Mimetic Processes within an Interorganizational Field: An Empirical Test

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The paper explores DiMaggio and Powell's thesis that under conditions of uncertainty organizational decision makers will mimic the behavior of other organizations in their environment. We add to their discussion by positing that managers are especially likely to mimic the behavior of organizations to which they have some type of network tie via boundary-spanning personnel. Data are presented on the charitable contributions of 75 business corporations to 198 nonprofit organizations in the Minneapolis-St. Paul metropolitan area in 1980 and 1984. Using logistic regression models, we found that a firm is likely to give more money to a nonprofit that was previously funded by companies whose CEOs and/or giving officers are known personally by the firm's boundary-spanning personnel. Firms are also likely to give greater contributions to a nonprofit that is viewed more favorably by the local philanthropic elite. We also found that a nonprofit is likely to receive more money from a corporation that previously gave money to nonprofits whose directors sit on the nonprofit's board. We concluded that managers utilize the information gathered through extraorganizational, interpersonal networks to make decisions on how to relate to other organizations in their task environment and achieve organizational ends.•

UNCERTAINTY, RATIONALITY, AND INSTITUTIONAL PROCESSES

The study of decision making under conditions of environmental uncertainty still occupies a central position in the organizational literature. Since the pioneering work of Simon (1965; March and Simon, 1958), it has been clear that while organizational decision makers may strive to make rational (i.e., fully informed) decisions, they often find themselves making decisions with less than complete information. Often managers find they do not have information on changes in their environment, how these changes will affect their organization, or if their response to these changes will have the intended consequence or effect (Milliken, 1987). Uncertainty is especially common in the interorganizational arena, inasmuch as the environment is made up of less than fully informed organizations that are making strategic choices in light of the strategic choices of other uninformed organizations.

Organizational theorists have been preoccupied with identifying various structural solutions to the problem of uninformed decisions. Management can invest in boundary-spanning roles (Aldrich, 1979), vertically integrate operations (Williamson, 1975, 1981), hire agents (Shapiro, 1987), or strategically fill board positions (Pfeffer, 1972, 1973; Burt, 1983). Although these strategies are ancillary to production functions, because the prospect of making uninformed decisions haunts administrators and managers, considerable time and effort is invested in them.

DiMaggio and Powell's (1983) contribution to this literature points out that decision making under conditions of uncertainty is often influenced by subtle social processes—coercive, normative, and mimetic. In an information vacuum, managers look for direction outside of their organizational boundaries and may find themselves pursuing options that

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have little to do with either efficiency or goal attainment. For example, managers may compulsively conform to rules and regulations postulated by the state or the norms of the larger society. While their actions may not make the organization more profitable or enable it to better achieve its ends, these measures will at least ensure the organization's legitimacy.

Alternatively, managers may model their organizations after other organizations in their field. They are especially likely to imitate organizations they perceive as more successful. Again, efficiency and goal attainment are of minimal importance. A sense of simply "doing something" or becoming identified with "successful" organizations is more critical. In a sense, mimicry is another way to accrue an external referent of prestige (Perrow, 1961). This a particularly attractive strategy when significant others in the organization's environment have little else upon which to judge an organization's actions.

Finally, managers may turn to norms and standards held sacred in their business and professional circles. These circles have a set of "routine" or "acceptable" solutions to certain managerial and professional problems. These solutions are institutionalized in the occupational subculture of the profession. In practice, these standards of behavior are communicated to managers in graduate school, workshops, seminars, training sessions, and through professional and trade magazines. Furthermore, as managers change jobs and move from one organization to another, they take with them these norms and problem-solving strategies.

One of the more attractive features of DiMaggio and Powell's thesis is that these processes can operate either through the conscious choice of managers, as suggested above, or without the principals' cognition. A common theme in the institutional literature is that certain organizational decisions are "taken for granted" or just seem "obvious." Decision makers do not consciously engage in a strategic choice but, rather, are "compelled" to take certain actions. For example, because of their socialization into societal or professional values and norms, managers pursue strategies without reflecting on alternative courses of action or consciously weighing options. Thus coercive, mimetic, and normative processes can be operative either with or without the knowledge of the decision maker.

Social Networks and Mimetic Processes

Recently, network analysts have offered their own set of strategies for decision making under conditions of uncertainty. In general terms, Granovetter (1985) argued that personal contacts across organizational boundaries can be extremely useful in overcoming the uncertainty and distrust that often plague economic transactions. Even though it may be less cost-effective in the short run to do business with a personal friend or acquaintance, managers will absorb the short-term cost so as to maintain a long-term and trustworthy relationship with the buyer/seller (see also Macaulay, 1963). Supposedly, doing business with a trustworthy other reduces the likelihood of opportunism.

Networks may also be a source of information and new ideas for organizational decision makers. By tapping those in their networks, managers learn about options and strategies that they themselves might adopt. The sociological literature on social contagion has extensively documented how ideas, information, and technology (or know-how) spread throughout a population via social networks (see Rogers, 1983, for a review). In general, this literature proposes that if two actors have a direct relationship with one another, they are more likely over time to think alike or behave similarly. The assumption is that actors will first exchange information and then one will persuade the other to "give it (an idea, style, or behavior) a try." Snow, Zurcher, and Ekland-Olson (1980) provided an excellent review of the literature that shows that members of social movement organizations, especially religious organizations, typically have been recruited by friends or acquaintances. There is also evidence of interpersonal influence effects in Coleman, Katz, and Menzel's (1966) study of medical innovation, and DiMaggio and Powell (1983) have noted the importance of social networks among professionals. Those who have direct and indirect ties to peers in other organizations are able to learn about the newest innovations in treatment or organizational design. They also learn what is and what is not acceptable to various stakeholders. Ideas and behaviors may also be diffused through interorganizational networks.

We argue that network ties between boundary-spanning personnel *across* organizational boundaries can act as a conduit to disseminate ideas and innovations throughout an organizational field. We argued earlier that managers operating under conditions of environmental uncertainty will mimic the behaviors of other organizations; however, it is very difficult to predict whom an organization will imitate, without knowing the network of ties extenuating from the organization through its boundary spanners. It is these network ties that allow organizational decision makers to see how other organizations cope with environmental conditions similar to their own and thus get some idea as to how to behave themselves. Our theoretical rationale for this "network effect" is quite simple: decision makers are more likely to mimic those whom they know and trust, and it's through the networks of boundary-spanning personnel that they come to know and trust one another.

