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RESOURCES, HOMOPHILY, AND DEPENDENCE: Agency Properties and Asymmetric Ties in Human Service Networks

James R. Lincoln

Indiana University, Bloomington
Department of Sociology

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ABSTRACT

The concerns of this paper are both methodological and substantive. It is argued that, with occasional exceptions, interorganizational researchers have been insufficiently attentive to problems of analyzing relational data, and that the contribution to knowledge of extant resesarch on interorganizational networks is therefore uncertain. A modeling strategy is proposed for analyzing interorganizational dyads with permits estimation of parameters for nodal, dyadic, reciprocity, and autoregression effects. Shading into substantive concerns is the paper's contention that the methods proposed here enable an investigator to measure with greater precision specific patterns of interorganizational relations identified by resource dependence and homophily theories. Data on interagency ties in three community-based networks of youth service agencies suggest that size, administrative position, and justice system connections condition the extent to which an agency is a source of influence, assistance, and support in the network. The data also suggest that boundary-spanning ties are denser between agencies with similar treatment ideologies and client racial compositions, and that size and justice system access reduce an agency's dependence on the network's administrative core. In the course of the discussion, a number of related issues and findings are addressed.

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Introduction

Empirical research on interorganizational relations has recently become a growth industry. Once the exclusive province of theorists, networks of organizations are now the topic of a significant body of research literature. Yet the contribution of this empirical work to cumulative understanding is uncertain. The poor correspondence between interorganizational research and theory is widely acknowledged. Such influential perspectives as resource dependence/exchange theory have produced few propositions which lent themselves to direct empirical test (Aldrich, 1979; Cook, 1977; Laumann, Galaskiewicz, and Marsden, 1978). The diversity of organizational networks studied and the range of causal forces shaping them have also contributed to noncomparable and therefore noncumulative research. But perhaps the most critical failing of existing work is its reliance on a set of research methodologies and modeling strategies which are often ill-suited to relational data. Such data, whether concerning the ties of organizations, persons, or other actors, present special analytic problems which students of interorganizational relations, with few exceptions, have failed to address. In the course of presenting new findings on three networks of agencies in a national

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youth treatment program, a considerable investment has been made in solving certain of these problems. The paper, then, is motivated by methodological, as well as substantive, concerns.

Empirical studies of networks can be conducted at three levels of analysis: network (including partial network), dyad, and node (Lincoln, 1982). The unit I examine is the interorganizational dyad: a pair of organizations with a nonzero probability of being linked. However, the analysis permits certain inferences to be made regarding network and nodal phenomena as well. Network theorists are often disdainful of dyadic or nodal inquiries (Aldrich, 1979:291), but it is rarely clear why a higher level of aggregation should be preferred. Indeed, most interorganizational theory concerns nodes and dyads and offers relatively few propositions at the network level.

Particular attention, for example, has been paid to the causes and consequences of centrality in an interorganizational network-- perhaps <u>the</u> nodal property. Aiken and Hage (1968) drew from open-systems theory to argue that organizations with organic structures seek dense links with their environments through joint ventures. Other writers have argued that size and resource base place an organization in a central network position, and that centrality, in turn, gives rise to power and influence (Benson, 1975; Knoke and Wood, 1981:165; Galaskiewicz, 1979). A major theme in past work which figures importantly in the present inquiry as well is that interorganizational networks are often formed in accordance with the broad designs of some external authority (Aldrich, 1976; Lehman, 1975; Warren, Rose, and Bergunder, 1970). Organizations representing that authority and controlling the critical resources of legal mandate and funding are invariably central actors, structuring the network through the dependencies they foster in others.

These examples testify that organizations vary in the total number of links they have to actors in their environments. The distinctive feature of such a nodal perspective on networks is that it needs no information on the characteristics of the actors with which a focal organization is tied. In contrast, a dyadic explanation demands simultaneous information on both parties to an interaction. Resource dependence theory, for instance, asserts that organizations form relations in order to exchange valued resources (Aldrich, 1976; Pfeffer and Salancik, 1978). The driving force behind the exchange is that one actor possesses the resource while the other does not but has need of it. Hence it is the <u>combination</u> of possession on the one side and need on the other that motivates the tie.

Much of the difficulty with resource dependence/exchange theory as a source of testable hypotheses is the problem of measuring resources. Virtually any organizational property can function as a resource creating the basis for an interorganizational exchange. However, Laumann, Galaskiewicz, and Marsden (1978) appear to identify the testable core of resource dependence-exchange theory in arguing that it predicts the linkage of actors with <u>complementary</u> characteristics. Despite the inevitable uncertainty regarding which organizational properties are resources and which are not, the logic of the exchange model predicts transactions between dissimilar organizations. Linkage as a function of dissimilarity or complementarity is also compatible with role theory (Lincoln, 1982; White, Boorman, and Breiger, 1976). But role theory is poorly suited to explaining interorganizational networks where authority structures and rules are often undeveloped and voluntary, free market coordination processes prevail (Warren, 1967).

Linkage due to dissimiliarity may be consistent with an exchange-theoretic interpretation as Laumann et al. suggest, but simple evidence of interaction between organizations with complementary attribute profiles fails to address the main question posed by resource dependence theory: how power dependence relations arise from the unequal distribution of resources in an interorganizational network (Pfeffer and Salancik, 1978:53). One reason interorganizational research has failed to speak to this question is because of its preoccupation with symmetric ties. Most studies query informants about very general kinds of network relations in which their organizations are involved: "contacts", "communications", "coordination". Data on such ties convey no information on the power and resource asymmetries which characterize the relation. Methodological motives may in part have dictated this focus on symmetric ties, for data analysis is considerably simpler when the direction of the relation is not an issue and there is no need to order nodes within a pair. But power dependence relations are intrinsically asymmetric: A's dependence on B for critical resources in no way implies B's dependence on A (Pfeffer and Leong, 1977). The present investigation will attempt to show that explict measurement of asymmetric interorganizational relationships combined with appropriate procedures for modeling dyadic data can yield important insights into the processes whereby organizational resources translate into power dependence relations.

The alternative principle identified by Laumann et al. (1978:461) for explaining dyadic ties is, unsurprisingly, similarity. This recalls the "homophily" hypothesis in interpersonal research-- that persons with similar values, preferences, and backgrounds will be mutually attracted (Lazarsfeld and Merton, 1954). Similar attraction processes operate among organizations.

