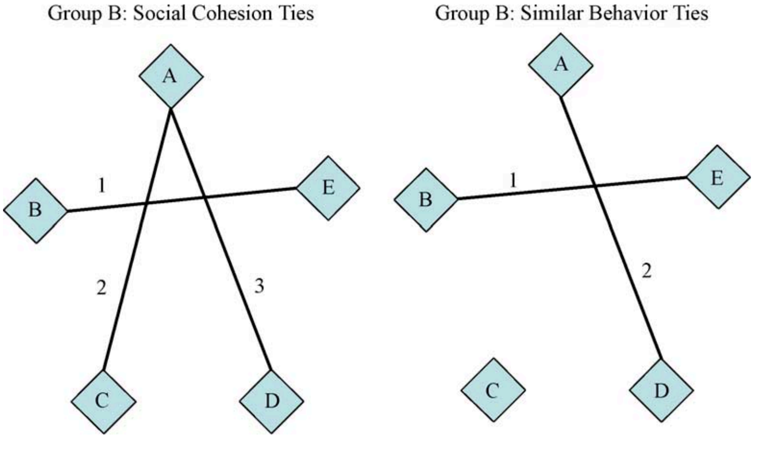

Fig. 2. Relation between social cohesion and similarity of behavior among dyads, II.

5. Dyadic versus system-level analysis: an examination

One possible criticism of the above example is that it assumes that what happens in a dyad is independent of the larger context within which the dyads exist. As Simmel noted, the character of a dyadic relation may change significantly once we take into account the effects of third and additional parties. Might dyadic effects therefore be either spurious consequences of larger network structures, or at least contingent on the nature of those structures? This is not an easy question to address without data on a large number of networks. We can begin to address it by comparing the ability of dyadic and system-level variables to account for an outcome variable. To do this, we shall apply data from the study of corporate political behavior (Mizruchi, 1992) described above.

5.1. Data

The data for this illustration come from a study of the political behavior of 57 large U.S. corporations in 1980. The year 1980 was a particularly significant year in American politics because there were an unusually large number of closely contested elections, an incumbent Democratic president was replaced by a Republican, and the Senate, which had been controlled by Democrats since 1955, was captured by the Republicans. In addition, corporations, which had engaged primarily in pragmatic strategies in prior years (contributing mainly to incumbents regardless of their ideology), began increasingly to contribute to candidates based on ideological predilection, even if it meant challenging a previously strong incumbent.

The 57 corporations were selected by identifying the three largest firms whose primary operations were in each of 19 two-digit (broad) industries and that maintained a political action committee (PAC) in the election cycle prior to the study. Virtually all of the largest U.S. corporations had established PACs by that point. A small number of industries were represented by either more than or fewer than three firms. Details on the data are available in Mizruchi (1992), and the data themselves are available at http://www-personal.umich.edu/∼mizruchi/.

The primary goal of the study was to examine the extent to which economic interdependence and social connections between firms affected their political unity, defined in terms of similarity of behavior. Because the dependent variable (similarity of behavior) and the independent variables (interdependence, common institutional stockholders, direct and indirect interlocks and several others, plus a series of controls) were relational, most of the analyses involved dyads, for the reasons discussed in the previous section. The concern was with questions such as whether pairs of firms that operated in heavily interdependent industries (with high levels of sales and purchases) were more likely to engage in similar political behavior than were pairs of firms in less interdependent industries. A group of 57 actors has 1596 possible dyadic relations. These 1596 dyads were the units of analysis for most components of the study.

Although the study included several dependent variables, our focus for this illustration will be on the extent to which firms contributed to the same political candidates. This measure was computed by the formula $S_{ij} = c_{ij}/(c_i \times c_j)^{1/2}$, where S_{ij} is the similarity of behavior of firms i and j, c_{ij} is the number of candidates to whom both i and j simultaneously contributed, and c_i and c_j are the total number of candidates to whom firms *i* and *j* contributed (used so that the similarity score was not a mere consequence of firms making a large number of total contributions).

For the current analysis, we shall examine only the four primary network variables. The analyses in the original study included several additional variables. The findings that we report here were robust across specifications that included controls that are not presented here. The four network variables are market constraint (our measure of economic interdependence), common stockholders, direct interlocks, and indirect interlocks. Market constraint, a concept developed by Burt (1983), is an indicator of the level of dependence of one industry on another for either sales and/or purchases, weighted by the concentration of the industry. Industry A will exercise a high level of market constraint over industry B to the extent that A is either a major customer or supplier of B and A is highly concentrated (meaning that B has few alternative firms within A with which to conduct business). Because input–output data are publicly available only at the industry level, Burt was forced to examine constraint at the industry level. Researchers in three subsequent studies (Galaskiewicz et al., 1985; Palmer et al., 1986; Burt, 1987) developed interfirm-level adaptations of Burt's measure. Mizruchi (1992) constructed a composite of these three measures by extracting the first principal component and using the resulting factor scores. We shall use that measure here. Common stockholders was measured by identifying the number of institutions that simultaneously held at least .5% of the stock of firms *i* and *j*. Direct interlocks represented the number of individuals who sat on the boards of directors of both firms. Indirect interlocks were computed by taking the number of the top 50 commercial banks and insurance companies with which firms *i* and *j* were simultaneously interlocked.