Mimicry, Networks, and Corporate Contributions

This paper focuses on corporate contributions to charitable organizations. In a corporate grants economy, for-profit business corporations make unreciprocated or unilateral transfer payments to not-for-profit organizations. These contributions are tax deductible and supposedly serve some public need (Useem, 1987). This organizational field is of interest to us because it is unclear what governs the allocation of resources among grant or gift recipients, given that supply and demand are irrelevant, and because the buyer (the corporate donor) of the service that the nonprofit provides is not the ultimate consumer of the service. The beneficiaries of the donor's largess are third parties to the transaction, e.g., students, patients, audiences, neighborhood residents, etc. This means the donor can seldom tell if there is any real demand for the services the nonprofit provides or if the supply of services is adequate. As Boulding (1973: 24) pointed out, most donors have to wait so long before they get any feedback on transactions that it is very unlikely enough discipline would develop within a grants economy to redirect the flow of resources. In contrast to market economies, in which actors can tell if they are better or worse off in a given transaction, in a grants economy the donor does not see or experience benefits until far into the future. Thus although donors may have preferences, feedback comes so slowly that donors often do not have the information they need to rechannel their resources to realize a more beneficial and efficient (i.e., less costly) outcome.

Given the uncertainty corporate donors face, we expect they will often mimic others in their environment to whom they have some ties. For instance, companies will look to opinion-leaders in the corporate philanthropic community, respected corporate executives who have spent a great deal of time working with nonprofits, and will tend to support organizations supported by these philanthropic activists. This is what Galaskiewicz (1985b) found in the Twin Cites in an earlier study. By funding the nonprofits the elites support, organizations enhanced their own status and received recognition from the elite, so they simultaneously enhanced their own legitimacy (Galaskiewicz, 1985b). Furthermore, firms are especially susceptible to being influenced by high-status opinion-leaders if the latter are in direct contact with the company's executives and thus often soliciting the firm for their favorite charities. Thus we expect that if a chief executive officer (CEO) is directly tied to a high-status opinion-leader, the CEO's firm will contribute to organizations favored by the elite group:

Hypothesis 1 (H_1): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit is well regarded by the local philanthropic elite.

Hypothesis 2 (H_2): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit is well regarded by the local philanthropic elite and the company's CEO is in direct contact with the local elite.

We also expect that corporate donations will be heavily influenced by peer networks. For instance, company giving should be influenced by the opinions and behaviors of those in the social networks of giving officers. These staff members are primarily responsible for accruing information on prospective donees. According to Galaskiewicz (1985a: 646), contributions officers rely heavily on peer contacts for information regarding nonprofits. If they do not have information on a prospective donee, officers will often contact a peer in another firm. Galaskiewicz (1985a: 656) also found that if two giving officers were in direct contact with each other, they were more likely to regard the same nonprofits in their task environment as having achieved extraordinary accomplishments. In other words, if two officers are in contact with each other, they are likely to evaluate nonprofits in their task environment similarly. We expect corporations will donate to nonprofits that the contacts of their giving officer think highly of and support. If actors in the giving officer's primary network regard the nonprofit highly and fund it, it will appear less risky to the donor:

Hypothesis 3 (H_3): Corporation *i* is likely to give a larger donation to nonprofit *j* if officers in other firms who had direct ties to the giving officer of corporation *i* think highly of the nonprofit.

Hypothesis 4 (H_4): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit previously received funding from firms whose giving officers have direct ties to the giving officer of corporation *i*.

Peer contacts among top executives of firms should also be an important source of information. Obviously these contacts are not created for the purpose of circulating information on nonprofit organizations but are created and maintained to provide information to executives on a wide range of topics. Yet we believe these contacts may be critical in influencing company contributions. As executives hear about different nonprofit organizations from their peers or see peers funding these organizations, they are more likely to direct their firms to support them with corporate donations:

Hypothesis 5 (H_5): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit previously received funding from firms whose CEOs have direct ties to the CEO of corporation *i*.

There is also considerable uncertainty on the donee's side. Nonprofit organizations must respond to two constituencies. On the one hand, there are clients, students, or members who are the recipients of the service the organization provides. Activities must be geared to meet their needs; however, this is not difficult, since it is easy to know what this constituency wants and needs. On the other hand, there are corporate donors, foundations, and government agencies that provide funding but do not consume the nonprofit's outputs. These actors have their own agenda, and the donee must also take these agenda into account. However, because these actors are not consumers and thus not easily accessible, it is difficult to know their priorities and what they are willing to fund.

Given the uncertainty nonprofits face, nonprofit administrators and fundraisers should find networks useful to gather information on prospective donors. Interlocking directorates with other nonprofit organizations may be an especially important source of information on prospective donors. Given that nonprofit providers typically do not have funders as clients, they have to rely, for their information, on others in the nonprofit community who have experience with funders. If one's directors are sitting on boards of nonprofits that have been funded by a corporation, there is ready access to an organization that has direct experience with the funder. Given that network ties are useful conduits through which information on the environment flows, we expect nonprofits will use their networks to secure information on prospective funders and to pursue these funders:

Hypothesis 6 (H_6): Nonprofit *j* is likely to receive a larger donation from corporation *i* if the corporation has previously funded nonprofits whose directors are represented on the board of nonprofit *j*.

We also expect indirect ties to be critical in disseminating information on prospective donees and donors. In contrast to a direct contact, an indirect contact is someone whom one does not know personally but who is known to one's contacts. In graph theoretical terms, the other is at a path distance of two from ego. Ego's indirect contacts are defined by the set of actors directly related to ego's contacts but who have no direct relationship to ego herself.[1]

We expect that officers and CEOs who are in direct contact with a firm's boundary spanners will occasionally act as references or brokers, passing information to these boundary spanners about the nonprofits *their* friends funded. These individuals are not affiliated with companies that funded a certain nonprofit, but they know someone who is affiliated with a firm that did. If ego trusts his or her direct contacts, the information passed through these actors may be very useful and influence ego's allocations:

Hypothesis 7 (H_7): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit previously received funding from firms whose officers have indirect ties to the giving officer of corporation *i*.