Shared goals spur organizations to pool resources and coordinate activities, for such joint efforts increase the probability of mutual goal attainment (Reid, 1969). Organizations subscribing to similar values and operating philosophies tend to be drawn to one another, while those which differ are repelled, since differences of this sort threaten claims to legitimacy and domain. Of considerable relevance to the present study is the observation of Miller, Baum, and McNeil (1968) that delinquency treatment agencies often have conflicting treatment ideologies, which obstruct coordination of services and exchange of clients. Resource dependence theorists have, in general, dismissed ideologies, sentiments, and values as reflections, not determinants, of interorganizational network structure (Aldrich, 1979; Benson, 1975). But there is little evidence to substantiate that claim. Indeed, Galaskiewicz and Shatin (1981) provide some evidence to the contrary in demonstrating that Chicago social service agencies whose leaders had various group affiliations (and therefore, presumably, values) in common were likely to form cooperative arrangements. Organizations having similar leaders and staffs, serving similar clients, offering similar services, and sharing similar values and philosophies of treatment find it easier to deal with one another and join together for the sake of common interest and mutual support.

The DSO Program: Community-Based Service Delivery to Problem Youth

The data for the present analysis were gathered as part of the National Evaluation of the Deinstitutionalization of Status Offenders programs (Kobrin and Klein, 1980). DSO was an LEAA-sponsored effort to encourage states and localities to cease remanding "status" offenders-- children apprehended for offenses which do not constitute adult crimes (e.g., truancy, runaway, drinking)-- to secure facilities and to return presently institutionalized

youth to the community. DSO thus reflected the dominant trend in human service delivery in the 1970's: to treat clients at the community-level through a network of available service organizations. Much of the impetus for interorganizational theory and research during this period came from the widespread policy concern with managing complex and largely voluntary networks of diverse agencies serving a common pool of clients (Aiken et al., 1975).

Although eight pilot programs were funded by LEAA, I consider only the three which were based in urban counties and therefore truly represent "community" interorganizational networks: Pima County (Tucson), Arizona, Alameda County (Oakland), California, and Spokane County (Spokane), Washington. With the exception of one other very small urban program, the remaining programs were statewide, and preliminary analyses revealed that much of their interorganizational structure reflected spatial constaints. The three western communities which mounted DSO programs differed in certain particulars from one another but were basically similar in overall design. In each, certain agencies were charged with disbursing DSO funds, overseeing the referral of clients for services, and generally coordinating the program (Kobrin and Klein, 1980). Thus, as is commonly the case in service delivery networks, these actors controlled the critical resources of legal authority and funding (Benson, 1975, Lehman, 1975:31). Their dense ties with others were thereby foreordained. In Tucson, three distinct agencies of the juvenile court shared the administrative role. Likewise in Oakland, three separate branches of an organization operated by the Alameda County Probation Department shared the local administrative function. In Spokane, the administrative agency was an independent organization whose program director was a juvenile court functionary. Formal justice institutions, then, played a significant role in organizing each DSO community network. However, the service-providing agencies recruited to the networks were a wide array of private not-for-profit organizations varying considerably in their approach to treating juveniles. Spokane and Oakland relied heavily upon the existing network of established youth service organizations in those communities. In Tucson, however, the usual organizations were for the most part bypassed, and a group of agencies which had been more or less marginal to the established youth referral network became the basis for the DSO program (Kobrin and Klein, 1980).

Methods of Data Collection

A distinctive feature of the present research is that interorganizational relations are measured as the aggregate boundary-spanning ties of organizational members. Although there are some precedents for this strategy (Hall et al., 1977), most interorganizational research ignores such boundary-spanning links and focuses instead on formal joint programs and other relations which organizational leaders can report. Ties of that sort do warrant study, and data concerning them are relatively easy to collect. But it is clear that interorganizational transactions regularly occur through the interpersonal relations which connect members at all levels of different organizations. In social service delivery systems, interorganizational ties are chiefly mediated through the professional contacts of practitioners whose organizational affiliations may be loose and shifting (Lipsky, 1980; Miller, 1980).

The total number of agencies examined in this investigation is 48: 16 in Tucson, 17 in Oakland, and 15 in Spokane. In each agency, data were collected by two methods: (1) through an interview with the agency director; (b) through questionnaires distributed to agency service workers who dealt with DSO clients. Not all agency workers received DSO client referrals, and only those

who did were included in the survey, since potential respondents were identified on a list of program participants provided by the grantee agency. Computed as the ratio of the number of respondents to the number of workers on the list, the response rate was 65% (Miller, 1978).

The data on interorganizational ties were gathered from the questionnaire survey of service workers in the following way. Each respondent was asked to name three persons in the local DSO program with whom s/he had five kinds of ties.[1] The respondent was given a list of all DSO practitioners in the community, whether employed by the respondent's agency or other agencies. In collecting these data, then, no formal distinction was drawn between intraorganizational and interorganizational ties. The number of sociometric reports which fell across agencies was simply totaled. This data collection strategy is consistent with the premise that researchers should not impose on respondents an arbitrary classification of internal versus boundary-spanning relations but should let any differences between the two emerge naturally from the analysis (Lincoln, 1982). The present focus, however, is on boundary-spanning ties, and no study of intraorganizational networks is attempted. As one might expect, the density of ties within agencies is considerably greater than that between them. Summing the ties reported on each of the three sociometric questions listed below, the agency mean for internal ties was 13.119 as compared with a mean number of boundary spanning ties equal to .449.

1. The pros and cons of fixed choice sociometric questions have been debated in recent years. The problems identified by Holland and Leinhardt (1973) are less pertinent here for two reasons. First, because respondent reports are aggregated to the agency level, errors in individuals' reports tend to average out. Second, because ties could be both within and between agencies, the outflow distribution of ties for agencies is not constrained to be invariant. The fixed choice criterion is advantageous in one respect, for it eliminates the possibility that a high volume of interorganizational ties reflects the boundary-spanning reports of a handful of well-connected persons.

Of the five network ties measured, the present inquiry deals just with three: influence, support, and assistance. The sociometric questions asked each repondent to name those persons in the DSO program who: (a) most influenced their work; (b) would support them in a dispute over DSO policy; and (c) would assist them in dealing with difficult clients. Each question produced a square matrix for each community whose cell entries were frequencies of reports from row agencies to column agencies.

All three questions clearly concern <u>asymmetric</u> transactions and are reasonably interpreted in power dependence terms. The two additional sociometric questions were less pertinent in this respect and were therefore not used. Although one might well expect networks based on influence, support, and assistance to diverge in form, these data suggest they map the same interorganizational relations. Computed over the 722 asymmetric agency pairs, the zero-order correlations were .891 between influence and support, .864 between influence and assistance, and .827 between support and assistance. Thus, relations in the DSO networks proved to be highly "multiplex". Boundary-spanning reports of the three kinds of tie were therefore summed, creating a single measure of linkage for interorganizational dyads. This simplifies the analysis and increases the density of the tie matrices to be analyzed, though these remain quite sparse.