6. Analysis

There are three components to our analysis. In the first, we perform a simple dyadic analysis of the effect of the four network variables on similarity of behavior. We then conduct two system-level analyses. In the first, we identify clusters of firms for each of the five networks (the four exogenous and one endogenous variables) and then examine, at the dyadic level, whether joint membership in particular independent variable clusters predicts joint membership in the similarity of behavior network clusters. In the second system-level analysis, we examine the centrality of each firm in the five networks and then see if a firm's centrality in particular independent variable networks predicts its centrality in the dependent variable network.

Table 1 presents a correlation matrix among all of the dyadic variables in the first two analyses. For the purpose of our initial analysis, only the odd-numbered variables in the table are of interest. Eq. (1) of Table 2 presents the effects of the four dyadic network variables on the similarity of political behavior. All of the effects were hypothesized to be positive. The dyads drawn from a group of actors are not statistically independent because each individual actor is represented multiple times. This problem can lead to an underestimation of standard errors, increasing the probability of Type I error. There are a number of ways to handle this issue. In these analyses, we use quadratic assignment, an approach that uses OLS regression but adjusts the probability values of the individual coefficients by computing,

Table 1
Means, standard deviations and correlations among dyadic and cluster variables ($N = 1596$)

	Variable	Mean	S.D.	2	3	4	5	6	7	8	9	10
1	Similarity (dyadic)	.233	.107	.273	.153	.175	.281	.200	.098	.020	.264	.123
2	Similarity (cluster)	.237	.425		.088	.153	.071	−.004	−.031	.016	.088	.088
3	Constraint (dyadic)	.000	1.00			.399	.047	.042	.001	−.033	.059	.018
4	Constraint (cluster)	.142	.349				.064	.020	−.006	.014	.079	−.002
5	Stockholders (dyadic)	1.16	.665					.484	.060	−.007	.175	.082
6	Stockholders (cluster)	.209	.407						.045	.005	.121	.040
7	Direct ilks (dyadic)	.048	.241							.271	.237	.156
8	Direct ilks (cluster)	.125	.331								.275	.096
9	Indirect ilks (dyadic)	.403	.719									.495
10	Indirect ilks (cluster)	.130	.336									

from a large number of trials, the probability that a coefficient as large (or small) as the observed coefficient would have occurred by chance, given the structures of the networks (see Krackhardt, 1988; Mizruchi, 1992, Chapter 5 for discussions of quadratic assignment).

All four of the coefficients in Eq. (1) of Table 2 are positive, and three of the four have probability levels below .05; the fourth, direct interlocks, has a probability level of less than .10. These four variables account for 14.4% of the variation in similarity of behavior.[3] Because this analysis uses dyadic variables exclusively, it can be viewed as our baseline for comparison.

For the first system-level analysis, we identified clusters of firms for all five variables. The goal here was to see if using system-level rather than dyadic properties to chart the relations among the firms would provide either superior or additional predictive power. Each of our original dyadic variables could be thought of as a network; those of firm-to-firm market constraint, common stockholders, direct and indirect interlocks, and similarity of contribution patterns. The values in the cells of the matrix represent the dyads, except that, given the symmetry of our relations, we need use only one-half of the non-diagonal cells. We used the clusters provided in the Appendix to Mizruchi (1992), which were extracted using a hierarchical cluster analysis. Firms were clustered together based on their profile similarity, in this case the correlation between the column of their relations with each of the other firms in the network. This means that firms were assigned to the same clusters based

[3] *R*-squares based on dyadic data tend to be systematically underestimated, although the extent of this underestimation is unclear (Hubert, 1987, p. 123). As with all *R*-squares they are best used for comparison purposes across equations within the same study. That is how we treat them here.