Hypothesis 8 (H_8): Corporation *i* is likely to give a larger donation to nonprofit *j* if the nonprofit previously received funding from firms whose CEOs have indirect ties to the CEO of corporation *i*.

Finally, we expect directors of nonprofit organizations will occasionally act as references or brokers, passing information to ego about the corporations that funded *their* contacts. Although a director may not serve on any boards that received funding from a donor, there may be others on his or her board who are affiliated with nonprofits that have received funding. If nonprofit administrators can "tap into" the contacts of their board members, they may learn more about prospective funders through these networks:

Hypothesis 9 (H_9): Nonprofit *j* is likely to receive a larger donation from corporation *i* if the corporation has previously funded nonprofits whose directors are indirectly represented on the board of nonprofit *j*.

Certainly there are other factors besides these influencing corporate contributions (see Useem, 1987). For instance, companies are more likely to fund a nonprofit if they have previously funded it. Furthermore, research has consistently shown that companies are more likely to fund a nonprofit if they have more pretax income (Burt, 1983; Galaskiewicz, 1985b; Nelson, 1970). Finally, companies are more likely to fund a nonprofit if their giving officers think highly of the organization (Galaskiewicz, 1985b). While we recognize the importance of these factors, our hypotheses focus on relational factors because mimetic processes operate at the interorganizational level. However, these other factors should be taken into account. After presenting the results of tests for our hypotheses, we present the results of additional multivariate models that included all the factors that we found significant in our bivariate analysis, as well as some of these control variables.

Finally, there is a set of variables measured on the nonprofit organization that we have not discussed but that may also have a strong impact on corporate contributions. Among these are nonprofit size, degree of professionalism, the prestige of the board, organizational mission, and a host of other variables that may influence the amount of corporate dollars nonprofits receive (Galaskiewicz, 1985b). Unfortunately, because of the complexity of the hypotheses we have outlined and the space limitations in this paper, we were not able to assess the impact of these variables on corporate contributions.

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Another way of thinking about network contacts is in the framework of structural equivalence (Burt, 1987). Traditionally, structurally equivalent sets are defined by similarity scores based on each actor's relational profile: actors in a structurally equivalent set have similar relational profiles. When considering the contacts of ego's principal contact, we are considering those actors in the network who are structurally equivalent to one particular actor—ego's principal alter. When considering all the contacts of ego's contacts, we are considering all those actors who are structurally equivalent to a whole subset of actors—all of ego's alters.

METHOD

Data

The data used in this paper were taken from two different studies: one looked at corporate giving in 1980 and 1981 (Galaskiewicz, 1985b), and the other examined the response of nonprofit organizations and institutional funders to funding cutbacks during the period 1980–1984 (Galaskiewicz, 1986; Galaskiewicz and Bielefeld, 1986). In 1981 we drew a 20 percent stratified sample from the population of 1,601 not-for-profit public charities (excluding churches and foundations) headquartered in the Minneapolis-St. Paul metropolitan area. Forty-two organizations could not be located, 18 were known to be defunct, 22 were only "paper" organizations (e.g., trusts), and 15 organizations refused to participate in the study. We successfully interviewed 229 organizations. Data for the year 1980 were collected on budget, income sources, size, clients, activities, goals, staffing, corporate contributions, and much more. In 1981 we also interviewed representatives of 150 of the 209 publicly held corporations headquartered in the Twin Cities regarding their corporate contributions.[2] A third set of interviews was conducted with a stratified sample of 80 prestigious individuals representing several Twin Cities' institutions. They were asked about their priorities for community funding and their own involvement in charitable or public service activities, among other things (Galaskiewicz, 1985b: Appendices A, B, and C).

In 1985 we returned to the field and reinterviewed the nonprofits we first interviewed in 1981. The purpose was to see how funding patterns had changed over the four years. We collected data on almost all the items we asked in 1981, plus several additional items on how the organizations were coping with government cutbacks. These second-wave data were current for 1984. Of the 229 nonprofits first interviewed in 1981, we successfully reinterviewed 201 organizations. Between 1981 and 1985, 22 had gone out of business, one became a governmental agency, two became for-profits, and three refused to be reinterviewed.

Transactions between corporations and nonprofits. In the course of the 1981 and 1985 interviews we asked the administrator of each nonprofit to look at a list of all the publicly held firms in the metro area for 1980 and 1984, respectively, and to tell us the amount of corporate contributions his or her organization received from each. Respondents were asked to use response categories, because pretests showed they would not be able to give exact dollar figures: (1) less than $1,000, (2) $1,000–$2,999, (3) $3,000–$6,999, (4) $7,000–$14,999, (5) $15,000–$30,999, (6) $31,000–$62,999, (7) $63,000–$126,999, and (8) $127,000 and over. This produced two matrices. The 1980 matrix was 209 (firms) × 229 (NPOs), and the 1984 matrix was 215 (firms) × 201 (NPOs). We decided to limit the analysis to 198 nonprofits, excluding 28 organizations we did not interview in 1985 and three organizations that did not provide information on contributions in either 1981 or 1985. We also limited the analysis to 75 firms, excluding firms that had fewer than 200 employees in 1980 and 23 firms that either had gone out of business, been sold, or moved between 1980 and 1984. Thus our two working

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There were 20 refusals, and 39 companies had either gone out of business, moved out of the area, been acquired by another company, or otherwise disappeared before we reached them.

matrices, Y_1 (CONTRIBS 80) and Y_2 (CONTRIBS 84), have the dimensions 75 × 198, as do all our other rectangular matrices. The density of the 98 × 229 1980 data matrix was 2.4 percent; the density of the 75 × 198 1984 data matrix was 3.2 percent.

Preferences. We conducted face-to-face interviews with giving officers in 61 of the 75 firms in 1981. We approached companies only if they made contributions in 1980 and had more than 200 employees. We gave respondents a list of all 326 nonprofits in our sample and asked them to go through the list and check off the organizations they recognized. Next we asked them to indicate those nonprofits they felt were providing very essential services to the community and to indicate those organizations they felt had achieved extraordinary accomplishments in their respective fields. This produced three arrays in which the rows were the 75 contributions officers (nonrespondents' rows received missing data codes) and the columns were the 198 nonprofits (pared down from 326). The binary entries in the three arrays indicated whether the staff person recognized the nonprofit, thought it essential, or regarded it as outstanding, respectively. These three matrices were summed, producing a single, rectangular array, X_R (OFFICER PREFS), with values 0, 1, 2, and 3 in the cells.

