INTERORGANIZATIONAL DATA ANALYSIS: A MULTIVARIATE APPROACH

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This paper discusses some issues and problems which arise when linear statistical models are applied to the analysis of interorganizational ties. We analyze data taken from an evaluation of three community-based interagency networks which were established under an LEAA pilot program to divert youthful "status offenders" from secure detention to local treatment-oriented agencies. Surveys of agency staff and directors produced measures on agency attributes and interagency relations. Relations between organizations were measured by aggregating agency workers' reports of ties to personnel in other agencies. Two operationalizations of such agency-level ties-- total ties directed from one agency to another and a proximity measure computed on the binarized matrix of interagency ties-- are shown to yield somewhat different results. Effects of agency attributes (e.g., size, client composition) on interagency ties are evaluated in the following way. Main effects of initiating and receiving agencies' scores on the same attribute are estimated as is the interaction of these scores. We note that previous pair analyses which assessed the impact of similarity/dissimilarity in the attributes of units forming pairs were sometimes subject to the same interpretation problems which plagued early studies of status inconsistency effects; i.e., no controls for the additive effects of attributes combined to form the dissimilarity index. Finally, we explore several procedures for evaluating the effect of reciprocity on the estimates of coefficients in models predicting pair relations from agency attributes.

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Introduction

The study of interorganizational relations in social service domains has in recent years become a growth industry (see, for example, Aldrich, 1976; Benson, 1975; Hall et al., 1977; Klonglan et al., 1976; Litwak and Rothman, 1970). The current interest of organizational scholars in problems of environmental embeddedness has dovetailed with the concerns of policy-makers and social service professionals in managing decentralized systems of service delivery agencies. Interest in interorganizational phenomena has also been fueled by the renaissance of network concepts and analytic tools in the social sciences (Burt, 1979). Yet no more than a cursory survey of empirical research on interagency networks reveals that the kind of technical rigor historically associated with sociometric analysis has failed to distinguish contemporary studies of organizational ties in service settings. Indeed, methodological questions have received almost no serious attention in interorganizational research, yet the measurement and data-analytic methods used with growing frequency pose an array of obstacles to the drawing of correct conclusions from empirical results. Our purpose in this paper is to apply a common statistical technique-- linear regression-- to observations on dyadic relations between agencies with the aim of addressing some of these obstacles. We make no claim for the sufficiency of our methods. But we do believe that both the theoretical and practical implications of interorganizational research demand a closer scrutiny of the forms of data collection and analysis than has heretofore appeared.

The Data: Community Agencies Serving Status Offenders

Our data come from an evaluation of three community-based programs which provided services to youthful clients under the national LEAA program, Deinstitutionalization of Status Offenders (Miller, 1977). One agency (or more) in each locality had been awarded a grant from LEAA to administer the provision of services to target youths by a variety of local public and private agencies. The DSO program was driven by much the same service philosophy which has guided policy in such other domains as mental health. Its goal was to reduce the separation of juveniles from the community and likewise to reduce dependence on formal justice system institutions as chief purveyors of services. Like other interorganizational systems, a key obstacle to the formation of such service delivery networks lay in coordinating the diverse and autonomous organizations brought under the program's umbrella. The pattern of interagency ties and their orchestration by the administrative agency were thus features of these programs with important implications for the effectiveness of individual agencies and the program as a whole.

Although seven programs received DSO funds to establish pilot service delivery networks, this paper examines just three: Pima County (Tucson), Arizona, Spokane County (Spokane), Washington, and Alameda County (Oakland), California. These programs were of roughly similar size and each was based in a single urban community. Other programs encompassed entire states or posed other obstacles to an investigation of their network properties. Agencies in the three selected communities were identified as participating in the program if any proportion of their personnel were involved in treating status offenders. The agency-level data which we analyze in this report were obtained in two ways: (a) a range of "global" agency attributes were measured through questionnaires sent to key informants, usually agency directors; (b) individual staff employed by the agency completed a questionnaire containing items pertaining to their professional training, treatment orientation, and contacts with other personnel on DSO-related matters.

Measuring Interorganizational Ties

Most interorganizational research focuses either on such formal public linkages as the occurrence of joint programs (Aiken and Hage, 1968) or only those relations which some key informant (such as a director) can report (Molnar and Rogers, 1979). Certainly this strategy minimizes data collection costs, as it often involves no more than one interview or questionnaire per agency. Yet it is equally certain that this methodology conceals a potentially vast array of boundary-spanning flows and contacts not officially codified or known to organizational elites. This shortcoming is particularly conspicuous in the case of social service organizations (as compared to business firms) where employees tend to be independent professionals whose links to other agencies are quite often informal and ad hoc. Thus, we have measured interorganizational relations among the DSO agencies by first surveying agency personnel concerning their work related ties, then aggregating individuals' reports of ties to the agency level. Although five sociometric questions were posed in the original questionnaire, only one-- the most general-- will provide the data for this analysis. The respondent was asked to name three persons whom he or she contacted most frequently on DSO-related matters.

Restricting respondents' choices to three citations was an unfortunate research decision which we can hardly retract now (see Holland and Leinhardt, 1973). It nonetheless seems a less serious source of measurement error in an analysis of aggregate between-agency ties than had inter-individual ties remained the object of concern. Note that respondents were not required to cite others in different agencies than their own. Herein lies another issue of interorganizational measurement which deserves more attention than it has received. Previous studies of interorganizational relations, including those few which aggregated multiple informants' reports of ties in generating an organization-level measure, confined reports to interorganizational ties. In the present analysis, we, too, consider only ties which span organizational boundaries, but in other analyses of these data we have compared the rate of inter- to intra-organizational contacts among DSO personnel (Miller, 1977). We might interpret the program goal of creating a viable interagency network as encouraging individual treatment staff to go outside their own agencies to acquire system-wide resources and skills. The extent to which resources are secured within as opposed to across organizational boundaries is thus information one might wish not to discard.