<u>Modeling and Estimation</u>

This section describes the statistical methods to be applied to the DSO data on interorganizational ties. The problem of modeling dyadic relations in social networks has recently attracted close methodological attention. Holland and Leinhardt (1981) have proposed a log-linear probability model for digraph data which specifies parameters for reciprocity, indegrees (inflow

ties), outdegrees (outflow ties), and density. Feinberg and Wasserman (1981) have extended the Holland-Leinhardt model to take into account data on multiplex relations and nodal attributes. However, their methods for incorporating nodal characteristics into such dyadic models are cumbersome and limit the inquiry to a small number of dichotomous attributes.

The methods suggested here are based on the more familiar procedures of linear regression analysis. While perhaps less elegant statistically than the aforementioned work, they can handle efficiently a large number of nodal properties, while including (as in the Holland/Leinhardt and Feinberg/Wasserman models) parameters for reciprocity, "productivity", "attractiveness", and density. In addition, a procedure is proposed for dealing with one obvious kind of nonindependence of pairs-- that of different dyads possessing a common node. Previous analysts of dyadic data simply assumed that pairs are independent and ignored the issue. My approach is an application of methods for modeling spatial autoregression to the problem of dyadic dependencies. The general form of the model for pairwise interorganizational ties is first discussed, then attention is given to the nonindependence problem.

Let TIES(IJ) be the frequency of boundary spanning ties organization I reports to organization J. TIES(JI) is its transpose: the frequency of ties from J to I. In the regression analyses reported below, these two variables are transformed to natural logarithms. This serves to stabilize their variances and linearize their relations with predictor variables. Reciprocity in the exchange of ties between I and J is measured by a parameter capturing the linear association of TIES(IJ) with TIES(JI). Let X(I) be a vector of K properties of organization I and X(J) be a vector of the same properties describing J. These are regarded as exogenous determinants, and may be incorporated,

along with TIES(JI), in the model predicting TIES(IJ) as follows:

$$TIES(IJ) = \alpha + \beta_{ij}TIES(JI) + \gamma_i'X_i + \delta_j'X_j + \varepsilon_{ij} \qquad 1.$$

The K x 1 coefficient vector, γ_i , measures the effects of I's characteristics on I's propensity to report boundary spanning ties. δ_j measures the effects of J's characteristics on its "attractiveness" or overall propensity to be cited.

Equation 1 models the nodal or "main" effects of agency characteristics on interagency ties. It does not address the question of whether the <u>combination</u> of I and J's characteristics affects the volume of relations between them. However, by modifying (1) to include a vector of product terms, X_iX_j' , such statistical interaction or "dyadic" effects can be evaluated.

$$TIES(IJ) = \alpha + \beta_{ij}TIES(JI) + \gamma_i'X_i + \delta_j'X_j + \lambda'X_iX_j' + \varepsilon_{ij} \qquad 2.$$

The coefficient vector, λ , measures the adjustments to the effects of X_i (or X_j) for different values of X_j (or X_i). If λ contains zeros, the hypothesis of dyadic effects is rejected: the influence of X_i does not depend on X_j and vice versa.

The virtue of this model is that it permits the analyst to distinguish between the effects of <u>nodal</u> and <u>dyadic</u> properties on interorganizational relations. Previous dyad-based analyses examined the association between a relational variable and one or more measures of the combined attributes of the pair (e.g., a similarity or dissimilarity measure). This approach confounds general tendencies of nodes to emit or receive ties with tendencies for given configurations of sender/receiver characteristics to intensify or weaken the bond between the pair. Equation 2, however, estimates dyadic or interaction effects of nodal characteristics net of the "main" or additive effects of

those same characteristics, thus avoiding such confounding. The product term, $X_i X_j'$, may be formed from the scores of actors i and j on the same variable, X, or on different variables. If X is a measure of the same characteristic for agency I and agency J, a positive λ coefficient is interpretable as a <u>similarity</u> effect and a negative λ implies a <u>dissimilarity</u> effect.[2] On the other hand, the product term might be formed from measures of different characteristics of I and J; e.g., $X_i Z_j$. In this case, one interprets λ to mean the change in the effect of either X_i or Z_j that occurs with a one unit change in the other. When nodal characteristics can be viewed as organizational resources, these interaction terms speak directly to the question of how complementary resources shape interorganizational transactions.

Ordinary least squares would be an acceptable mode of estimating γ_i, δ_j, and λ, but β_{ij}, the reciprocity parameter, demands a different technique. The reason is that TIES(IJ) and TIES(JI) are simultaneously determined. Indeed, an equation can be written for TIES(JI) which is identical in form to (2):

$$\text{TIES(JI)} = \alpha + \beta_{ji}\text{TIES(IJ)} + \gamma_j' X_j + \delta_i' X_i + \lambda' X_j X_i' + \varepsilon_{ij} \qquad 3.$$

This equation is wholly redundant with (2), for $\gamma_j = \gamma_i$, $\delta_i = \delta_j$, and $\lambda = \lambda$. In addition, it is plausible to assume that $\beta_{ij} = \beta_{ji}$, since the ordering of i and j is arbitrary, having meaning only for a given pair. Indeed, by constraining the β's to be equal and the ε's to be uncorrelated between

2. A positive interaction, $X_i' X_j$, means that, as X_i and X_j change in the same direction (e.g., agencies I and J increase in size), the number of ties between agencies I and J also increases at a rate greater than that attributable to the additive linear effects of X_i and X_j. A negative interaction effect would mean that shifts in the same direction of X_i and X_j produce a net decrement in the ties between the pair. Similarity/dissimilarity seems a reasonable interpretation of these effects, even though some forms of similarity or dissimilarity can be envisioned which the product terms do not adequately represent. See Lincoln and Miller (1980) for a more detailed discussion of similarity/dissimilarity effects as measured by interaction terms.

equations, the model specifying TIES(IJ) and TIES(JI) as endogenous and the X's as exogenous is just-identified and is estimable with a regression program that performs simultaneous equation estimation with constraints imposed on parameter estimates. The program used here was LISREL IV which provides full information maximum likelihood estimates of endogenous variable coefficients. OLS overestimates the β's and thereby biases other model coefficients as well.

The final problem of model specification and estimation is that of observations on dyads failing to satisfy the independence assumption. This problem has long been acknowledged by network researchers modeling dyadic ties but solutions to it have not yet been found. The present solution is admittedly partial, dealing with only one obvious source of dependency. Yet that source looms particularly large as an obstacle in this analysis, and some attempt to deal with it seems mandatory.