We also surveyed corporate philanthropic leaders and recorded their opinions of local nonprofit organizations. In Galaskiewicz's (1985b) earlier study of corporate giving a sample of 80 members of the local community elite who were interviewed were asked to identify individuals "who were very instrumental in raising the level of corporate contributions in the Twin Cities." Those individuals who received three or more nominations were labeled the "philanthropic elite." There were 30 men in this elite. Of the 30, 23 had been born in Minnesota, Iowa, or the Dakotas. Of the 17 who had been CEOs, presidents, or chairmen of Fortune 50 or 500 firms, 13 were born in Minnesota or the Dakotas, and three had lived in the Twin Cities since 1921, 1942, and 1946, respectively. Thus this elite included a substantial number of individuals who occupied powerful corporate positions and had deep roots in the area (details in Galaskiewicz, 1985b: chap. 2; 1987).

We interviewed 26 of the 28 living members of the elite. In the course of the interview each of the 26 respondents was handed a list of the 326 nonprofits in the sample and was asked to indicate which organizations they recognized, thought essential, and regarded as outstanding. Each nonprofit then received a score of 1, 2, or 3 (recognize only; recognize and essential or outstanding; recognize, essential, and outstanding). We then aggregated the responses of the 26 informants. A score for each nonprofit was then entered into the vector, A_N (ELITE PREFS). The higher the score for a given nonprofit, the more leaders recognized an NPO and thought it essential and outstanding. In the subsequent analysis these scores were dichotomized at the median such that those nonprofits in the second category were highly recognized and viewed as important by the elite, while those in the first category were not recognized or thought as worthy in the eyes of the elite.

During the interviews with the 26 corporate philanthropic leaders in 1981, we also handed each of them a list of the 209 publicly held companies in the study and asked them to check off the firms in which they knew personally an officer or a board member—someone they knew on a first-name basis and whom they could call for lunch, drinks, or golf. We then tallied the number of philanthropic leaders who checked a given firm, and this was used as one indicator of how well a firm's executives were integrated into elite circles.

To get a second measure of corporate-elite linkages we scanned the rosters of the area's three major metropolitan clubs (the Minnesota Club, the Minneapolis Club, and the Women's Club for 1978–1981) and the two most prestigious country clubs (Woodhill Country Club and Somerset Country Club for 1978–1981) for the names of the elite, company CEOs, and their wives. We did the same for the boards of the eight most prestigious cultural organizations (the Guthrie Theatre, the Minnesota Orchestral Society, the Society of Fine Arts, the Children's Theatre, the Walker Art Center, the St. Paul Chamber Orchestra, Minnesota Public Radio, and the Minnesota Opera for 1978–1981) and of the 21 Fortune 500 or Fortune 50 firms (excluding cooperatives, for 1980) headquartered in the Twin Cities metro area. This allowed us to construct a 28 $\times$ 209 matrix in which the rows represented the 28 living members of the corporate philanthropic elite, the columns represented the 209 CEOs, and the entries the number of clubs or boards a CEO and a member of the elite (or the spouse) were both affiliated with. We then tallied down each column, giving us the number of clubs and boards that a firm's CEO shared with the elite. This was a second indicator of how well the firm's executives were integrated into elite circles.

To combine these two measures of corporate-elite integration into a single construct we did a principle components analysis.[3] Factor scores derived from the principle components analysis for each firm were entered into a vector, A_C (PROX TO ELITE). These scores were also dichotomized at the median.

Dyadic constraints. Networks among those responsible for corporate giving programs were recovered in the course of the 1981 interviews and are summarized in Galaskiewicz (1985a). In each firm the principal functionary responsible for corporate contributions was asked to look over a list of other firms in the area and to tell us if he or she knew someone personally in these firms who was responsible for corporate contributions. We stipulated that staff in two companies were linked if staff in *both* companies acknowledged they knew someone in the other firm. We then derived a 75 $\times$ 75 binary adjacency matrix, X_S (OFFICER NETS), summarizing linkages among staff in different firms. However, because we had data on only 61 officers, a number of cells were assigned a missing-data code.

To reconstruct the network among the chief executive officers we obtained rosters of the boards and executives of Fortune 50 and Fortune 500 firms and the most prestigious cultural organizations and private clubs in the Twin Cities (details in Galaskiewicz, 1985b; Galaskiewicz and Rauschenbach,

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Pearson's correlation between the two indicators of executive contact with the philanthropic elite was .717 for the 98 firms with 200 or more employees in 1980. Although there are simpler ways to combine variables into a single construct, we settled on principle components analysis as a convenient way to derive a weighted sum of two variables. The larger eigenvalue for the covariance matrix was 1.72, which explained 85.9 percent of the variance in our data.

1988). We then generated a 75×75 binary matrix, X_C (CEO NETS), where the entry in the cell was equal to 1 if the two CEOs belonged to the same boards or clubs over the period from 1977 to 1981 and was zero otherwise. There were no missing data.

To reconstruct the network ties among donees in 1981 we asked the administrators of the 229 nonprofits to tell us the names of those who sat on their boards of directors. After checking on the names, we pared the organizations list and constructed a 198×198 symmetric adjacency matrix, X_B (NPO NETS), where 1 indicated that two nonprofits had the same individual(s) on their boards and zero that they did not. There were no missing data for this array either.

Multiplicative terms. We also included eight multiplicative terms in the analysis. Six of these were formed by combining the relational X variables and Y_1: three were direct network variables, and three were indirect network variables. One of the remaining multiplicative variables was a network variable combined with two relational variables, and the last combined two attribute variables.

The three direct process variables were defined as follows: X_SY_1 measures the interaction between the donation officer's network and time 1 transactions; X_CY_1 measures the interaction between the CEO's club/board network and time 1 transactions; Y_1X_B measures the interaction between time 1 transactions and the nonprofit board interlock network. The three indirect process variables ($X_SX_SY_1$, $X_CX_CY_1$, $Y_1X_BX_B$) measure the interactions between the direct process variables described above and the three relational variables, X_S, X_C, and X_B, respectively. All of these variables are described in more detail below.