A key feature of our research is the dual operationalization of an interagency relation which we employ. On the one hand, we take as the datum to be explained, F_{ij}, the total number of ties reported by members of agency i to members of agency j. Unlike other network analysts who begin by symmetrizing their tie matrices, thus making an ij relation indistinguishable from its ji counterpart, we treat elements on both sides of the diagonal as separate observations (Laumann and Pappi, 1976). Secondly, we define a proximity measure which transforms the frequencies of ties between agencies as follows. The matrix of reported ties between agencies was binarized using the alpha criterion of blockmodeling: an element is coded "1" if the density of reported ties from agency i to agency j equals or exceeds the matrix density, otherwise it is coded "0". The work contacts matrices for agencies in the three community programs are quite sparse, so that only agency pairs with zero or a very low rate of reported individual-level ties are classed as "0" on this dimension. We then computed the graph-theoretic "path-distance" on the binary matrix for each program (Harary et al., 1965). Path distance is the shortest number of interagency links necessary for agency i to reach agency j in the network. Finally, path distance was normed to produce a proximity measure, P_{ij}, such that nonreachable pairs are coded "0", directly linked pairs (i.e., those scored "1" in the binary matrix) are coded "1", and intervening values are the cumulative proportions of pairs whose path distances are D,..,4,3,2 where D is the largest observed distance of a connected pair of points in the graph. This norming procedure, which Burt (1976) proposed, thus assigns weights as a function of the proportion of points reachable at each distance in the graph.

Clearly, there are significant differences between F_{ij} and P_{ij}. Pairs assigned a range of nonzero values on F_{ij} are made indistinguishable with values of "1" on P_{ij}. Conversely, values between zero and one on P_{ij}, indicating indirect ties of varying lengths, are all "0" on F_{ij}. It seems wholly plausible that the conditions

determining the one might differ from those determining the other, and it is therefore useful to compare results for these two relational measures throughout the analysis. As Aldrich (1976) has pointed out, the measurement of indirect ties as achieved through P_{ij} lends a particularly strong "network" flavor to the analysis, since it allows inferences regarding resource and other flows through channels linking multiple nodes. The focus on F_{ij}, by contrast, suggests a focus on individual dyads more or less severed from their network context.

Mode of Analysis

We use a linear regression technique to model the $\sum_{k=1}^{3}(n_k^2-n_k)$ observations on asymmetric interagency ties as a function of agency attributes. With 16 agencies in Tucson, 19 in Alameda, and 15 in Spokane, we have 240+342+210= 792 observations. One or another version of this method accounts for the majority of research investigations of interorganizational relations, and it would thus seem that the issues we discuss would have some general relevance.

Perhaps the central difficulty we see in past work which adapts the regression model to observations on interorganizational or, for that matter, interpersonal relations lies in the procedures used to combine the attributes of organizations or individuals into meaningful measures for pairs. A common approach is simply to compute the similarity or dissimilarity of dyad members on each attribute of interest (Laumann and Pappi, 1976; Molnar and Rogers, 1979). There are several theoretical rationales for this measurement strategy. Individuals have long been thought to interact in proportion to the "homophily" of their values, statuses, and other traits (Lazarsfeld and Merton, 1954; Rogers and Bhowmik, 1971). Likewise service organizations with similar treatment philosophies, client and staff compositions, etc., are perceived by interorganizational theory as likely to forge ties. On the other hand, exchange theories are widely invoked to explain both interpersonal and interorganizational phenomena, and these postulate ties as a function of complementary resources and needs (Benson, 1975; Blau, 1964; Aldrich, 1976). Thus, actors with divergent attribute profiles are believed most likely to be linked. Organization-environment theory lays particular stress on the processes whereby organizations strive to manage dependencies on other organizations (Aldrich, 1979; Thompson, 1967). Since interorganizational relations are the media through which individual units meet their resource needs, such dependencies are a pervasive feature of organizational environments.

While we suggest that relations based on dissimilarity are consonant with an exchange or resource dependency theory of interorganizational relations, another somewhat simpler inference also may be drawn from this perspective. Because certain units command key resources upon which the entire population depends, they engage in extensive relations with all others. In each of the networks we studied, for example, one or more agencies controlled the DSO funds which were dispensed to form the local program. We would predict a high volume of relations both to and from these central actors without regard to differences among the units with which they happen to be paired.

The question here is when does knowledge of the attributes of an organization suffice to explain its ties with others, and when is it necessary to know those others' attributes as well? To cast the matter in more concrete terms, envision the $n_k \times n_k$ matrix of reported contact flows among the n_k agencies in community k. The row and column totals of this table capture patterns of sociometric "status" or "centrality". That is, they reveal variations among organizations in the volume of relations each has with the population as a whole. The cells of the matrix, by contrast, must be analyzed to ascertain whether ties are more or less dense for given pairs of organizations; whether the sending or receiving of ties by agency A varies with which of the other $n_k - 1$ organizations is considered.

It has long been known that the pattern of cell entries in a cross-classification is in part a function of the marginal frequencies. Hauser (1980) attributes cell frequencies to a combination of "prevalence" and "interaction" effects, the former

due to the marginal skews, the latter net of these. A recent analysis of interorganizational ties by Galaskiewicz and Marsden (1978) used Goodman's log-linear method to advantage in separating marginal and higher-order (interaction) effects. These investigators made no use of background attribute data on the organizations in their sample, and they were thus limited to some rather formal statements regarding symmetry/asymmetry and the coincidence of different types of relations. Our approach is different, although we regard the hierarchical decomposition of effects on ties performed by Galaskiewicz and Marsden as an important step. If, instead of a cross-tabulation of ties by senders and receivers, we group organizations into levels of theoretically specified attributes, we are permitted inferences regarding the variables which shape interorganizational relations, while retaining the distinction between "prevalence" or "main" and "interaction" effects.

In this respect, however, we depart from the prevailing tradition of interorganizational studies in which pair relations are typically measured as a function of pair similarity or dissimilarity of organizational traits. This empirical literature is plagued, in other words, by very similar defects to those afflicting early studies of status inconsistency (Blalock, 1966; Hodge and Siegel, 1970). To regress (or cross-tabulate) some attitudinal dependent variable for individuals on a difference score computed from two or more status variables confounds the main or additive effects of the status measures with any effect which might uniquely be attributed to their combination. In this paper, we adapt the solution proposed by Duncan (1966) and others for the status inconsistency problem to an analysis of how organizational attributes influence interorganizational relations. That is, we equate the similarity/dissimilarity effect of agency attributes on agency ties with any statistical interaction that might be found between the pair of agencies' traits.