Table 2
Determinants of same position within campaign contribution network—correlation position measure ($N = 1596$)

	Eq. (1) Similarity (dyadic)	Eq. (2) Similarity (cluster)	Eq. (3) Similarity (dyadic)	Eq. (4) Similarity (dyadic)	Eq. (5) Similarity (cluster)
Constant	.176 (1.000)	.197 (.999)	.210 (1.00)	.175 (.999)	.148 (.997)
Market constraint dyadic measure	.014*** (.003)			.009*** (.034)	.013** (.014)
Common stockholders dyadic measure	.038*** (.005)			.032** (.013)	.048** (.036)
Dyadic measure direct interlocks	.015* (.070)			.015* (.070)	−.108 (.005)
Dyadic measure indirect interlocks	.030**** (.001)			.030*** (.002)	.029 (.113)
Same position market constraint network		.187**** (.000)	.052**** (.000)	.034*** (.005)	.161**** (.001)
Same position common stockholders network		−.011 (.217)	.050*** (.001)	.0191* (.052)	−.052 (.027)
Same position direct interlocks network		.007 (.185)	.002 (.204)	.002 (.195)	.032* (.073)
Same position indirect interlocks network		.111*** (.004)	.037*** (.008)	−.001 (.248)	.083** (.023)
R-square	.144	.031	.082	.158	.036

All probability values are one-tailed except those of the constants. OLS regression coefficients are presented, with quadratic assignment probabilities in parentheses.
* $p < .1$.
** $p < .05$.
*** $p < .01$.
**** $p < .001$.

on their degree of structural equivalence.[4] Once firms were assigned to clusters, we created a set of dyad-level dummy variables, coded 1 if the firms were members of the same cluster and 0 otherwise.

Eq. (2) of Table 2 is identical to Eq. (1) except that all five variables consist of the dummy variables representing joint membership in a cluster.[5] Although two of the four predictors (market constraint and indirect interlocks) have significant positive effects on similarity of behavior, the effects of common stockholders and direct interlocks are no longer significant

[4] For those interested in using the cluster data from this study, please note that the column headings in Mizruchi's Table A.3 (1992, pp. 266–267) are incorrect. The headings (in order) should be "Si, St, Mc, Ii, and Di."

[5] Although our dependent variable in this model is dichotomous, we continue to use OLS regression because the significance tests in the quadratic assignment procedure are non-parametric and because the mean of the dependent variable (.237) is acceptably distant from the tail of the logistic function. Probability values in quadratic assignment are computed by taking the proportion of coefficients from the random simulations that exceed the observed coefficient. In 1000 trials, for example, if a variable's coefficient exceeds the observed coefficient 35 times, the probability value for the observed coefficient is .035. A logistic regression analysis of this model yielded identical substantive conclusions.

(the former even has a negative coefficient) and the model *R*-square is far lower. In Eq. (3), we include the same cluster independent variables but use them to predict the dyadic similarity of behavior measure. Interestingly, the cluster membership independent variables do a better job of predicting the raw dyadic similarity of behavior measure than they do the same similarity of behavior cluster membership. Not only do the market constraint and indirect interlock variables remain significant, but the common stockholders variable returns to significance as well, and the model *R*-square increases from .031 to .082.

In Eqs. (4) and (5) of Table 2, we combine the dyadic and cluster-level variables into the same models. In Eq. (4) our dependent variable is the dyadic similarity of behavior. In Eq. (5) the dependent variable is membership in the same similarity of behavior cluster. All of the variables from Eq. (1) remain significant in Eq. (4) if we use a .10 significance level, although the probability level of the direct interlocks effect remains above .05. In contrast, among the same cluster variables, only market constraint is significant at a level below .05, with a probability value that is actually lower than that of the dyadic constraint variable. The common stockholders variable has a probability level of slightly greater than .05. Note also, however, that the coefficient of determination for Eq. (4) is .158. This means that the addition of the cluster variables adds only 1.4% to the explained variance in the equation containing the raw dyadic variables.

One possible reason for the greater power of the raw dyadic variables in Eq. (4) is that the dependent variable is also in raw dyadic units. Perhaps were we to use membership in the same similarity of behavior cluster as our dependent variable, the cluster variables would have greater relative power. As Eq. (5) indicates, this is true, but only because the power of the model as a whole declines. Three of the four network variables of both the raw dyadic and the same cluster measures have probability levels below .10 in this model, and two of the four are below .05, but overall, the model explains only 3.6% of the variance. Clearly, the models using the raw dyadic variables perform better than those using the common cluster variables.

One could argue that these analyses are stacked toward finding a stronger effect for the raw dyadic variables, in that presence in the same cluster is a discrete variable that by definition involves collapsing a considerable amount of quantitative information into a more general indicator. Because the analysis itself is dyadic, it may therefore not be surprising that the measures that take the full range of values into account perform better than those that involve at least partially arbitrary classifications into clusters. The point is, the classification into clusters, defined at the system level, does not improve our understanding of the effects of various interfirm relations on similarity of political behavior beyond that already available from our raw dyadic measures.