An entry in X_SY_1 is a weighted sum. It is the number of officers in other firms, known by the donation officer of firm i whose firm gave money to nonprofit j in 1980, weighted by the size of the gift. An entry in X_CY_1 is the number of CEOs who share club and board memberships with the CEO of firm i whose firm gave money to nonprofit j in 1980, weighted by the size of the gift. The third direct process variable, Y_1X_B, is the number of nonprofits that interlock with nonprofit j and that received a gift from corporation i in 1980, weighted by the size of the gift. In mathematical terms,

$$X_SY_1\,(i, j) = \sum_{k=1}^{75} X_S\,(i, k)\,Y_1\,(k, j) \qquad (1)$$

$$X_CY_1\,(i, j) = \sum_{k=1}^{75} X_C\,(i, k)\,Y_1\,(k, j) \qquad (2)$$

$$Y_1X_B\,(i, j) = \sum_{k=1}^{198} Y_1\,(i, k)\,X_B\,(k, j) \qquad (3)$$

We coded the three direct process variables so that each has three categories, and roughly one-third of the dyads are in each ordinal category. For the first two direct process variables, a low value indicates that the companies in the networks of firm i gave little or no money to nonprofit j, while a high value indicates that they did. For the third direct process variable, a low value indicates that the NPOs that interlock with nonprofit j received little or no money from corporation i, while a high value indicates that they did.

The three indirect network variables take into account indirect links between companies and between nonprofits. The first two indirect network variables examine the 1980 gifts of companies linked indirectly (at a graph distance equal to two; see Harary, Norman, and Cartwright, 1965) to donor i in the X_C or X_S corporate networks. The third indirect process variable examines the 1980 gifts received by nonprofits linked indirectly (at a graph distance equal to two) to donee j in the X_B nonprofit network. To specify these definitions mathematically, we have

$$X_S X_S Y_1 (i, j) = \sum_{k=1}^{75} \sum_{l=1}^{75} X_S (i, l) X_S (l, k) Y_1 (k, j) \tag{4}$$

$$X_C X_C Y_1 (i, j) = \sum_{k=1}^{75} \sum_{l=1}^{75} X_C (i, l) X_C (l, k) Y_1 (k, j) \tag{5}$$

$$Y_1 X_B X_B (i, j) = \sum_{k=1}^{198} Y_1 (i, k) \sum_{l=1}^{198} X_B (k, l) X_B (l, j) \tag{6}$$

We coded the indirect network variables as follows: $X_S X_S Y_1$ —four categories; $X_C X_C Y_1$—three categories; and $Y_1 X_B X_B$— four categories. Again, the categories are all ordinal, and roughly an even number of dyads are in each category. The first two indirect process variables have low values when those corporations linked *indirectly* to firm i do not give much money to nonprofit j and high values when they made substantial donations. The third indirect process variable has low values when nonprofits linked *indirectly* to nonprofit j received little from corporation i and high values when they received substantial donations.

There are two other multiplicative variables that need to be discussed. The first is $X_S X_R$. The relational recognition variable X_R is the sum of three binary matrices indicating how contribution officers within the firms viewed a nonprofit (whether they recognized it, thought it essential, and thought it outstanding). The direct process variable $X_S X_R$ aggregates the attitudes toward nonprofit j of donation officers linked to the donation officer of firm i. Mathematically,

$$X_S X_R (i, j) = \sum_{k=1}^{75} X_S (i, k) X_R (k, j) \tag{7}$$

This variable is ordinal and is coded to have four categories with roughly equal numbers of dyads in each category. A low value indicates that those in the network of the donation officer of firm i have low recognition and regard for nonprofit j, and a high value indicates high recognition and regard.

The next multiplicative variable combines two attribute variables measured on the corporation, A_C and A_T. These two variables, along with A_N, were continuous but were recoded as dichotomous in order to partition the corporations and nonprofits into discrete subgroupings, as recommended by Fienberg and Wasserman (1981a) and Wasserman and Anderson (1987). Variable A_C measures the corporation's contact with the elite, and A_T measures corporate pretax income (1984), using proxy statements and 10-K reports. The combination of the two attribute variables, $A_C A_T$, allowed us to partition the 75 corporations into 2 × 2 = 4 categories defined as follows: (1) low pretax 1984 income and low firm contact with the elite; (2) low pretax income and high elite contact; (3) high pretax income and low elite contact; and (4) high pretax income and high elite contact. The last term, $A_CA_T \times A_N$, is a statistically defined interaction effect between two predictor variables, A_CA_T and A_N. In substantive terms this interaction effect allowed us to test the proposition that the contribution from corporation *i* to nonprofit *j* is greater if company executives are socially linked to the local elite (A_C), the company has higher pretax income (A_T), and the nonprofit is recognized and viewed as important by the elite (A_N). This variable was dichotomized with roughly equal numbers of dyads in each category. Table 1 summarizes the variables and terms used in the analysis.

Hypotheses and Models

We tested the hypotheses outlined in the theory section above, using the size of the donation made by corporate