Consider a linear regression model of the following form:

(a) $$F_{ij} = a + bX_i + cX_j + dX_iX_j + e_{ij}$$

where F_{ij} (or P_{ij}) is our measure of the asymmetric flow of ties from agency i to agency j; X_i is a characteristic of agency i; X_j is the same or another characteristic measured for agency j; X_iX_j is the product of the two; and e_{ij} is the usual stochastic error term. a, b, c, and d are ordinary least squares parameter estimates. Rearranging (a) gives equations (b) and (c):

(b) $$F_{ij} = (a + cX_j) + (b + dX_j)X_i + e_{ij}$$

(c) $$F_{ij} = (a + bX_i) + (c + dX_i)X_j + e_{ij}$$

Equation (b) says that both the intercept and the slope of the regression of F_{ij} on X_i are linear functions of X_j. If, however, d, the coefficient on the product term, is zero, the slope of F_{ij} on X_i is invariant with respect to values of X_j. Likewise, if c, the coefficient on X_j, is zero, the intercept from this equation is a constant. An exposition in terms of calculus may also be helpful. The first partial derivative of Y_{ij} with respect to X_i is: $\frac{\partial F_{ij}}{\partial X_i} = b + dX_j$. For a linear function, this measures the change in F_{ij} induced by a change in X_i, holding constant other variables in the equation. Taking the second partial derivative with respect to X_j yields: $\frac{\partial^2 F_{ij}}{\partial X_i \partial X_j} = d$. Thus, d, the coefficient associated with the product term, measures the change in the effect of X_i on F_{ij} for a given change in X_j, and, in so doing, captures exactly the meaning of statistical interaction. Reversing the roles of X_i and X_j, these same interpretations may be applied to equation (c).

Let us consider the case wherein X_i and X_j are the same variable measured for different agencies. We would interpret the coefficient, d, as a similarity/dissimilarity effect on interorganizational ties in the following way. If d is positive, the effect of X_i (or X_j) on F_{ij} is a positive linear function of X_j (or X_i). Figure 1a illustrates. When X_j is high, a positive change in X_i engenders a positive change in F_{ij}. When X_j is low, on the other hand, a positive change in X_i causes a negative change in F_{ij}. Suppose X is agency size. This example suggests that increases in the size of agency i stimulate ties to agency j when the j's are large. When they

are small, increasing the size of i produces fewer ties to j. Figure 1b reverses the scoring of X_j to demonstrate a dissimilarity effect. When X_j takes on low values (e.g., 1), F_{ij} rises with increments in X_i. When X_j is high, incrementing X_i reduces F_{ij}.

Note the implication in Figure 1 that if X_j takes on an intermediate value such as "3" the slope of the relation of F_{ij} to X_i is flat; there is no association. In this instance, we seem to find some slippage between the notion of a similarity/dissimilarity effect and its operationalization as statistical interaction. The flat slope suggests that for intermediate values of X_j, change in X_i produces no change in F_{ij}, even when such changes move X_i toward greater similarity or dissimilarity with X_j. Still, the basic notion that a similarity effect can be understood as a tendency for the effect of X_i (X_j) on the tie from i to j to shift from negative to positive as values of X_j (X_i) change from low to high has considerable intuitive appeal. Moreover, it has the crucial advantage of permitting us to test the hypothesis of interdependent X_i and X_j effects on ties against the simpler alternative of separate additive effects.

Measuring Reciprocity

While we would like to think that the procedures outlined so far overcome some obstacles to a successful modeling of interorganizational relations as a function of organizational attributes, others remain. A central problem concerns the influence of reciprocity on the relations extended by one organization to another. A tie from agency i to j may be traceable only in part to the attribute profiles of the organizations involved. It may in addition be due to the presence of a tie from j to i. The reciprocity effect need not be positive, of course. For certain kinds of relations (e.g., power), we would expect it to be negative. The critical issue, however, is that we can hardly ignore the influence of either negative or positive reciprocity if we hope to find unbiased estimates of the effects of organizational attributes on interorganizational relations. For if we presume that F_{ij} depends on X_i and X_j, the logic of the problem forces us to acknowledge that F_{ji} depends on them, too. To exclude F_{ji} from an equation for F_{ij} would thus produce biased coefficient estimates for X_i and X_j (and any interaction between them).

Before proceeding further, however, we should spell out in greater detail how F_{ij} and F_{ji} are defined as regards our data (the following generalizes to P_{ij} and P_{ji} as well). Consider $\mathbf{F}_k$, the $n_k \times n_k$ matrix of interagency staff ties, for a particular community program k. Excluding diagonal elements, we might array the n_k columns of that matrix in a single $(n_k^2 - n_k) \times 1$ vector. That vector constitutes the F_{ij} variable discussed thus far. Suppose now that we take the transpose of the original square matrix, $\mathbf{F}_k'$, and sequence its columns in the same fashion. Combining the two vectors produces an $(n_k^2 - n_k) \times 2$ matrix, any row of which records the number of ties sent from i to j as well as the number sent from j to i. Note that the same pair of values appears twice in this bivariate distribution, once as ij, ji and again as ji, ij. If we compute a covariance $[\mathrm{cov}(F_{ij},F_{ji}) = \sum(F_{ij}-\bar{F}_{ij})(F_{ji}-\bar{F}_{ji})/(n_k^2 - n_k)]$ for these data, we count the same cross-product twice. This double-counting has no effect on the result, since a covariance is a mean cross-product. However, this approach to measuring the reciprocity of ties need not yield the same value as an alternative: we might have correlated corresponding elements on both sides of the main diagonal of $\mathbf{F}_k$, so that a single joint observation on F_{ij} and F_{ji} is made for each symmetric pair. This mode of defining F_{ij} and F_{ji} assigns them separate values and therefore different means and variances. For reasons to be discussed next, we have found it more advantageous to let F_{ij} and F_{ji} equal the elements of F_k and F_k', respectively.[1]

One approach, then, to estimating and controlling the reciprocity effect might appear to be that of entering F_{ji} in the equation determining F_{ij}. Yet this strategy constitutes a serious misspecification of the processes under consideration. Even though F_{ij} and F_{ji} run over the same values and are thus in a sense the "same" variables, for any particular joint observation it cannot reasonably be asserted that the

tie from i to j depends on that from j to i but not vice versa. In a recent study, Tuma and Hallinan (1980) solved this problem by measuring the ji tie at a previous point in time to the ij relation. They could thus reasonably regress (in our notation) $F_{ij}(t+\Delta t)$ on $F_{ji}(t)$ and X_i, X_j, and X_iX_j. We might note, however, that for certain interactions (e.g., face-to-face or telephone) the assumption of a lagged reciprocity effect may be less tenable than an instantaneous one. In any case, this option is only available to investigators fortunate enough to have panel data at their disposal.