7. Centrality

An alternative way to take system-level information into account is to examine the effect of a firm's centrality in the larger network. The concept of structural equivalence, discussed above, was originally designed to identify actors that play similar roles in a network. Structural equivalence is highly restrictive, however, because equivalence is defined in terms of actors' ties to the same third parties. Yet there are situations in which actors are in similar structural positions and/or have similar kinds of ties, but the ties are not to the same alters. As Winship (1988) noted, two fathers would be structurally equivalent only if they had the same children. There have been a number of attempts to conceptualize and measure this broader form of equivalence, which has been referred to by such terms as role, regular and automorphic equivalence.[6] We shall use the term role equivalence here.

As with structural equivalence, role equivalence is a dyadic property that can only be known by looking at the entire network of actors. Researchers have had limited success showing empirically that role equivalent actors behave similarly. One possible reason for this, suggested in an earlier study by Mizruchi (1993), is that role equivalence may operate differently at different parts of a network. This can be illustrated by considering the role of network centrality. In the 1993 paper, Mizruchi found that pairs of firms that had high levels of centrality had relatively high levels of similarity of political behavior, even controlling for whether they had direct ties to one another. Pairs of firms with simultaneously low levels of centrality tended to have low similarity of behavior. From this finding, Mizruchi suggested a distinction between what he called “central” and “peripheral” role equivalence. Simultaneously high centrality, he argued, might represent a social role that could lead to similar behavior.

Centrality is actually an individual-level variable, associated with a particular actor. It can only be computed by taking the entire network into account, however. Common centrality between actors is a dyadic variable, but one that is also based on system-level properties. In this section we examine the effect of firm centrality on similarity of political behavior, using two different approaches. In the first, we treat joint centrality as a dyadic variable and include it, in various ways, in a dyadic analysis. In the second, we examine the effects of a firm’s centrality in our four independent variable networks on its centrality in the similarity of behavior network.

We used Bonacich’s (1972) original eigenvector approach to computing centrality. This measure is computed by the formula $C_i = 1/\lambda\,\Sigma(r_{ij} \times C_j)$, where C_i equals the centrality of actor i, r_{ij} equals the strength of the association between actor i and a given alter j (in our case, the strength of the association is simply the value of the particular dyadic variable), C_j equals actor j’s centrality and λ equals the eigenvalue of the first eigenvector of the matrix of associations between each i and j.

In the first examination of the effects of joint actor centrality, we took our raw dyadic measures and standardized them based on the firms’ centrality. To do this, we divided the value of each variable by the geometric mean of the two firms’ individual centralities $(C_i \times C_j)^{1/2}$. We computed this value for common stockholders and direct and indirect interlocks. It was not necessary to adjust the value for market constraint because the constraint variable by definition already takes into account the actors’ joint centrality. The results of this analysis are presented in Eq. (1) of Table 4. Descriptive statistics and correlations among the variables in this analysis are presented in the first five rows and columns of Table 3. As Eq. (1) of Table 4 indicates, the effects of our four primary variables, controlling for the firms’ network centrality, are very similar to those based on the raw dyadic measures, except for the effect of direct interlocks, which does not even approach statistical significance here.

[6] These different terms are distinct, both conceptually and operationally. They are all designed to identify actors that play similar social roles, however.

Table 3
Means, standard deviations and correlations among similarity of behavior, dyadic network variables and joint centrality variables ($N = 1596$)

		Mean	S.D.	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Similarity (standardized)	.341	.115	.076	.164	.013	.155	.916	.130	.205	.073	.199	.046	−.079	.203	−.073	.096	.079	.200	−.007
2	Constraint (standardized)	−.351	4.34		.020	−.026	−.017	.089	.630	.023	−.003	.002	.163	−.175	−.030	.002	.019	.014	.029	−.008
3	Common stockholder (standardized)	1.82	.887			.006	.064	.210	.040	.891	.056	.104	−.054	−.035	.432	−.170	.131	.060	.161	.014
4	Direct interlocks (standardized)	.569	9.85				.071	.016	−.031	−.003	.251	.053	−.008	.008	.004	.006	.004	−.034	.072	−.034
5	Indirect interlocks (standardized)	1.11	2.14					.154	.036	.081	.209	.747	.055	−.013	.081	−.039	.130	−.025	.234	−.067
6	Similarity	.233	.107						.153	.281	.098	.264	.042	−.059	.294	−.103	.145	.114	.291	.008
7	Constraint	.000	1.00							.047	.001	.059	.370	−.298	−.033	.008	.025	.036	.105	.014
8	Stockholders	1.16	.665								.060	.175	−.076	−.027	.670	−.303	.190	.133	.269	.027
9	Direct ilks	.048	.241									.237	.022	−.004	.099	−.056	.319	−.060	.191	−.069
10	Indirect ilks	.403	.719										.145	−.039	.208	−.089	.247	.035	.543	−.165
11	High–high constraint	.254	.436											−.594	−.090	.025	−.014	.003	.054	.019
12	High–low constraint	.508	.500												.004	−.002	.014	−.015	.004	−.010
13	High–high stockholders	.331	.471													−.698	.259	.133	.378	−.034
14	High–low stockholders	.496	.500														−.150	.052	−.208	.178
15	High–high direct ilks	.075	.364															−.238	.337	.101
16	High–low direct ilks	.411	.492																.107	.210
17	High–high indirect ilks	.188	.391																	−.482
18	High–low indirect ilks	.501	.500																	