Table 1

Variables and Terms

Variable	Description
Relational	
Y_1	Coded cash contributions from corporations to nonprofits in 1980 (75 × 198) (CONTRIBS 80)
Y_2	Coded cash contributions from corporations to nonprofits in 1984 (75 × 198) (CONTRIBS 84)
X_C	Common boards/club memberships shared by CEOs of corporations in 1980 (75 × 75) (CEO NETS)
X_S	Acquaintance network of donation officers of corporations in 1980 (75 × 75) (OFFICER NETS)
X_B	Nonprofit board interlock network in 1980 (198 × 198) (NPO NETS)
X_R	Three arrays indicating the degree to which donation officers recognize, think essential, and think outstanding the nonprofits in our sample in 1980 (75 × 198) (OFFICER PREFS)
Nodal	
A_N	Attribute variable measuring the degree to which philanthropic leaders recognized, thought essential, and thought outstanding the nonprofits in our sample in 1980 (198) (ELITE PREFS)
A_C	Factor analysis scores of corporations based on philanthropic leaders' contact with corporation CEO/officers in 1980 (75) (PROX TO ELITE)
A_T	Corporations' pretax 1984 income (75) (PRETAX 84)
Multiplicative	
X_SY_1	The number of officers in other firms, known by the donation officer of firm *i* whose firms gave money to nonprofit *j* in 1980, weighted by the size of the gift (75 × 198) (OFFICER NETS*CONTRIBS 80)
X_CY_1	The number of CEOs who share club and board memberships with the CEO of firm *i* whose firms gave money to nonprofit *j* in 1980, weighted by the size of the gift (75 × 198) (CEO NETS*CONTRIBS 80)
Y_1X_B	The number of nonprofits that interlock with nonprofit *j* and that received gifts from corporation *i* in 1980, weighted by the size of the gift (75 × 198) (CONTRIBS 80*NPO NETS)
$X_SX_SY_1$	The number of officers in other firms known by the direct contacts of the donation officer in firm *i* whose firms gave money to nonprofit *j* in 1980, weighted by the size of the gift (75 × 198) (IND OFFICER NETS*CONTRIBS 80)
$X_CX_CY_1$	The number of CEOs who share club and board memberships with the contacts of the CEO in firm *i* whose firms gave money to nonprofit *j* in 1980, weighted by the size of the gift (75 × 198) (IND CEO NETS*CONTRIBS 80)
$Y_1X_BX_B$	The number of nonprofits that interlock with those nonprofits that interlock with nonprofit *j* that received gifts from corporation *i* in 1980, weighted by the size of the gift (75 × 198) (CONTRIBS 80*IND NPO NETS)
X_SX_R	The number of giving officers in other firms known by the giving officer in firm *i* who have favorable attitudes toward nonprofit j, weighted by how favorably they view the nonprofit (75 × 198) (OFFICER NETS*OFFICER PREFS)
A_CA_T	The extent to which corporation *i* has high earnings and company executives of *i* are socially linked to the local elite (75) (PROX TO ELITE*PRETAX 84)
$A_CA_T \times A_N$	The extent to which corporation *i* has high earnings, company executives of *i* are socially linked to the local elite, and the nonprofit is recognized and viewed as important by the elite (75 × 198) (PROX TO ELITE*PRETAX 84 × ELITE PREFS)

donor i to nonprofit donee j in 1984 (Y_2) as the dependent variable. Our goal was to construct predictive models for Y_2 based on the size of the donation made by donor i to donee j in 1980 (Y_1) and some subset of the explanatory variables listed in Table 1. The units of analysis were the dyads formed by the 75 corporations and 198 nonprofits in the study population. The goal of this analysis was to identify a set of variables that have statistically significant effects on the size of contributions that corporation i made to nonprofit j in 1984.

In order to keep the analyses as orderly as possible, we postulated nine models for the dependence of corporate-to-nonprofit transactions in 1984 (Y_2) on the explanatory variables that correspond directly to the nine hypotheses:

H_1: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit is well regarded by the local philanthropic elite (controlling for the size of the contribution at t_1, the pretax income of the firm at t_2, and the preferences of the giving officer at t_1):

(H_1) $Y_2 = f(X_R, A_N, A_T, Y_1)$.

H_2: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit is well regarded by the local philanthropic elite and the company's CEO is in direct contact with the local elite (controlling for the size of the contribution at t_1, the pretax income of the firm at t_2, the proximity of the company's executives to the elite at t_1, and the preferences of the elite at t_1):

(H_2) $Y_2 = f(A_C A_T, A_N, Y_1, A_C A_T \times A_N)$.

H_3: Corporation i is likely to give a larger donation to nonprofit j if officers in other firms who had direct ties to the giving officer of corporation i think highly of the nonprofit (controlling for the size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_3) $Y_2 = f(X_S X_R, A_T, Y_1)$.

H_4: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit previously received funding from firms whose giving officers have direct ties to the giving officer of corporation i (controlling for the size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_4) $Y_2 = f(X_S Y_1, A_T, Y_1)$.

H_5: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit previously received funding from firms whose CEOs have direct ties to the CEO of corporation i (controlling for the size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_5) $Y_2 = f(X_C Y_1, A_T, Y_1)$.

H_6: Nonprofit j is likely to receive a larger donation from corporation i if the corporation had previously funded nonprofits whose directors are represented on the board of nonprofit j (controlling for the size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_6) $Y_2 = f(Y_1 X_B, A_T, Y_1)$.

H_7: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit previously received funding from firms whose officers have indirect ties to the giving officer of corporation i (controlling for the size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_7) $Y_2 = f(X_S X_S Y_1, A_T, Y_1)$.

H_8: Corporation i is likely to give a larger donation to nonprofit j if the nonprofit previously received funding from firms whose CEOs have indirect ties to the CEO of corporation i (controlling for size of the contribution at t_1 and the pretax income of the firm at t_2):

(H_8) $Y_2 = f(X_C X_C Y_1, A_T, Y_1)$.

H_9: Nonprofit *j* is likely to receive a larger donation from corporation *i* if the corporation has previously funded nonprofits whose directors are indirectly represented on the board of nonprofit *j* (controlling for size of the contribution at t_1 and the pretax income of the firm at t_2):

$(H_9)\ Y_2 = f(Y_1 X_B X_B, A_T, Y_1)$.

Although the 1980 and 1984 contribution variables had nine categories, the distributions across the categories were very skewed (in 1984 more than 50 percent of the transactions were less than $7,000). The two variables, Y_1 and Y_2, were therefore recoded to have three categories each: low donations (less than $3,000), medium donations ($3,000–$30,999), and high donations ($31,000 and up). Each of the 75 $\times$ 198 = 14,850 dyads has a value for both Y_1 and Y_2. Each of the nine models uses time 2 transactions (Y_2) as the "response" variable and a number of attribute (A) and relational (X) variables as explanatory variables. More specifically, all nine models use time 1 transactions (Y_1) as a predictor variable. Model H_1 and models H_3 to H_9 use the 1984 pretax income variable (A_T) as a predictor, and model H_2 includes the multiplicative term, $A_C A_T$. Of interest in all nine models are the main effects of the explanatory variables on the response variable.