The dependency in question stems from the occurrence of the same nodes in different dyads. Table 1 illustrates for the case of four nodes.

Table 1 about here

The rows and columns of the tables are all the pairs (excluding loops) that can be formed from a network of four nodes. A "1" in the table means that two pairs involve the same node, and a "0" means there is no common node.

The statistical literature on spatial autocorrelation suggests ways of dealing with these dependencies. In two recent papers, Doreian (1980; 1981) has reviewed certain of these techniques and discussed some sociological applications. Doreian's methods, which derive from the work of Cliff and Ord (1973), require one to represent the structure of dependencies among the observations in the form of a matrix, W. W has a zero diagonal, and cell

entries of zero where rows and columns are presumed independent. For dependent observations, an entry is made equal to the inverse of the number of dependencies in a given row. Replacing the "1"'s in each row of Table 1 with the inverse of the row sum would transform that matrix to such a "W".

Once a satisfactory W matrix is devised, a test for autocorrelation can be performed.[3] If that test proves negative, the values of a dependent variable may be presumed independent, and no estimation problem is posed. If it is positive, one is faced with a choice between modeling the autoregressive process as a predetermined variable or as part of the error structure of the equation. In this analysis, the autoregression term appears as another regressor in the model. Thus, the full model proposed for analyzing dyadic tie data is:

$$TIES(IJ) = \alpha + \rho WTIES(IJ) + \beta_{ij} TIES(JI) + \gamma_i' X_i + \delta_j' X_j + \lambda X_i X_j' + \varepsilon_{ij} \quad 4.$$

where WTIES(IJ) is the matrix product of W (G x G) and TIES(IJ) (G X 1). Assuming the presence of dependent pairs, ρ will absorb the nodal effects not conveyed by the X's. The LISREL estimate of ρ in this model is equivalent to an OLS estimate and is thus less satisfactory than the complex maximum-likelihood estimates discussed in detail by Doreian. However, Doreian (1981) has suggested that the savings in computational effort gained by OLS may, in practical applications, offset the loss in estimation precision. Illustrative results he presents indicate few large differences in the parameter estimates arrived at by ML and OLS techniques.

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3. The test, discussed by Doreian (1980:54), is based on the normal statistic: $Z = (N/T)(y'Wy/y'y)$, where N is the number of cases (here pairs), T is the sum of the elements of W, and y is the vector of dependent variable observations.

Characteristics of Organizations

This section lists the properties of DSO agencies to be treated by the analysis, describes their measurement, and presents hypotheses relating them to interorganizational ties.

1. Agency size (NRES). Always an important variable in organizational research, size in an investigation of the volume of interorganizational boundary-spanning takes on special significance. The indicator of size to be used in this analysis is the number of respondents in the agency. Since interorganizational relations are measured here as the sum of interpersonal ties that span agency boundaries, it is critical that a control be imposed on the number of persons eligible to make those reports. An agency might have a high volume of ties simply because it has more people reporting them.

Other dimensions of agency size which might have a bearing on network ties are total staff size and number of clients. Since not all agency staff served DSO clients, the total staff did not necessarily equal the DSO staff. Of these three size measures, however, only the number of respondents proved to have significant effects on interorganizational relations which were stable under alternative model specifications. However, zero order correlations involving client and staff size are presented to convey a sense of agency variation on these dimensions.

2. Agency age (AGE). New human service organizations-- particularly of the private nonprofit sort-- face formidable barriers to entry and have a high turnover rate. Acquiring a client base and other resources that circulate in a service delivery network are critical needs of young agencies (Lincoln, 1979). They are thus highly dependent actors whose survival depends on their abilities to secure resources from older, well established agencies. With

age, an agency acquires legitimacy, clients, and an established set of network relationships which provide it with access to resources and a relatively secure niche in the interorganizational system.

3. Number of services provided (NSERV). The range of services a youth agency provides (counseling, job training, outreach, crisis intervention, medical care, recreation) is an important resource dimension on which agencies vary. Agencies delivering many different services are able to treat clients with diverse needs. Their power and autonomy in the network are likely to be high, for they are less dependent on the services of other agencies and can accept referrals from a wide array of sources (Kobrin and Klein, 1980).

4. Proportion of professional staff (PROF). Youth service agencies rely heavily upon volunteers and low-paid service workers with little formal training. The proportion of staff consisting of trained counselors, social workers, medical professionals, and similar occupational groups reflects the professionalization of the agency. A high proportion of professionals might appear to be valuable resource in a service network. However, agencies treating problem youth may prefer to recruit "street-smart" volunteers with little formal training who know the local neighborhood and can better relate to clients.

5. Adminstrative status (ADMIN). In each DSO network, one or more agencies were charged with the administrative authority to coordinate the program and to allocate funds to other program organizations. Control of these paramount resources of legal authority and funding guaranteed the formation of dense dependence ties with these agencies. ADMIN was coded "1" for agencies occupying the administrative position, "0" for others (Miller, 1978). As noted earlier, three agencies are designated as the administration in both

Tucson and Oakland, whereas in Spokane only one agency performed this role.

6. Ties to community institutions. A community-based network of service delivery agencies develops stable ties to major local institutions. The types of institutions an agency is linked to and the strength of the linkage is an important source of differentiation among youth agencies. Respondents in each DSO agency were asked to rate the amount of contact they had with each of the following institutions on a six-point scale from "almost constantly" to "less than once a week."

a. Contacts with police and courts (JUS). The formal justice institutions of police and courts influence a network of youth service organizations in important ways. They are major sources of clients, funding, and authority for service agencies. Indeed, because youth service providers such as the DSO agencies are often highly dependent on the justice system, some critics have argued that they convey to children the labeling effects of justice contacts (Polk and Kobrin, 1976). A key rationale for diversion and deinstitutionalization programs, of course, is that of keeping to a minimum the exposure of juveniles to justice system labeling processes.

b. Contacts with schools (SCHL). A second major source of clients and other resources is community schools. Schools regularly refer problem children to youth agencies and may also supply agencies with funding and legitimacy. Schools frequently set up programs whereby agencies can provide services to students on school premises, thus facilitating service delivery and agency access to clients.

c. Contacts with churches (CHRCH). The third community institution is churches and other religious organizations. Religious groups often

sponsor youth agencies and programs serving youth. Like schools and justice agencies, they are sources of clients, funds, and legitimacy. Religious organizations, being private voluntary associations, however, are likely to represent a different segment of the service network from agencies closely allied with the justice system (Spergel, 1976).