We propose the nonrecursive structural model in Figure 2 as our approach to the estimation of reciprocity effects. For ease of exposition, no interaction is specified between X_i and X_j. By virtue of the nature of the problem and data we deal with, it has certain unique features. First of all, it is unidentified. With only six estimating equations available, there are seven unknown parameters to be estimated. The usual approach to identifying a simultaneous model of this sort is to find an exogenous variable to serve as an instrument for one endogenous term but which would be presumed independent of the other and its error term. To pursue that strategy would necessarily mean that we drop the assumption that an interagency relation, F_{ij}, may depend on both the sender and receiver agencies' levels of the same attribute (X_i and X_j). In regard to certain agency attributes, rationales for this approach might be found. That is, some X would be viewed as conditioning either the sending of ties or their receipt but not both. Thus, the Figure 2 model would be identified if we set $a_{ij,i} = a_{ji,j} = 0$, or, alternatively, that $a_{ji,i} = a_{ij,j} = 0$.

The approach we have taken is to impose a different kind of constraint on the model, one which seems highly appropriate and perhaps unavoidable, given our conceptualization of F_{ij}, F_{ji}, and the process presumed to relate them. That constraint is to set $b_{ij} = b_{ji}$. Under this assumption, the model is just-identified and can be estimated with a regression routine which permits constraints to be imposed upon parameter estimates. We have used LISREL IV, which generates full-information maximum likelihood estimates for structural equation models of fully observed variables.

We find it difficult to conceive of b_{ij} and b_{ji} taking on different values even if it were possible to estimate them. F_{ij} and F_{ji}, after all, are identically distributed. They differ only in the order in which their values appear. As variables, the distinction between them is thererfore arbitrary, even though for any given agency pair they convey different information. It is not possible that the effect of one on the other could be any different from the reverse effect.

With the equality constraint imposed on the endogenous variable coefficients, certain other distinctive features of the model become apparent. The equations for F_{ij} and F_{ji} now contain completely redundant information. Not only does $b_{ij} = b_{ji}$, but $a_{ij,i} = a_{ji,j}$ and $a_{ji,i} = a_{ij,j}$. A little thought should make this obvious to the reader. If X_i and X_j are the same variable measured for organizations i and j, respectively, and if $i = 1,..,n_k$, $j = 1,..,n_k$ with $i \neq j$, then X_i and X_j have exactly the same relations to F_{ij} that X_j and X_i have to F_{ji}. This is not to say, however, that each half of the model could have been estimated ignoring the other half. If F_{ij} were simply regressed with OLS on F_{ji}, X_i, and X_j, we would again produce coefficients equal to those generated by a regression of F_{ji} on F_{ij}, X_i, and X_j but they would not be the ones implied under the model in Figure 2. Furthermore, despite the similiarity of the equations constituting it, the Figure 2 model must be appraised as a whole in order to understand the processes it represents. The _indirect_ effects which the reciprocity relation mediates should, in particular, receive attention. Studying these demonstrates the importance of specifying and estimating the influences of reciprocity in models of social network processes. Consider the reduced form of the F_{ij} equation:

(d) $$F_{ij} = q_{ij,i}X_i + q_{ij,j}X_j + e_{ij}$$

Expressed in terms of the structural coefficients, the reduced form coefficients are:

(e) $$q_{ij,i} = \frac{b_{ij}a_{ji,i} + a_{ij,i}}{1-b_{ij}b_{ji}}$$

(f) $$q_{ij,j} = \frac{b_{ij}a_{ji,j} + a_{ij,j}}{1-b_{ij}b_{ji}}$$

These results make plain that each reduced form coefficient is a nonlinear function of a direct effect ($a_{ij,i}$ and $a_{ij,j}$) and an indirect component of each exogenous variable effect as mediated through the simultaneously determined endogenous variables. Suppose that $a_{ij,i} = 0$ and $a_{ji,i} > 0$. That is, the sending agency's level of X has no effect on the ties it communicates to the receiving agency but the latter's X has a positive effect. Assuming that $b_{ij} = b_{ji} > 0$, the reduced form coefficient associated with X_i would be nonzero. Thus, the presence of reciprocity, unless explicitly represented in the model, can lead to wholly spurious conclusions regarding the effect of X_i and X_j on the sending or receiving of interorganizational ties. Indeed, how such a spurious interpretation might arise is amply demonstrated in the data analysis to which we now turn our attention.

Measures of Agency Attributes

In this section,we present the independent variables which we believe may influence the tie between each agency pair in these three community networks. Recall that we measure that tie with two distinct indices, F_{ij} and P_{ij}. Since our concern here is more with analytical procedure than substance, we no more than briefly justify our selection of these attributes as determining conditions.

1. ADMIN: a dummy variable indicating whether (=1) or not (=0) an agency was the DSO grant recipient charged with coordinating the interorganizational network in one of the three communities. Multiple agencies could receive this designation if they were separate units of the same overall organization.

2. STAFF: total employed staff. We have two rationales for including the organization's staff size as an independent variable. First, we would expect the number of ties from agency i to j to depend to some degree on the number of persons available to report them. Second, large organizations are viewed within the resource dependency framework as connected extensively to their environments (Aldrich, 1979).