Table 4
Determinants of similarity of campaign contributions controlling for network prominence dummy variables ($N = 1596$)

	Eq. (1) Similarity (dyadic)•	Eq. (2) Similarity (dyadic)	Eq. (3) Similarity (dyadic)	Eq. (4) Similarity (dyadic)	Eq. (5) Similarity (dyadic)
Constant	.297 (1.00)	.174 (.983)	.202 (.999)	.167 (.996)	.186 (.998)
Stockholders				.012 (.107)	.020* (.054)
Direct ilks				.010* (.090)	.009* (.094)
Indirect ilks				.019*** (.009)	.021*** (.005)
Constraint				.014*** (.005)	.014*** (.003)
Stockholders[a]	.019*** (.001)				
Direct Ilks[a]	.000 (.236)				
Indirect Ilks[a]	.008**** (.000)				
Constraint[a]	.002*** (.007)				
High–high constraint		.005 (.227)	.013 (.139)	−.007 (.234)	−.003 (.218)
High–low constraint		−.010 (.268)		−.006 (.327)	
High–high stockholders		.065** (.026)	.049*** (.007)	.052* (.071)	.032* (.055)
High–low stockholders		.028* (.079)		.024 (.163)	
High–high direct ilks		.010 (.198)	.009 (.188)	.003 (.224)	.001 (.233)
High–low direct ilks		.005 (.421)		.006 (.400)	
High–high indirect ilks		.069** (.027)	.054*** (.007)	.042 (.081)	.030* (.059)
High–low indirect ilks		.024 (.132)		.018 (.195)	
R-square	054	.155	.127	.185	.168

All probability values are one-tailed except those of the constants and the ‘high–low’ variables. OLS regression coefficients are presented, with quadratic assignment probabilities in parentheses.

[a] Standardized by centrality.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

**** $p < .001$.

Market constraint, common stockholders and indirect interlocks remain positively associated with similarity of behavior. The explained variance of the model declines sharply, however, possibly because of the reduced variance of the independent variables created by the standardization.

The findings in this analysis suggest that taking the firms’ positions in the larger network into account has little effect on our results. Three of the four original dyadic variables continue to have significant effects on the similarity of political behavior. This analysis does not tell us anything about the effects of joint centrality per se, however. It is possible, based on the above discussion of central and peripheral role equivalence, that firms’ joint centrality will itself have a significant effect on similarity. One way to handle this would be to simply include the geometric mean of the firms’ centrality as a predictor in the equation. The problem with this is that it fails to account for the similarity of the firms’ centralities. To take an example, consider the centralities of four firms in the market constraint network: General Electric (.807), International Harvester (.282), LTV (.509) and Dow Chemical (.445). The joint centrality of the General Electric-International Harvester dyad (.477) is virtually identical to that of the LTV-Dow dyad (.476), yet in the former case there is a large difference between the two firms' individual centralities while in the latter case the two are similar. If we are interested in joint centrality as a form of role equivalence, this measure is clearly inadequate. Taking the raw difference between individual centralities may not be useful either, however, because it assumes that eigenvector centrality operates in a linear fashion. This is doubtful; there is little assurance that the difference between a firm with a centrality of .9 and another with a centrality of .5 is equivalent to the difference between the latter firm and one with a centrality of .1. Difference in centrality rank might be a useful measure, but that ignores potentially unequal gaps between different ranks.

The preceding discussion suggests that it is useful to consider a number of possible measures of joint centrality. As an initial formulation, we shall operationalize joint centrality as an interaction between two dummy variables: whether each firm has higher or lower than average centrality on that variable. For each firm, we code whether the firm's centrality for that network exceeds the network mean. We then create two dummy variables, one for situations in which both firms' centralities are above the mean ("high–high" centrality) and one for situations in which one firm's centrality is above the mean and the other's is not ("high–low" centrality). Situations in which both firms' centralities are below the mean ("low–low" centrality) constitutes the reference category. We created eight such dummy variables, two for each of our four network variables.