6. Treatment ideology (BLAME). Another variable differentiating agencies providing services to problem youth is dominant treatment ideology or perspective on client problems. Although several such ideologies can be identified, clearly one with implications for service provision to problem youth and relations among youth serving agencies is what might be called the "blame-and-punishment" orientation. Staff respondents were asked to rate, on 9-point scales: (1) whether they felt juveniles in trouble were usually to blame for their problems or usually not to blame; (2) whether the best strategy in dealing with juveniles in trouble was providing punishment versus not providing punishment. The two items correlated .40. To form the agency measure, the mean of their sum was taken over all respondents in each agency.

8. Proportion of white clients (WHITE). The final agency property examined in the analysis is the proportion of whites among the agency's clientele. Just as interpersonal networks are heavily segregated by race, agency networks are segmented by the race and ethnic composition of their clients. Agencies serving nonwhite ghetto youth are unlikely to develop close ties with agencies whose clients are primarily suburban, white, and middle-class (Spergel, 1976).

9. Community network affiliation (SPOK, OAK). The present inquiry is not primarily concerned with sources of uniqueness in the three community DSO programs, and thus the agency dyads from each network are pooled to produce a

total of 722 asymmetric pairs: $(16^2 - 16) + (17^2 - 17) + (15^2 - 15)$. Separate analyses of the dyads for each community revealed general similarity in the effects of agency properties on interorganizational ties. Global network differences are assessed, however, by adding dummy variables representing the three communities to the regression models. The coefficient estimates for the dummies measure site differences in the total number of ties reported, thereby permitting inferences regarding the relative density of the three community networks. The dummy variables are coded for Spokane and Oakland. This coding is consistent with the hypothesis that the Tucson area agencies, being outside the established youth service network, were less likely to be densely linked to one another (Kobrin and Klein, 1980). Positive coefficients on the SPOK and OAK dummies would support this hypothesis.

Analysis

It is instructive to examine the zero-order correlations among the measures of DSO agency traits (Table 2). It would appear that

Table 2 about here

administrative agencies have more respondents, clients, and justice contacts than other DSO agencies but provide fewer services. Agencies with large staffs provide more services but are less professionalized. Professionalized agencies, moreover, have higher proportions of white clients. Agencies providing more services are older and are more likely to take a blame-and-punishment approach to clients. Not surprisingly, a blame-and-punishment orientation is correlated with justice system connections.

The first issue concerning the dependent variable, interorganizational ties, is autoregression stemming from the effects of common nodes. Applying the test discussed by Doreian to the measure of ties in each community

network confirms the presence of autocorrelation. Its calculated value is 3.842 in Tucson, 7.829 in Oakland, and 5.714 in Spokane, each of which is significant beyond the .001 probability level. The "N" on which each test is based is the number of asymmetric dyads ($G^2 - G$ where G is the number of agencies in each community): 240 in Tucson, 272 in Oakland, and 210 in Spokane.

Although TIES(IJ) takes on 722 distinct values across the three community networks, the t-values of the following regression estimates are computed on degrees of freedom equal to 361, the number of symmetric pairs. This seems preferable to setting the "N" equal to 722. The present modeling strategy involves estimating two simultaneous equations with endogenous variables, TIES(IJ) and TIES(JI). Each array contains the same 722 observations but their ordering differs. Thus, there are only 361 distinct joint observations on the two endogenous variables.[4]

Even with the reduced degrees of freedom, autoregression of TIES(IJ) is still in evidence. Regressing TIES(IJ) on WTIES(IJ), the autoregression term, yields a metric coefficient of .1291, a standardized coefficient of .093, and a t-statistic of 1.775 with df = 359. Given a one-tailed test (appropriate since a negative slope is meaningless), the null hypothesis of independent values of TIES(IJ) is rejected at the .05 level. The issue from here on is

4. An alternative modeling strategy is to split the sample into two distinct distributions of 361 observations each by arbitrarily labeling the value associated with one ordering of a pair, TIES(IJ), and that associated with the reverse ordering, TIES(JI). The drawback of this method is that the two estimating equations are no longer identical, although the differences can be attributed to sampling error. The present method which makes TIES(JI) the transposed TIES(IJ) ensures that the equation for each is a mirror image of the equation for the other. This approach is also analogous to the method of tabular analysis of sociometric data proposed by Holland and Leinhardt (1981) and Feinberg and Wasserman (1981). For each pair they define a four-fold table, the two binary (present or absent) dimensions of which represent the I to J tie and the J to I tie.

whether these dependencies are captured by the agency properties for which measures exist in the data set. That question is addressed by retaining WTIES(IJ) in the regression models and evaluating its coefficient estimate.

Table 3 presents the estimates for the TIES(IJ) equation in a

Table 3 about here

two-equation LISREL model where TIES(IJ) and TIES(JI) are the endogenous variables. Two equations are presented: with and without ADMIN(I) and ADMIN(J). It is useful to observe how the results change when these important predictors are added. First note that the autoregressive effect has vanished. The reciprocity and nodal paramaters in the model apparently suffice to account for the measurable similarities of pairs with common nodes. Also note that the reciprocity parameter has a positive and significant estimate. Despite the clear asymmetry of the ties examined here, if agency I reports that it is supported, influenced, or assisted by agency J, then J is likely to make similar reports of I.

The dummy variables representing Spokane and Oakland relative to Tucson have significant positive coefficients in Model 3.1. This is consistent with the hypothesis that, because the Tucson program had been organized outside the established network of youth service providers, the density of ties among its participating agencies is lower than in other programs.

Some discussion of the meaning of the effects of agency properties is in order. It is important to stress that coefficients associated with such properties in Table 3 represent <u>nodal</u> effects: the contribution of a property to an aggregate tendency for an agency to send or receive ties. These coefficients say nothing about the contribution made by a combination of sender and receiver characteristics to the frequency of ties. Such <u>dyadic</u> effects are

taken up in later analyses. Secondly, "sending" ties in the sense of making sociometric reports amounts to "receiving" in terms of the substantive relationships involved. That is, an organization which makes many reports is the object of influence, support, or assistance from other agencies. An agency named in a sociometric report is the source of these relations. An agency property labeled "I" refers to the level of that property for the agency in the dyad which is reporting ties and is thus the object of the relations. The same property labeled "J" refers to that characteristic of the agency doing the influencing, supporting, or assisting. For example, NRES(I) in Model 3.1 has a positive (but not significant at the .10 level) effect on the number of ties in the dyad.[5] Such an effect was anticipated on the ground that more respondents in an agency increases the number of reports that can be made.[6] However, no similar "necessary" effect of NRES(J) is presumed.