They have access to numerous environmental channels through which their own resources may be secured, and they themselves are pools of resources sought by other units.

3. NSERV: total number of different services offered to clients. Organizations providing a wide array of services are more self-sufficient than their specialized counterparts and more sought out by other organizations in need of their skills.

4. PROF: the proportion of professionally trained staff. This is the final organizational resource variable. Blau (1955) has shown that professional workers who possess special task-related expertise are the objects of relations initiated by less skilled colleagues. We suppose the same pattern holds among organizations.

5. WHITE: the proportion of the agency's clients who are white. Although the race and ethnic composition of an agency's clientele might be a proxy for the size of its resource base, we hypothesize that networks of agencies, like networks of people, are partitioned by race, so that units with similar client compositions tend to forge ties.

6. BLAME: presence of a staff ideology blaming the client for his or her difficulties and prescribing punishment as the appropriate societal response. Our measure is the mean of two questionnaire items which are correlated .39:

a. "To what extent are juveniles in trouble responsible for their own problems?" (1= juvenile not to blame; 9= juvenile to blame)

b. "What is the best strategy for dealing with juveniles in trouble?" (1= juveniles should not be punished; 9= juveniles should be punished)

Our prediction is that agencies with similar client ideologies are most closely linked.

7. COERCE: the coerciveness of sanctions imposed for client misbehavior. This measure is the number of agency rule violations evoking "coercive" sanctions divided by the sum of sanction scores for thirty violations. Again our prediction rests on a "homophily" assumption: agencies with similar strategies for dealing with client infractions of agency norms should be more closely and frequently linked in the network than agencies which differ on this dimension.

Analysis and Results

Table 1 presents the zero-order correlations among the seven attributes of agencies we examine. In Table 2, four equations are presented which differ on two dimensions.[2] First, both dependent variables, F_{ij} and P_{ij}, are specified

(Table 1 and 2 about here)

as linear and additive functions of the same agency characteristics. Second, for each, an equation is given with and without the simultaneous reciprocity effect specified. A useful exercise is to evaluate the changes in the parameter estimates for the attribute measures which arise by alternating the model specification in this respect. Although the Table shows only the dependence of F_{ij} (P_{ij}) on F_{ji} (P_{ji}), the estimates given were found by LISREL for a model specifying simultaneously determined endogenous variables under an equality constraint.

In this analysis, permitting only main effects of agency attributes on interagency ties, few strong influences appear. It is dramatically evident that the administrative agencies charged with organizing the network draw many and close ties; the coefficient on $ADMIN_j$ is large and significant at a high level of confidence. Whether one infers that they also dispense ties at a disproportionately high rate depends on which equation is considered. With no reciprocity specified, the equation for F_{ij} displays a significant positive influence of the source agency's administrative position on the number of ties it sends to the recipient agency. However, this effect is appreciably smaller than that exercised by whether the recipient agency is an administrative unit or not. Furthermore, the comparable equation for P_{ij} provides no corroborative evidence for the proposition that administrative agencies establish close ties across the board, although it does strongly replicate the finding that such organizations are the objects of connections initiated by others.

When we change the model by estimating the reciprocity effect, the positive coefficient on $ADMIN_i$ in the equation for F_{ij} goes to zero. As expected, the reciprocity coefficients are positive and highly significant, this effect being particularly strong in the case of F_{ij}. Although other estimates do not appear to be influenced, this high sensitivity of the $ADMIN_i$ coefficient to the presence or absence of the reciprocity estimate highlights the importance of correct specification in models of this sort. We conclude that agencies in each program's administrative core generate no greater volume of ties than other organizations in their domains. But because the administrative core pulls ties in at such a high rate, and because ties flowing one way between a pair of agencies strongly influence the ties flowing the other way, an equation which fails to specify reciprocity spuriously attributes an influence to the administrative status of the source organization.

Of the other statistically significant effects which Table 2 shows these attributes to have on either tie measure, the most interesting concerns the coerciveness variable. In terms of F_{ij}, more coercive agencies send fewer ties, while, in terms of P_{ij}, they are also less likely to receive close relations. A coercive strategy for dealing with client disregard of agency norms thus seems to be a source of relative isolation in these networks. We also witness a positive effect of a blame-and-punishment orientation on P_{ij}, but the standardized coefficient is small and other table entries do not corroborate the importance of this predictor. Finally, significant differences among the three community-based programs are found to exist. The Tucson network reveals a lower average frequency of ties, while Oakland (Alameda County) has a higher (adjusted) mean on P_{ij}. We might expect network differences to be more pronounced when measured in terms of P_{ij}, as the construction of this measure is more dependent on global program-specific network properties (e.g., reachability) than is the case with F_{ij}.

The remaining attributes of agencies exhibit no additive effects on either F_{ij} or P_{ij}. We turn, then, to a consideration of whether they combine to produce interaction effects; whether, that is, the impact of agency i's position on some variable is contingent upon agency j's level of the same or another variable. This distinction between interactions generated by same or different attributes is substantively important. The notion of a "homophily" effect which is so pervasive in social networks research finds an operational counterpart in a significant positive regression coefficient on the product term, X_iX_j, where X is a single characteristic on which agencies may be differentiated. The alternative hypothesis of an "exchange" or "heterophily" effect would be supported by a negative coefficient estimated for such a product term. Perhaps less easily cast in theoretical terms but no less plausible are interactions of the form, X_iZ_j or X_jZ_i, where X and Z are <u>different</u> agency characteristics and i and j stand for senders and receivers of ties as before. One can imagine a variety of configurations of source and recipient agency traits which might make network connections more or less likely. In the present substantive context, we should be alerted especially to properties of agencies which shape their degree of dependence on each community program's administrative core-- which agencies are engaged in close or frequent relations either to or from the central organizations charged with coordinating the system. In fact, in this analysis we confine our attention to cross-attribute interactions involving ADMIN and ignore the other possible product terms which could be computed and entered in these regressions. Without clear hypotheses pinpointing relevant configurations of agency traits, it is probably unwise to slog through the profusion of empirical detail which generating all forty-nine possible interactions would entail.

Table 3 presents t-values and significance levels for these interaction effects.