Table 3 presents descriptive statistics for these variables and correlations among them, as well as among them and the raw dyadic measures. Eq. (2) of Table 4 presents a regression equation with the eight dummy variables as predictors. We expect the "high–high" variables to have positive effects. We make no specific predictions for the "high–low" variables. As the table indicates, the results are mixed. The high–high stockholders and indirect interlocks variables are significant predictors of similarity of behavior, with probability levels below .05. The high–low stockholders effect has a marginally significant coefficient. Consistent with the finding in Eq. (1), the effect of direct interlocks is not significant. Unlike our earlier findings, the effect of market constraint is also not significant.

One interesting aspect of these findings is that despite the relative weakness of the individual effects, the model *R*-square is relatively high, at .155. A look at the correlation matrix provides a possible explanation for the lack of significance of the individual effects. The correlation between the high–high and the high–low constraint variables is −.594, that between the high–high and high–low common stockholders variables is −.698, and that between the high–high and high–low indirect interlocks variables is −482. If we remove the high–low variables from the model, it is possible that the individual effects will be stronger and we will lose little predictive power. Eq. (3) of Table 4 includes the same model as Eq. (2) except that the high–low dummies have been removed. As in Eq. (2), only the coefficients for common stockholders and indirect interlocks are statistically significant in Eq. (3), but the probability levels are considerably smaller than in the previous analysis. The model *R*-square of .127 is lower than the .155 of Eq. (2) because we have removed the high–low common stockholders variable, which was significant in Eq. (2). The predictive power of this model still exceeds that of Eq. (1), in which we included the raw dyadic variables standardized by joint centrality. The joint centrality effects, at least of stockholdings and indirect interlocks, are quite strong.

In Eq. (4), we re-insert the raw dyadic variables into the model from Eq. (2). The *R*-square from Eq. (2) increases by only .030, to .185, but none of the centrality dummy variables has a probability level below .05 and only the common stockholders and indirect interlocks coefficients have probabilities below .10. The only effects in the model with probabilities below .05 are the raw dyadic variables for market constraint and indirect interlocks. The direct interlocks effect has a marginally significant (<.10) probability. As in Eq. (2), multicollinearity is a possible explanation for the relatively high strength of the overall model combined with non or marginally significant individual effects. Another look at the correlation matrix confirms these suspicions. The correlations between the raw dyadic variables and the high–high centrality variables are underlined. Note that the common stockholders dyadic variable is correlated .670 with the high–high stockholder dummy. As we saw earlier, the high–high stockholder dummy is also correlated −.698 with the high–low stockholder dummy. Although the raw dyadic stockholder variable is correlated only −.303 with the high–low stockholder dummy, the combined high correlation among these three variables undoubtedly has a depressing effect on the significance of their coefficients. The relatively low correlations between the raw market constraint variable and the high–high and high–low market constraint centrality variables (.370 and −.298, respectively) combined with the relatively high correlation between the high–high and high–low constraint variables (−.594) may explain why the dyadic constraint variable is significant in Eq. (4) while the other effects are not.

To see if multicollinearity was the cause of the absence of significant effects in Eq. (4), we removed the high–low variables from the model and recomputed the equation. The results of this analysis appear in Eq. (5) of Table 4. The findings suggest that the raw dyadic variables do a better job of predicting than do the joint centrality variables. The removal of four of the model's twelve variables dropped the R-square only .017, from .185 to .168. The coefficients of the market constraint and indirect interlocks raw dyadic effects remain strongly significant, with probability levels slightly below those of Eq. (4). The common stockholders and direct interlocks raw dyadic variables have marginally significant (<.10) effects. Two of the joint centrality effects, common stockholders and indirect interlocks, remain marginally significant, at probability levels slightly below those of Eq. (4).

Overall, these findings suggest that taking the system-wide property of joint centrality into account does not provide additional predictive power beyond that already accounted for by the raw dyadic measures. The difference is not large, but the explained variance of the model is driven more strongly by the dyadic effects than by the joint centrality measures. The original dyadic model accounted for 14.4% of the variation in similarity. The addition of the four high–high joint centrality variables adds 2.4% to that figure. The joint centrality model with only the high–high variables accounted for 12.7% of the variation in similarity. The addition of the four dyadic variables adds 4.1% to that figure. The dyadic variables remain better predictors when the two groups are combined into a single model.