RESULTS

As noted above, there are 14,850 dyads, each consisting of a corporation and a nonprofit. We postulate a logit model for the state of every dyad for each model (see Appendix for a discussion of these models).[4] For example, model H_1 contains Y_1, the attribute variables A_T and A_N, and the relational variable X_R, as well as the response variable Y_2. We state

$$\log\{\Pr(Y_2 = \ell \mid Y_1 = k, X_R, \text{ and the type of dyad defined by } A_T \text{ and } A_N)\} = w + w_1 + w_2 + w_3 + w_4 + w_{12} + w_{13} + w_{23} + w_{14} + w_{24} + w_{34} + w_{123} + w_{124} + w_{134} + w_{234} + w_{1234} \quad (8)$$

where the subscripts are defined as 1 = type of corporation (A_T), 2 = type of nonprofit (A_N), 3 = degree of recognition of nonprofit by corporate donation officer (X_R), and 4 = level of donation at time 1 (Y_1). The parameters should be subscripted to depend on ℓ, the level of donation at time 2. Such predictive models were introduced by Wasserman (1987) and Wasserman and Iacobucci (1988a). As mentioned in the Appendix, this model is fit to a five-way contingency table (one dimension for each variable) defined by the cross-classification of variables 1, 2, 3, 4, and the response variables Y_2. Effects w_i (i = 1, 2, 3, 4) are main effects, and the others are first-, second-, or third-order interactions. We used this methodology to test the dependence of the explanatory variables on the response variable, as postulated by each of the nine models.

As mentioned in the Appendix, we judge the statistical significance of the main effects in each model by entering different main effects one at a time. Table 2 presents the test statistics, degrees of freedom, and p-values for all main-effect parameters for each model. The table gives only one interaction: the substantively interesting one between $A_C A_T$ and A_N. The interactions associated with combinations of variables are discussed below. The test statistics are all likelihood-ratio statistics (G^2s) that are distributed asymptotically

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We decided to use logit models with a trichotomized dependent variable for four reasons. First, the distribution across the nine categories of the dependent variable was highly skewed. Second, when we regressed log Y_2 on log Y_1 we found that the residuals were not normally distributed about the regression line. Third, we fit a number of logit models without collapsing the categories of Y_1 and Y_2 and found negligible differences between these models and models for which Y_1 and Y_2 had just three categories. Fourth, using only three categories for these two primary variables enabled us to add more variables to the models and thus enhance the explanatory power of the models.

Table 2

Likelihood Ratios (G^2s) and p-values for the Nine Substantive Models

Predictor variables	Models (Response variable = CONTRIBS 84) (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	d.f.
Y_1 = CONTRIBS 80	528.4 .000	528.3 .000	528.5 .000	528.7 .000	528.3 .000	528.6 .000	528.5 .000	528.2 .000	528.4 .000	4
A_T = PRETAX 84	100.2 .000		100.1 .000	100.2 .000	98.8 .000	99.6 .000	101.6 .000	99.2 .000	101.4 .000	2
X_R = OFFICER PREFS	12.9 .044									6
A_N = ELITE PREFS	179.4 .000	179.3 .000								2
A_CA_T = PROX TO ELITE*PRETAX 84		157.7 .000								6
$A_CA_T \times A_N$ = PROX TO ELITE* PRETAX 84 × ELITE PREFS		2.2 .897								6
X_SX_R = OFFICER NETS* OFFICER PREFS			64.3 .000							6
X_SY_1 = OFFICER NETS* CONTRIBS 80				438.6 .000						4
X_CY_1 = CEO NETS* CONTRIBS 80					487.0 .000					4
Y_1X_B = CONTRIBS 80* NPO NETS						522.8 .000				4
$X_SX_SY_1$ = IND OFFICER NETS* CONTRIBS 80							482.0 .000			6
$X_CX_CY_1$ = IND CEO NETS* CONTRIBS 80								427.6 .000		4
$Y_1X_BX_B$ = CONTRIBS 80* IND NPO NETS									555.6 .000	6

as chi-squared random variables with the appropriate degrees of freedom (d.f.).

As can be seen in Table 2, almost all the main effects are important. The only marginally significant effect is X_R (OFFICER PREFS), and the main effect for X_SX_R (OFFICER NETS/OFFICER PREFS) is considerably weaker than the other main effects. The postulated interaction between the attribute variables ($A_CA_T \times A_N$) in model H_2 is also statistically quite small. These results suggest the evaluation of a particular nonprofit by a corporate donation officer at time 1 (X_R) has little direct effect on her or his firm supporting that nonprofit at time 2. Also the opinions of those in the networks of donation officers at time 1 (X_SX_R) seem to have little effect on donations at time 2. Furthermore, there is not a strong interaction between A_N (ELITE PREFS) and A_CA_T (PROX TO ELITE * PRETAX 84). This implies that, after controlling for pretax 1984 income, the elite does not influence company donations through their social ties to officers in the firm. The preferences of giving officers, the preferences of giving officers in other firms, and the preferences of local elites in the firm's networks had little effect on company contributions.

In order to assess the independent effects of all the variables that have some significant effect on contributions at time 2, we considered two additional models:

(H_{10}) $Y_2 = f(X_SY_1, X_CY_1, Y_1X_B, A_T, A_N, Y_1)$

(H_{11}) $Y_2 = f(X_SX_SY_1, X_CX_CY_1, Y_1X_SX_S, A_T, A_N, Y_1)$.

Models H_{10} and H_{11} both contain Y_1 and Y_2, the substantively important corporate attribute variable A_T (PRETAX 84), and the nonprofit attribute variable A_N (ELITE PREFS). The difference between models H_{10} and H_{11} is that the first contains the multiplicative terms, X_SY_1, X_CY_1, and Y_1X_B, while the latter contains the multiplicative terms, $X_SX_SY_1$, $X_CX_CY_1$, and $Y_1X_SX_S$. In order to fit these models, we had to recode the variables again to keep the sizes of the associated contingency tables small. Some of these multinomial predictor variables were recoded at the median to have only two categories (low/high). Variable Y_2 always had three (low/medium/high) categories. We categorized the other variables using either median splits (to obtain two-category variables) or third-splits (to obtain three-category variables). We attempted to have equal counts in the cells of the categorical variables but were not always successful, due to the skewed distributions. The models were derived by considering the relative importance of the main effects shown in Table 2. The two models, and the test statistics for their main effects, are given in Table 3.