(Table 3 about here)

Each interaction was evaluated by entering the product term singly in the equations for F_{ij} and P_{ij} as presented in Table 2. The collinearity induced by the large number of intercorrelated product terms forbade including them simultaneously in the same regression. The first seven rows of Table 3 test the "homophily" and "exchange" hypotheses alluded to earlier. All evaluate interactions produced by products of the i and j agencies' values on the same trait. We observe first that all the t-values which achieve statistical significance are positively signed. We therefore conclude that this analysis produces no evidence for what we have called "exchange" or "heterophily" effects whose existence we would have inferred from negative interaction terms. The data favor exclusively a homophily interpretation of how agencies' similarities or differences on the same attributes shape their relations.

Although the t-values are for the most part larger in regard to P_{ij}, with one exception these interaction terms are not greatly dissimilar between the two dependent variables. The glaring exception is XADMIN, the interaction of the administrative status dummy variables. A strong positive interaction materializes between the administrative positions of parties to the relation when F_{ij} is the criterion variable. But in the case of P_{ij} this effect is wholly absent. Recall that F_{ij} may take on a range of values which would all be scored 1 on P_{ij}. We might infer that direct connections (i.e., P_{ij}=1) are no more probable between agencies sharing administrative responsibility for the program than between other organizations. But the density of ties constituting this connection may be much greater when both organizations occupy the administrative core than when they do not.

The other same-trait interaction effects which are statistically significant in regard to either or both relational dependent variables involve the blame-and-punishment orientation and the proportion of clients who are white. Whether we examine F_{ij} or P_{ij}, we find evidence that the effect of client racial composition on an agency's ties to others depends upon the racial makeup of those others' clients as well. Thus, agencies processing predominantly white clients may be linked as are agencies providing services to a predominantly nonwhite group. But the [redacted] interactions of the proportion white attribute suggest that organizations with racially different clienteles are less likely to be tied.

If we are less than surprised that service agency networks prove to be partitioned on the basis of the racial composition of their clients, the effect of compatible blame-and-punishment ideologies as revealed in Table 3 also appeals to our intuition. It is especially with regard to treatment philosophy dimensions of this sort that we would expect homophily to shape interorganizational relations. Organizations with widely divergent conceptions of clients are unlikely to see themselves gaining much from relationships except negative reinforcement for their respective views. Close connections are apt to evolve chiefly among the ideologically aligned.

We would like to underscore how this set of results demonstrates the point that Tables 2 and 3 yield different kinds of information on how attributes of organizations shape their ties. Table 2 gave no evidence that WHITE was an important variable but Table 3 tells a different story: XWHITE is the only interaction to significantly affect both F_{ij} and P_{ij}. The opposite circumstance holds concerning agency coeriveness: Tables 2 and 3 provide evidence of significant main effects but no interaction. It is precisely the capability of differentiating between these situations that our methodology provides but previous analyses of interorganizational data concealed. Our data suggest some tendency for coercive organizations to be isolated in these networks but no tendency for the degree of alignment or differentiation of agency pairs on this dimension to influence their ties. The racial composition of an organization's clients, on the other hand, does not condition the centrality of its network position as a source or recipient of relations, yet interagency similarity in this respect does promote connections in agency dyads.

If the tie from one organization to another is not contingent on their respective coerciveness levels, the cross-attribute interactions involving ADMIN which Table 3 also presents suggest again that coercive sanctions depress integration with other units, only now we narrow our consideration to relations which include the administrative core. With F_{ij} as the dependent variable, the t-ratios for the interaction between the source agency's administrative status and the repretation associated with F_{ij} seems a real advantage. Moreover, particularly in the analysis of the cross-attribute interaction effects, the results we obtained based on F_{ij} seemed clearer and more easily intuited in terms of our substantive beliefs about the dynamics of interagency networks. Beyond these two, of course, there remains an array of relational measures appropriate to dyadic analyses which might be adopted and which might introduce variation into a set of empirical results. The decision as to which of these is most appropriate for a particular substantive problem in network research cannot as yet, unfortunately, be well-informed.

In closing, we might comment on the differences between a linear modeling approach to pairwise relations and other approaches to network analysis which focus on "global" structures or group properties. The cost of treating dyadic relations as separate units of observation is precisely that we lose track of how those relations combine to form an entire network. Indeed, by pooling pairs from different networks, we further obscure the macro-network properties unique to a given community program. We ourselves have argued elsewhere, in fact, that definite limits may exist to the extent that network ties are interpretable in terms of actor attributes. Rather than larger structures forming through processes of aggregating dyadic ties, it may at times be more profitable to consider the reverse phenomenon and view each separate relation as determined by the larger system of which it is a part. Yet if one's primary concern is to ascertain how the attributes of actors condition their relations-- which is the preoccupation of most interorganizational research-- we think the strategy we described to be the best way of adapting linear regression techniques to relational data. Methods such as blockmodeling which are focused on group structures have not thus far lent themselves easily to descriptions in terms of actor attributes.

FOOTNOTES

1. The point here is that if F_{ij} and F_{ji} are defined over different pairs, we cannot assume that their reciprocal effects are equal. However, we may be able to assume that these effects, as well as those of agency attributes, differ by no more than sampling error. The decision to assign pair 1,2 to the F_{ij} distribution and pair 2,1 to the F_{ji} distribution, for example, is an arbitrary one. There is no basis for distinguishing between the two distributions except that they contain different pairs. Preserving only this latter constraint, pairs could be switched between F_{ij} and F_{ji} at will. This component of random variation between the equations estimated for F_{ij} and F_{ji} seems a needless complexity which we eliminate by allowing both relational variables to run over all asymmetric pairs.