As for the other terms in Model 3.1, neither the service range nor the professionalization of the agency conditions its propensity to send or receive interorganizational ties. There is, however, support in this model for the hypothesis that young agencies are highly dependent: the negative coefficient on AGE(I) means that, with age, DSO organizations are less frequently the objects of these relations.

Other substantively interesting findings concern the measures of contact with community institutions. Agencies extensively linked to the police and

5. Having previously made the conservative decision to base the degrees of freedom on the number of symmetric rather than asymmetric pairs, the liberal decision is now made to use a minimum significance level of .10 in judging a regression estimate to be nonzero. This is warranted by the sparseness of the tie matrices and therefore the small variance of TIES(IJ).
6. This is not a mathematically necessary and hence trivial relation, however, since respondents could identify others within their own agencies as sources of these relations.

courts are central actors, i.e., their capacities to dispense influence, support, or assistance are significantly enhanced. The opposite is true of church-linked agencies: they are a source of fewer such relations. Ties with schools make no difference in the rate at which agencies emit ties. Moreover, linkage with all three institutions apparently has nothing to do with whether an agency receives or is the object of such relations.

Finally, Model 3.1 shows that the proportion of white clients in an agency has a nearly significant effect on the emission of boundary-spanning ties. This seems counter-intuitive, for one would normally expect a high proportion of white clients to be a resource in an American service-delivery network. Speculation on this finding is withheld, however, until other results are in, for it vanishes in Model 3.2 when the control for agency administrative status is imposed, and it proves to be contingent on the properties of the other organizations with which each agency is paired.

Indeed, 3.2 reveals that other results change when the ADMIN terms are added to the equation. The effect of agency age is wholly demolished, and those of church ties and membership in the Spokane network are no longer significant. The effect of justice contacts is likewise reduced but remains significant, while those of reciprocity and the number of respondents (I) are slightly enhanced. The influence of all other terms in the model pale, however, in comparison to the strong effect of administrative position on the agency's propensity to emit ties. Adding ADMIN(I) and ADMIN(J) to the model reduces the error variance by 18%, but this increment in predictive power is not shared equally. Whether an agency holds the administrative status is not related to its tendency to receive influence, assistance, or support from others. But that status has a very pronounced impact on whether other agencies

are the objects of relations emanating from it. Administrative agencies are clearly a major source of interorganizational influence, support, and assistance in these networks, implying a broad pattern of dependence upon them arising from their control of funding and authority.

To summarize, agencies in the DSO networks reciprocate ties of influence, assistance, and support, the Tucson network is less dense than the Spokane and Oakland networks, the number of respondents in an agency increases the number of boundary-spanning ties it reports, and justice contacts and administrative status are resources which foster dependence on the organizations which possess them. Suggestive evidence in Model 3.1 that religious affiliations and age shape ties did not hold up in Model 3.2 which controlled for the administrative role. Still, given the sizable correlations among some agency properties, and the overwhelming influence of ADMIN, perhaps one should not be too quick to discount these theoretically meaningful effects.

Dyadic Effects: Similarity/Dissimilarity

Now the focus of the analysis shifts and consideration is given to the effects of dyadic combinations of agency properties. Table 4 addresses the influence on ties of

Table 4 about here

agency similarity/dissimilarity on each nodal property. Each interaction term is the product of the I and J agencies' scores on the same agency measure. The regression coefficients and t-values were obtained by estimating ten equations, each containing all the terms in Model 3.2 plus one product term. The collinearity of the product terms with their components and one another precluded entering them all in a single regression model. Earlier sections argued that dissimilarity effects are compatible with an exchange theoretic

interpretation of interorganizational relations. This was contrasted with a "homophily" perspective, holding that organizations, like individuals, are attracted to one another when they have in common values, ideologies, clientele, and other characteristics.

The interaction effects of the source and object agencies' levels of the same properties reveal no support for a dissimilarity or exchange interpretation. Two are indeed negatively signed but their size is negligible. On the other hand, three positive coefficients are statistically significant, and one is nearly so. First, there is a pronounced tendency for agencies with similar "blame-and-punishment" views to be linked. Thus, treatment ideology does indeed segment service delivery networks as argued by previous observers. Secondly, the hypothesis that interorganizational networks are divided by race and ethnicity finds support in the interaction effect of agency race composition (cf. Galaskiewicz and Shatin, 1981). Agencies similar in this regard are significantly more prone to influence, support, and assistance transactions. Before attributing this result to the impact of racist sentiments on referral decisions, however, it should be acknowledged that client race composition may be a proxy for other agency characteristics. As Spergel (1976) has pointed out, agencies serving low income nonwhite youth tend to be publicly sponsored inner city organizations, whereas agencies serving middle class whites are more often private and suburban.

Another significant dyadic effect in Table 4 involves the administrative status of the agency. One would expect that in the two networks (Tucson and Oakland) where multiple agencies comprise the DSO administration there would be numerous transactions between them. Indeed, the coefficient on the ADMIN product term is probably attenuated by inclusion of the observations on

Spokane where the administration consisted of a single agency.

Finally, a positive coefficient on the interaction of NSERV(I) and NSERV(J) is nearly significant at the .10 level. Thus, agencies with similar service patterns have a greater frequency of boundary-spanning ties.

In the DSO networks, then, similarity or homophily with respect to treatment ideology, client race, administrative status, and (to a slight extent) service range are forces stimulating the interorganizational flow of influence, support, and assistance.

Dyadic Effects: Agency-Administration Combinations

Table 4 dealt with the question of whether similarity or dissimilarity of agency dyads on single organizational characteristics conditioned the volume of ties. Earlier, dissimilarity effects were judged consonant with the reasoning of exchange theory, whereas similarity effects were believed implied by a "homophily" interpretation of interorganizational relations. No dissimilarity effects (negative interactions) were detected in the data, but it would be wrong on the basis of this evidence alone to reject a resource dependence or exchange perspective. Indeed, the notion of complementarity derived from this perspective is only partly tapped by a measure of the joint position of two organizations on the same dimension. It further implies that organizations with different combinations of resources are likely to be drawn into exchange relations. Moreover, resource dependence theory further stipulates that access to alternative resources may modify the power relationships that resource dependencies create. That is, A's dependence on B for resource X may not imply power of B over A to the extent that A controls resource Z. This line of thought leads to an examination of the combinations of different properties of the agencies which are source and object of influence, assistance,

and support relations. With the 10 agency properties measured here, 90 product terms (100 minus the 10 considered in Table 4) can be computed to represent the effects of dyadic combinations of agency characteristics. If one could meet the theoretical challenge of specifying all the resource exchanges possible in a network (e.g., professional expertise for justice system authority), evaluation of the full set of dyadic effects might be worthwhile. Without such encompassing theory, however, a wholesale survey of all possible interactions seems unwise. Yet one set of combinations is clearly worth examining. Occupancy of the administrative position has proven by far the most critical resource determining an agency's overall network centrality. It remains to determine whether the degree of agency dependency on the administrations of the three programs is a constant, or whether control of alternative resources may modify that dependence in distinct and measurable ways.