7.1. Centrality analysis of the individual firms

An alternative way to examine the role of network centrality is to treat the firm as the unit of analysis and see if a firm's centrality in one network can account for its centrality in another. In this analysis, our units are the 57 firms, which gives us far fewer degrees

Table 5
Means, standard deviations and correlations among firm centrality variables ($N = 57$)

		Mean	S.D.	2	3	4	5
1.	Similarity	.671	.181	.108	.383	.328	.434
2.	Constraint	.495	.225		−.083	.172	.258
3.	Stockholders	.612	.206			.249	.323
4.	Direct interlocks	.157	.221				.542
5.	Indirect interlocks	.308	.257				

of freedom than in the dyadic analyses. Centrality in the similarity of behavior network indicates the extent to which a firm's contribution patterns overlap with those of other firms, especially firms that are themselves central. If we treat the firm's centrality in the similarity of behavior network as the dependent variable, then we can examine the effect of the firm's centrality in the four independent variable networks. Table 5 includes the descriptive statistics and correlations among the variables. Table 6 provides the results of this analysis.

In Eq. (1), we include all four independent variables. Centrality in the common stockholders and indirect interlocks networks were both significantly associated with centrality in the similarity of behavior network. Consistent with the results of other analyses, centrality in the direct interlocks network was not a significant predictor. Contrary to several of our earlier results, centrality in the market constraint network also failed to reach statistical significance. Both coefficients were positive, however (the expected direction). The model R-square, .263, is somewhat higher than those in our earlier models, due primarily to the smaller ratio of residual to regression degrees of freedom as well as the fact that these are not dyadic data.

Although the partial effect of indirect interlocks is statistically significant, the variable also has a substantial correlation (.542) with direct interlocks. One correlation of this size is generally not high enough to suggest a problem with multicollinearity, but given the relatively small sample size in this analysis and the fact that both direct and indirect interlocks

Table 6
Effects of centrality in organizational networks on centrality in similarity of political behavior network ($N = 57$)

	Eq. (1) Similarity centrality	Eq. (2) Similarity centrality	Eq. (3) Similarity centrality
Constant	.435**** (5.008)	.430**** (4.989)	.423**** (4.773)
Market constraint centrality	.033 (.323)	.037 (.368)	.078 (.773)
Common stockholders centrality	.238** (2.104)	.246** (2.200)	.294*** (2.633)
Direct interlocks centrality	.083 (.713)		.187** (1.779)
Indirect interlocks centrality	.198** (1.872)	.234*** (2.523)	
R-square	.263	.256	.213

All probability values are one-tailed except those of the constants. Metric coefficients are reported, with T-statistics in parentheses.
** $p < .05$.
*** $p < .01$.
**** $p < .001$.

had sizeable simple correlations with similarity of behavior, we decided to remove each variable separately and re-run the model.

Eq. (2) presents the analysis with centrality in the direct interlocks network removed. Eq. (3) presents the analysis with centrality in the indirect interlocks network removed. It is not surprising that the indirect interlocks variable remains significant in Eq. (2). The removal of direct interlocks had virtually no impact on the model *R*-square, however, dropping it from .263 to .256. Meanwhile, the *T*-statistic for the indirect interlocks variable increased from 1.872 to 2.523. Interestingly, when we re-inserted the direct interlocks variable into the equation and removed indirect interlocks, the former also reached statistical significance, with a *T*-statistic of 1.779, compared to .713 in Eq. (1). The coefficient for direct interlocks more than doubled, from .083 to .187. The *R*-square for the model substituting direct for indirect interlocks was considerably lower, however: .213 versus .256. Most important, considering our dyadic analyses, is the fact that market constraint was not a significant predictor in any of these equations. The model based on the raw dyadic measures of both the dependent and independent variables provides the most consistent and strongest support for our hypotheses.

8. Discussion

The results of the preceding illustration suggest that when our concern is with the relations among actors, the dyad is the most appropriate unit of analysis. This may not always be the case. Whether it is depends on the nature of our dependent variable. If we are studying a particular outcome that represents a discrete event, such as the adoption of an innovation, an individual-level analysis with a built-in variable for network effects may be more feasible. If we have a quantitative outcome variable but our predictors are primarily individual-level variables, then a network effect may be handled with a network autocorrelation model, in which case we would also operate at the individual level.

There are two conditions under which a dyadic-level analysis is clearly preferable to an individual-level one, we believe. The first is in situations in which our dependent variable is quantitative and our predictors are relational variables. The second is in cases in which our dependent variable is a composite of a large number of individual events. We illustrated these points by applying data from a study of corporate political behavior. Corporate political action committees tend to contribute to a large number of candidates. Had we treated each individual decision to contribute as a discrete event, it would have required more than 2000 regression equations. Because we were concerned substantively with the extent to which pairs of firms behaved similarly, these individual decisions, taken separately, were not of interest. In this situation, it was preferable to use a measure of similarity that was a composite of a pair of firms' entire constellation of decisions.