2. Inferential statistics require an assumption of independent observations (error terms, in a linear modeling framework) which may not be met when observations are on pairs. Reciprocity is one obvious source of nonindependence between ij and ji pairs which our model, which explicitly represents a reciprocity process, has controlled. Another form of noninterdependence is not so easily dealt with. Pairs involving the same agency (i.e., 1,2 1,3 1,4 ... $1,n_k$) have a constant component associated with the attributes of the particular agency. This kind of dependency is analogous to that found in pooled time-series and cross-sectional observations. Unfortunately, the solution of partialling out the constant component appropriate to that context is not available to us. To enter dummy variables for each agency (less one) in an equation such as (a) or to residualize our relational dependent variables on their agency-specific means would nullify the coefficients estimated for any agency-level attributes. This problem is not unique to network data. Analyses of group or organization effects on individuals confront

the same obstacle: observations on members of a common group are dependent, but controlling for "group" per se effectively excludes the possibility of testing for the effects of particular group attributes. Essentially this is a specification problem, and like all problems of this genre it can only be resolved on theoretical grounds. Were we confident that our model incorporated those attributes of agencies which in fact account for the variation in interagency ties, we could rest assured that no residual agency effect remained.

Figure 1. Positive and Negative Dependencies of the F_{ij}, X_i Relation on X_j.

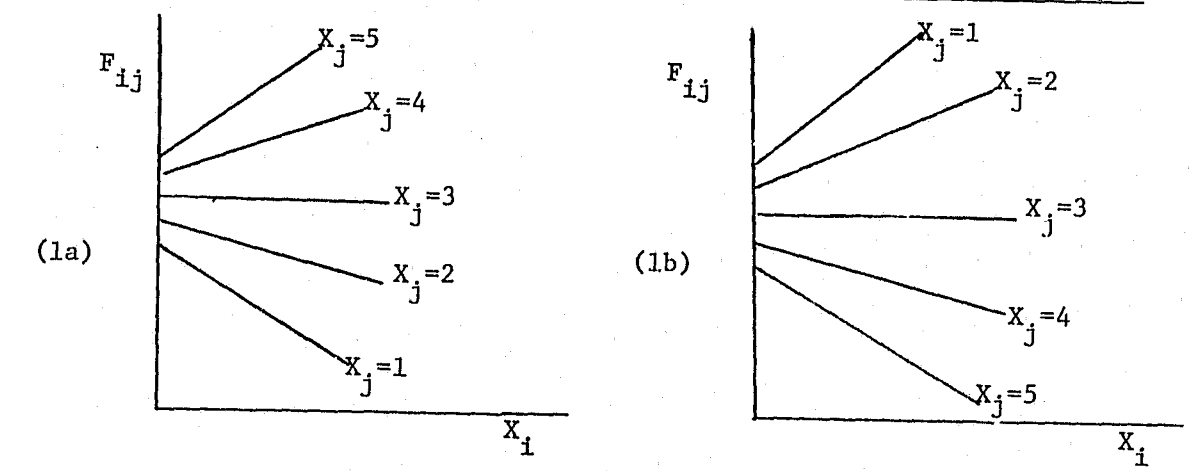

Figure 2. A Model of Interagency Reciprocity Effects

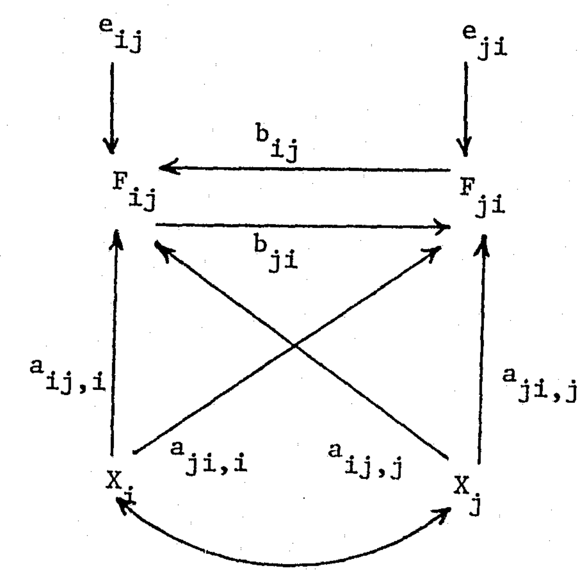

Table 1. Zero-Order Correlations of Agency Attributes

	2	3	4	5	6	7
1 ADMIN	-.024	-.454	-.032	-.023	.107	-.157
2 STAFF		.236	-.207	.084	-.100	.239
3 NSERV			-.118	.089	.220	-.056
4 PROF				.444	.012	.237
5 WHITE					.106	.239
6 BLAME						.026
7 COERCE						

Table 2. Standardized and Unstandardized Coefficients for Additive Effects of Agency Attributes on Interagency Relations

Independent Variables	Dependent Variables											
	F_{ij}			F_{ij}			P_{ij}			P_{ij}		
	B	b	SE(b)	B	b	SE(b)	B	b	SE(b)	B	b	SE(b)
F_{ji}	-----	-----	-----	.390	.390***	.015	-----	-----	-----	-----	-----	-----
P_{ji}	-----	-----	-----	-----	-----	-----	-----	-----	-----	.144	.144***	.017
$ADMIN_i$	.132	.439**	.131	-.013	-.043	.104	-.027	-.019	.023	-.090	-.063*	.022
$ADMIN_j$	.370	1.235***	.131	.319	1.064***	.104	.439	.308***	.023	.443	.311***	.022
$STAFF_i$	.005	.000	.002	.016	.001	.001	-.008	-.000	.000	-.006	-.000	.000
$STAFF_j$	-.029	-.001	.002	-.031	-.001	.001	-.013	-.000	.000	-.011	-.000	.000
$NSERV_i$	-.046	-.018	.018	-.017	-.007	.014	-.035	-.003	.003	-.035	-.003	.003
$NSERV_j$	-.073	-.029	.018	-.055	-.022	.014	-.005	-.000	.003	-.000	-.000	.003
$PROF_i$	-.010	-.000	.060	.010	.000	.001	-.032	-.000	.000	-.025	-.000	.000
$PROF_j$	-.053	-.002	-.002	-.049	-.002	.001	-.046	-.000	.000	-.042	-.037	.000
$WHITE_i$	.020	.001	.002	.017	.001	.001	-.041	-.000	.000	-.045	-.000	.000
$WHITE_j$	.009	.000	.002	.001	.000	.001	.028	.000	.000	.034	.000	.000
$BLAME_i$	.043	.005	.045	.047	.050	.035	.071	.019*	.008	.073	.019*	.008
$BLAME_j$	-.010	-.013	.045	-.027	-.034	.035	-.012	-.003	.008	-.022	-.006	.000
$COERCE_i$	-.069	-.288	.154	-.068	-.282*	.120	-.063	-.055	.027	-.042	-.037	.026
$COERCE_j$	-.004	-.017	.154	.023	.095	.120	-.144	-.125**	.027	-.135	-.117**	-.028
ARIZ	-.122	-.346	.192	-.074	-.211*	-.098	-.055	-.033	.033	-.047	-.028	.155
ALAM	-.061	-.160	.175	-.037	-.098	.137	.326	.181***	.031	.279	.155***	.029
R^2		.197			.499			.451			.484	