Table 5 addresses this question in presenting slope coefficients and t-values

Table 5 about here

for interaction terms represented by the products of ADMIN(I) and ADMIN(J) with the remaining nine properties of source and recipient agencies. Each pair of product terms was added to equation 3.2 to produce the regression statistics in each row of the table. These effects are interpretable as follows. The coefficient estimated for the product of ADMIN(J) with X(I) records the change in the effect of the administrative role on production of ties with increases in the level of X of the agencies receiving them. Alternatively viewed, it is the difference in X(I)'s effect when the source of the relation is an administrative as opposed to nonadministrative agency. A similar

interpretation reversing I and J can be made of the coefficient on the product, ADMIN(I)*X(J).

An important inference to be drawn from Table 5 is that size and justice system contacts are resources which reverse the general pattern of agency dependence on the DSO administrative organizations. In the case of each such property, the two interactions with ADMIN have opposite signs depending on the flow of the relation. The terms denoting the adjustments to the effect of ADMIN(J) with size or justice contacts have negative coefficients. This means that administrative agencies are less a source of these relations when the other party to the dyad is large or has strong justice connections. But the terms indicating the adjustment to the ADMIN(I) effect are positive, i.e., administrative agencies are themselves objects of more influence, assistance, and support from organizations that are large or are linked to justice institutions. In other words, size and justice access reduce an agency's dependence on the local DSO administration while increasing the administration's dependence on agencies possessing those resources.

Note further that, despite the very small size of some coefficients, all the ADMIN(J) interactions with agency properties which can reasonably be viewed as resources (all, that is, but BLAME) show negative coefficients. This pattern is consistent with the expectation that an agency's resources enable it to reduce its dependence on the administration. In addition to the size and justice coefficients, however, only three of these effects reach statistical significance: those of service range, school contacts, and the proportion of white clients. On the other hand, these resources, unlike size and justice connections, do not foster the administration's dependence on the agency controlling the resource. The ADMIN(I)*X(J) term is nonsignificant in

each such case.

The results in Table 5 regarding blame-and-punishment ideology constitute a strong pattern of a different order. Both its interactions with ADMIN are positive and significant. That is, a higher than average number of mutual ties flow between DSO administrators and agencies holding an unsympathetic and punitive view of clients. From one perspective, this is a surprising outcome, since a retributive approach to juvenile offenders hardly seems consistent with the goals of the DSO program. Possibly such relations grew out of the administrative organizations' attempts to monitor and control the treatments punitively-oriented agencies gave to clients. This would support the view that DSO principles discouraged client orientations of this sort, for agencies holding to a rehabilitative stance would require less supervision. But this argument is weakened by the lack of evidence in Table 2 that the DSO administrators take a stand one way or another on the blame and punishment issue: the ADMIN-BLAME correlation is zero. An alternative interpretation stresses less the administration's close ties with agencies believing in blame and punishment and more its weak exchanges with agencies opposing this approach. Organizations philosophically opposed to blame and punishment may be somewhat marginal to the established youth service network, if not the DSO network per se. That they are younger, provide fewer services, and have fewer justice contacts also suggests this (Table 2). The DSO administrative agencies have close ties to courts and police, both in terms of their organizational makeup and their pattern of staff contacts. Even though the DSO administrators do not necessarily subscribe to blame-and-punishment as the appropriate way to deal with problem youth, their position in the community youth service system may have led to weak ties with treatment agencies taking a strongly rehabilitative and

antipunitive approach to clients.

Conclusions

The results presented here regarding the effects of agency properties on asymmetric ties in the three DSO community networks are suggestive evidence of resource dependence and homophily influences on interorganizational exchanges. Focusing on relations which were interpretable in power dependence terms-- the flow of influence, support, and assistance from one organization to another in a network-- the objective of this research was to model asymmetric relations in interorganizational dyads in a fashion permitting strong interpretations of the effects of organizational properties. How to evaluate the impact of nodal variables on relational outcomes has long vexed network researchers. The procedures proposed here are, in general, not complex computationally; they allow the analyst to simultaneously handle a large number of nodal measures; they deal with such additional matters as reciprocity and nonindependence of pairs; and they permit evaluation of nodal effects in a way that speaks to certain key issues in interorganizational theory.

The present results address dominant network theories somewhat more directly than does past research. First, there is "homophily" theory, which has different forms and labels but at its core a stress on values, sentiments, and related bases for the attraction of like organizations. Previous interorganizational network research has examined similarity or homophily effects on dyadic ties, but the credibility of this work is often cast in doubt by the absence of controls for main effects of nodal attributes. Associations between difference or similarity scores for dyads and relational measures are suspect when no attempt has been made to adjust such associations for nodal tendencies to vary in total ties sent or received. Secondly, there is the dominant

paradigm, resource dependence/exchange theory. But the evidence to date which bears on it is very indirect at best. I would argue that the analysis exemplified by Table 5 is particularly well suited for addressing the question of how organizations with complementary resources form power dependence ties. That analysis was only a first and partial step toward specifying the kinds of resource configurations that shape transactions between organizations in the DSO networks, but its results were highly suggestive nonetheless.

The key substantive findings of the investigation are the following. Despite the attempt of interorganizational theorists to downplay the importance of ideologies and values, the impact of agency treatment ideology on the DSO networks is dramatic. A clear tendency toward homophily in this regard was evident in the data: the volume of ties between two organizations increased as they shifted in the same direction on the blame-and-punishment measure. Moreover, ties with the DSO administration were strongly influenced by treatment ideology: mutual exchange of ties with the administrative nodes increased as agencies showed greater tendencies to adhere to blame-and-punishment views. Secondly, while other possible interpretations were noted, the evidence that agencies with similar client racial makeups have more frequent exchanges may well mean that deep-rooted racial prejudices and tensions in American society operate to fragment interorganizational networks and erect barrers to service delivery coordination.