One criticism that has been raised against dyadic analyses is that they fail to take into account system-level factors. This criticism dates back to Simmel's discussion of the differences between dyads and triads. By reducing relations to those between pairs of actors, the criticism goes, researchers ignore the extent to which dyadic relations are affected by larger system properties. We addressed this issue in two ways, first logically and then empirically. Logically, we showed that using one set of system-level properties to predict another such set fails to account for whether the specific within-group relations on one set of properties corresponds to the specific within-group relations on the second set of properties. As Fig. 1 demonstrated, it is possible to observe a high correlation between group cohesion and similarity of behavior across groups, even if the relation between the two variables at the level of inter-actor ties is negative. Only by breaking down the relations between actors into their individual parts is it possible to see whether one type of tie between actors is associated with another type of tie.

It is also possible to examine dyadic relations while taking the structure of the larger system into account. To illustrate this, we used data from a study of corporate political behavior and constructed equations with both raw dyadic variables and variables drawn from system-level properties. Using similarity of political contributions as our dependent variable, we examined the effects of four relational variables: market constraint, common stockholders, direct interlocks and indirect interlocks. We then performed a series of modifications of these variables, all of which incorporated the firms' positions within the full network. We created clusters of structurally equivalent actors and examined the extent to which joint membership in clusters of our four independent variables predicted joint cluster membership on our dependent variable. We standardized our dyadic variables to take into account the firms' centrality in each of the five networks. We created a measure of "central role equivalence," based on the idea that two highly central actors will behave similarly regardless of whether they have direct ties with either one another or with the same third parties, and we used that to predict similarity of behavior. And finally, we looked at the firms themselves and examined whether their centrality in the four independent variable networks predicted their centrality in the dependent variable network.

Although many of the results using these alternative variables yielded significant predictors of similar political behavior, the raw dyadic measures remained the most consistently strong. Once we took the raw dyadic variables into account, the variables adjusted for system-level effects added little to our explanatory power. We acknowledge that this example may be "stacked" toward finding relatively strong dyadic effects. The study was designed with dyads in mind, and each variable that took system-level effects into account contained lost information. The cluster variables, for example, were binary, meaning that two firms were either in the same cluster or not. There was no provision for specifically how similar they were. In an analysis not shown here, however, we found that even raw quantitative measures of structural equivalence (the basis for common cluster membership) did not predict similarity of behavior as strongly as did the raw dyadic measures. This is only one case, of course, and it is possible that a different study might yield different findings. We have shown, however, that dyadic analysis can be a powerful approach to handling relational data.

9. Conclusion

Although the formation of social networks has received increased attention in recent years, the staple of network theory remains the effect of network structures on behavior. Exactly how these structures influence behavior has been the source of intense controversy for the past two decades. Much of the debate has revolved around the mechanism by which social influence occurs, in particular whether behavior spreads by direct influence (cohesion) or indirect influence/competition (structural equivalence). Although this debate is in part a disagreement about the level at which network effects occur, it has generally not been couched in such terms. Do network effects occur primarily at the interpersonal or system level, and how are they best captured? We have argued that dyadic analysis is a flexible means by which researchers can examine multiple network effects at multiple levels. They do not involve the network per se as an independent variable; instead, they involve a relation between actors as both independent and dependent variables. We have argued that dyads provide more grounded information about network effects than do system-level data, and that they have the flexibility to take system-level factors into account.

We are not suggesting that individual or system-level analyses are never superior to dyadic-level ones. We have described situations under which dyads are preferable to individual-level data, and vice versa. We do want to close by mentioning an additional reason that network-level analyses will be difficult to conduct. In an early study (Mizruchi, 1982), the first author examined changes in the American corporate network at seven time points over a 70-year period. This involved a detailed analysis of seven different networks of 167 firms each, yet the historical comparisons were made across what in effect were seven observations. We do not want to denigrate this study, or other panel network studies. We want to point out, however, how difficult it is to operate with the network itself as the unit of analysis. It is possible to generate larger numbers of networks in studies of small groups, or when researchers are examining subsets of a larger network, such as local ties within a national interlock network (Marquis, 2003), and the use of computer simulations has greatly increased our ability to examine the effects of structures on individual outcomes (see Mizruchi and Potts, 1998, for an example). Even these studies could benefit from a more detailed examination of the individual relations within the networks, however. We have no intention of discouraging researchers from conducting system-level studies. We only want to raise the caution that not only are the costs often prohibitive, but system-level analyses, by themselves, may leave certain important information unexamined.

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