+Notes: F_{ij} is the number of ties from agency i to j. P_{ij} is the proximity of i to j in the network (see text). B= standardized coefficient, b= unstandardized coefficient, and SE(b) is the standard error of b. One, two, and three asterisks indicate significance levels of .05, .01, and .001, respectively.

Table 3. T-tests for Interaction Terms[+]

	F_{ij}	P_{ij}
XADMIN	6.482***	-0.107
XSTAFF	-0.224	-0.203
XNSERV	1.181	1.830
XPROF	0.462	1.578
XWHITE	2.579**	5.725***
XBLAME	1.163	7.357***
XCOERCE	-0.281	-0.305
XADSTAFF	-0.214	-1.076
XSTAFFAD	-1.790	1.426
XADNSERV	-4.214***	2.089*
XNSERVAD	-3.985***	-0.409
XADPROF	-0.280	0.671
XPROFAD	0.918	0.542
XADWHITE	-0.240	0.598
XWHITEAD	0.918	-1.200
XADBLAME	1.033	-4.502***
XBLAMEAD	2.776**	0.222
XADCOERCE	-2.984**	-0.333
XCOERCEAD	-3.286**	-2.118*

[+]Notes: XADMIN - XCOERCE are interaction terms formed as the product of agencies' i and j's values on the same attribute. The remaining terms are products of $ADMIN_i$ and $ADMIN_j$ with the other six attributes (e.g., XADSTAFF = $ADMIN_i$*$STAFF_J$; XSTAFFAD = $STAFF_i$*$ADMIN_J$). One, two, and three asterisks indicate significance levels of .05, .01, and .001, respectively.

REFERENCES

Aiken, Michael and Jerald Hage

1968 "Organizational interdependence and intraorganizational structure." American Sociological Review 33 (December): 912-930.

Aldrich, Howard

1976 "Resource dependence and interorganizational relations: relations between local employment service offices and social services sector organizations." Administration and Society 7 (February): 419-454.

1979 Organizations and Environments. Englewood Cliffs, New Jersey: Prentice-Hall.

Benson, J. Kenneth

1975 "The interorganizational network as a political economy." Administrative Science Quarterly 20 (June): 229-249.

Blalock, Hubert M.

1966 "The identification problem and theory building: the case of status inconsistency." American Sociological Review 31 (February): 52-61.

Blau, Peter M.

1955 The Dynamics of Bureaucracy. Chicago: University of Chicago Press.

1964 Exchange and Power in Social Life. New York: Wiley.

Burt, Ronald S.

1976 "Positions in networks." Social Forces 55 (September): 93-122.

Burt, Ronald S. (ed.)

1978 Applied Network Analysis (Special Issue of Sociologial Methods and Research). Volume 7 (November).

Duncan, Otis Dudley

1966 "Methodological issues in the analysis of social mobility." In Neil Smelser and Seymour M. Lipset (eds.): Social Structure and Mobility in Economic Development. Chicago: Aldine.

Galaskiewicz, Joseph and Peter V. Marsden

1978 "Interorganizational resource networks: formal patterns of overlap." Social Science Research 7 (June): 89-107.

Hall, Richard H., John P. Clark, Peggy C. Giordano, Paul V. Johnson, and Martha Van Roekel

1977 "Patterns of interorganizational relationships." Administrative Science Quarterly 22 (September): 457-474.

Hauser, Robert M.

1980 "Some exploratory methods for modeling mobility tables and other cross-classified data." Pp. 413-458 in Karl F. Schuessler (ed.): Sociological Methodology 1980. San Francisco: Jossey-Bass.

Hodge, Robert W. and Paul M. Siegel

1970 "Nonvertical dimensions of social stratification." Pp. 512-520 in E. O. Laumann, P. M. Siegel, and R. W. Hodge (eds.): The Logic of Social Hierarchies. Chicago: Markham.

Holland, Paul W. and Samuel Leinhardt

1973 "The structural implications of measurement error in sociometry." Journal of Mathematical Sociology 3:84-112.

Klonglan, Gerald E., Richard D. Warren, Judy M. Winkelpleck, and Steven K. Paulson

1976 "Interorganizational measurement in the social services sector: differences by hierarchical level." Administrative Science Quarterly 21 (December): 675-687.

Laumann, Edward O. and Franz U. Pappi

1976 Networks of Collective Action: A Perspective on Community Influence Systems. New York: Academic.

Lazarsfeld, Paul F. and Robert K. Merton

1954 "Friendship as a social process." In M. Berger, T. Abel, and C. H. Page (eds.): Freedom and Control in Modern Society. Princeton: Van Nostrand.

Litwak, Eugene and Jack Rothman

1970 "Towards the theory and practice of coordination between formal organizations." In W. Rosengren and M. Lefton (eds.): Organizations and Clients. Columbus, Ohio: Merrill.

Miller, Jon

1978 "The organizational properties of seven programs for the Deinstitutionalization of Status Offenders." Unpublished report, Social Science Research Institute, University of Southern California.

Molnar, Joseph L. and David L. Rogers

1979 "A comparative model of interorganizational conflict." Administrative Science Quarterly 24 (September): 404-425.

Rogers, E. M. and D. K. Bhowmik

1971 "Homophily-heterophily: relational concepts for communication research." Public Opinion Quarterly 34 (Winter): 523-538.

Tuma, Nancy Brandon and Maureen T. Hallinan

1979 "The effects of sex, race, and achievement on schoolchildren's friendships." Social Forces 57 (June): 1265-1285.