Also dramatically displayed in these data is the impact of legal authority and funding control as measured by occupancy of the DSO administrative status. This was by far the best predictor of whether an agency was cited as a source of influence, assistance, or support. But perhaps most interesting

was the suggestive evidence that the influence of the administrative position proved contingent on the level of resources controlled by member agencies in the networks. Large agencies and agencies with justice system connections saw the administration less often as a source of influence, assistance, or support, but were themselves cited by the administrative organizations as sources of these relations. Other resource characteristics of agencies likewise operated in such a way as to suggest reduction in those agencies' dependence on the administration. These findings are fairly direct testimony for the proposition that unequal and diverse resources in an interorganizational network give rise to a complex matrix of cross-cutting and offsetting power dependence ties. Devising empirical models with the precision to adequately describe such networks is the major challenge currently facing interorganizational research.

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Table 1: Matrix of Pair Dependencies in the Case of Four Nodes

	1,2	1,3	1,4	2,1	2,3	2,4	3,1	3,2	3,4	4,1	4,2	4,3
1,2	0	1	1	1	1	1	1	1	0	1	1	0
1,3	1	0	1	1	1	0	1	1	1	1	0	1
1,4	1	1	0	1	0	1	1	0	1	1	1	1
2,1	1	1	1	0	1	1	1	1	0	1	1	0
2,3	1	1	0	1	0	1	1	1	1	0	1	1
2,4	1	0	1	1	1	0	0	1	1	1	1	1
3,1	1	1	1	1	1	0	0	1	1	1	0	1
3,2	1	1	0	1	1	1	1	0	1	0	1	1
3,4	0	1	1	0	1	1	1	1	0	1	1	1
4,1	1	1	1	1	0	1	1	0	1	0	1	1
4,2	1	0	1	1	1	1	0	1	1	1	0	1
4,3	0	1	1	0	1	1	1	1	1	1	1	0

Table 2. Zero-Order Correlations among Agency Variables

		2	3	4	5	6	7	8	9	10	11	12
NRES	1	033	516	-273	577	-287	-220	497	-177	176	-053	-154
STAFF	2		033	-026	-001	-206	230	-015	-176	-092	-103	094
KIDS	3			-144	654	-025	-228	577	-049	050	032	074
AGE	4				-188	019	252	-325	-005	-154	359	252
ADMIN	5					-025	-365	528	-085	002	072	019
PROF	6						-121	007	022	-162	010	451
NSERV	7							-157	-118	192	258	088
JUS	8								096	292	244	184
SCHL	9									138	018	-206
CHRCH	10										019	-208
BLAME	11											133
WHITE	12											

Decimal points have been omitted.

Table 3. Regressions of TIES(IJ) on Agency Properties

	Model			
	(3.1)		(3.2)	
Predictor Variable	b (t-value)	B	b (t-value)	B
WTIES(IJ)	-.0752	-.054	-.0790	-.057
	(0.885)		(0.079)	
TIES(JI)	.0622**	.062	.0831***	.083
	(2.369)		(3.173)	
SPOK	.2278**	.216	.1269	.120
	(1.986)		(1.181)	
ALAM	.1856**	.188	.1589**	.161
	(2.128)		(1.975)	
NRES(I)	.0200	.121	.0225*	.136
	(1.576)		(1.845)	
NRES(J)	.0164	.099	-.0163	-.098
	(1.314)		(1.339)	
NSERV(I)	-.0001	-.008	-.0002	-.011
	(0.126)		(0.191)	
NSERV(J)	.0003	.002	-.0006	-.004
	(0.033)		(0.059)	
PROF(I)	.0323	.042	.0404	.053
	(0.656)		(0.891)	
PROF(J)	-.0003	-.019	-.0002	-.015
	(0.309)		(0.277)	
AGE(I)	-.0211**	-.142	-.0009	-.006
	(2.319)		(0.102)	
AGE(J)	-.0011	.040	-.0009	-.032
	(0.592)		(0.508)	
JUS(I)	-.0019	-.00	.0045	.011
	(0.0477)		(0.116)	
JUS(J)	.1675***	.390	.0977***	.226
	(4.528)		(2.759)	
SCHL(I)	.0125	.036	.0112	.032
	(0.651)		(0.631)	
SCHL(J)	-.0129	-.037	-.0064	-.018
	(0.573)		(0.309)	
CHRCH(I)	-.0471	-.061	-.0506	-.066
	(1.078)		(1.254)	
CHRCH(J)	-.0762*	-.099	-.0323	-.042
	(1.742)		(0.797)	
BLAME(I)	-.0226	-.051	-.0224	-.050
	(0.882)		(-.0224)	
BLAME(J)	.0143	.032	.0281	.063
	(0.581)		(1.243)	
WHITE(I)	-.0001	-.006	-.0001	-.008
	(0.082)		(0.123)	

(Table 3 continued)

WHITE(J)	-.0002	-.105	-.0009	-.055
	(1.600)		(0.898)	
ADMIN(I)	----	----	-.0645	-.048
	----		(0.758)	
ADMIN(J)	----	----	.6535***	.484
	----		(7.976)	
R^2	.375		.554	

* p < .10 by a two-tailed test with df = 336.
** p < .05.
*** p < .01.
b is the metric regression slope and B is the standardized slope.

Table 4. Interactions of I and J Agencies' Levels of Same Properties

Interaction Term	b	t-value
NRES(I*J)	.0018	0.718
NSERV(I*J)	.0010	1.621
PROF(I*J)	.00001	0.597
AGE(I*J)	.00002	0.394
JUS(I*J)	.0081	0.430
SCHL(I*J)	-.0043	-0.455
CHRCH(I*J)	-.0164	-0.369
BLAME(I*J)	.1475***	7.498
WHITE(I*J)	.00003**	2.475
ADMIN(I*J)	.3926**	2.156

* p < .10 by a two-tailed test with df = 335.
** p < .05.
*** p < .01.

These results were obtained by entering each interaction term singly in Model 3.2.

Table 5. ADMIN Interactions with Other Agency Properties

	ADMIN(I)		ADMIN(J)	
Agency Property	b	t-value	b	t-value
NRES	.0667***	3.134	-.0362*	-1.676
NSERV	-.0140	-0.692	-.0442**	-2.204
PROF	-.0009	-0.461	-.0003	-0.133
AGE	.0010	0.239	-.0025	-0.602
JUS	.1287**	2.212	-.0955*	-1.640
SCHL	-.0272	0.676	-.0837**	-2.086
CHRCH	-.1021	-1.152	-.0495	-0.558
BLAME	.2013***	3.383	.2235***	3.737
WHITE	.0010	0.478	-.0044**	-2.180

* p < .10 by a two-tailed test with df = 334.
** p < .05.
*** p < .01.

These results were obtained by entering each pair of interactions with ADMIN (e.g., ADMIN(I)*NSERV(J) and ADMIN(J)*NSERV(I)) in Model 3.2.

END

MF-1