Table 3

Main Effect Statistics for the Syntheses of the Nine Substantive Models

Predictor variables	Models (Response variable = CONTRIBS 84) (10)	(11)	d.f.
Y_1 = CONTRIBS 80	508.4 .000	507.7 .000	2
A_T = PRETAX 84	100.1 .000	101.1 .000	2
A_N = ELITE PREFS	179.3 .000	180.2 .000	2
X_SY_1 = OFFICER NETS* CONTRIBS 80	330.9 .000		2
X_CY_1 = CEO NETS* CONTRIBS 80	378.7 .000		2
Y_1X_B = CONTRIBS 80* NPO NETS	432.7 .000		2
$X_SX_SY_1$ = IND OFFICER NETS* CONTRIBS 80		206.9 .000	2
$X_CX_CY_1$ = IND CEO NETS* CONTRIBS 80		327.5 .000	2
$Y_1X_BX_B$ = CONTRIBS 80* IND NPO NETS		377.8 .000	2

All of the hypothesized effects in models H_{10} and H_{11} are statistically significant. The relative strength of Y_1, A_T, and A_N, measured in terms of differences in G^2, is about the same in both models. However, the multiplicative effects are somewhat weaker in the combined models.

The next task was to assess the direction and strength of the effects we found to be statistically significant by returning to the models in which we found statistically significant main effects. We calculated the main effect parameter estimates for the variables specified in models H_1–H_9. The values of these parameter estimates were centered so they sum to zero for each category of the response variable, Y_2. The results, and the models from which the parameters came, are presented in Table 4.

1980 corporate donations (Y_1) was statistically significant in all the models. The effect parameters in Table 4 confirm the association was positive: a firm that gave more money to a nonprofit in 1980 tended to give it more money in 1984. The opinions of the philanthropic elite (A_N) also had the hypothe-

Table 4

Main Effect Parameter Estimates from Logit Models H_1–H_9

Predictor Variables	Response variable = CONTRIBS 84 (Y_2) Low	Medium	High
Y_1 = CONTRIBS 80 (model H_1)			
Low	2.588	−.799	−1.789
Medium	−.674	.439	.236
High	−1.913	.361	1.553
A_T = PRETAX 84 (model H_1)			
Low	.572	−.505	−.067
High	−.572	.505	.067
A_N = ELITE PREFS (model H_2)			
Low recognition/respect	1.977	.554	−2.531
High recognition/respect	−1.977	−.554	2.531
X_SY_1 = OFFICER NETS* CONTRIBS 80 (model H_4)			
None or few donations	1.373	−.369	−1.004
Some donations	.005	−.156	.150
Many donations	−1.378	.524	.854
X_CY_1 = CEO NETS* CONTRIBS 80 (model H_5)			
None or few donations	1.325	−.517	−.807
Some donations	.130	−.007	−.122
Many donations	−1.455	.524	.930
Y_1X_B = CONTRIBS 80* NPO NETS (model H_6)			
None or few donations	1.770	−.416	−1.353
Some donations	.119	.241	−.122
Many donations	−1.650	.175	1.475
$X_SX_SY_1$ = INDIRECT OFFICER NETS* CONTRIBS 80 (model H_7)			
None or few donations	1.531	−.522	−1.008
Moderate donations	.115	−.080	.196
Some donations	.056	.071	−.128
Many donations	−1.473	.532	.940
$X_CX_CY_1$ = INDIRECT CEO NETS* CONTRIBS 80 (model H_8)			
None or few donations	1.195	−.433	−.763
Some donations	.172	−.109	−.064
Many donations	−1.368	.541	.827
$Y_1X_BX_B$ = CONTRIBS 80* INDIRECT NPO NETS (model H_9)			
None or few donations	1.233	−.888	−.345
Moderate donations	1.799	1.499	−3.298
Some donations	−.764	−.386	1.150
Many donations	−2.269	−.224	2.492

sized effect on giving: nonprofits that were recognized and valued by the elite in 1980 tended to receive greater corporate contributions in 1984. However, the pretax net income of the firm in 1984 (A_T) had a curious effect on 1984 contributions: firms that had greater pretax net income in 1984 tended to make medium-sized contributions in 1984, while those that were less profitable tended to make smaller gifts. However, pretax net income in 1984 had almost no effect on the largest contributions. This suggests that both profitable and not-so-profitable firms made substantial gifts to charity in 1984.

The effects of all the direct and indirect network variables were as we had hypothesized. First, a firm *i* tended to give more money to a nonprofit *j* in 1984 if the donation officer in *i* knew several other donation officers whose firms gave substantial amounts to the nonprofit in 1980. Second, a firm *i* tended to give more money to a nonprofit *j* in 1984 if the CEO in *i* knew several other CEOs whose firms gave substantial amounts to the nonprofit in 1980. Third, a nonprofit *j* tended to receive more money from a firm *i* in 1984 if several board members of *j* were on the boards of other nonprofits who received significant funding from the firm in 1980. Fourth, a firm *i* tended to give more money to a nonprofit *j* in 1984 if the donation officer in *i* was indirectly linked (at a path distance of two) to several other donation officers whose firms gave substantial amounts to the nonprofit in 1980. Fifth, a firm *i* tended to give more money to a nonprofit *j* in 1984 if the CEO in *i* was indirectly linked (at a path distance of two) to several other CEOs whose firms gave substantial amounts to the nonprofit in 1980. Finally, a nonprofit *j* tended to receive more money from a firm *i* in 1984 if more members of *j*'s board sat on other boards with directors whose nonprofits received significant fundings from firm *i* in 1980.

The final set of analyses focused on significant interaction effects we found in models H_1 through H_9 but did not hypothesize. There were remarkably few significant interaction effects. For each of the nine models, we tested every possible higher-order interaction but found only three significant effects in two models—H_4 and H_6. Table 5 shows the parameter estimates for the only three significant interaction

Table 5

Interaction Effect Parameter Estimates from Logit Models H_4 and H_6

	Response variable = CONTRIBS 84 (Y_2)		
	Low	Medium	High
Panel A			
A_T = PRETAX 84 × X_SY_1 = OFFICER NETS* CONTRIBS 80			
A_T = Low			
X_SY_1 =			
None or few donations	.042	−.349	.306
Many donations	−.042	.349	−.306
A_T = High			
X_SY_1 =			
None or few donations	−.042	.349	−.306
Many donations	.042	−.349	.306
Panel B			
Y_1 = CONTRIBS 80 × X_SY_1 = OFFICER NETS* CONTRIBS			
Y_1 = Small			
X_SY_1 =			
None or few donations	.399	−.208	−.192
Many donations	−.399	.208	.192
Y_1 = Large			
X_SY_1 =			
None or few donations	−.399	.208	.192
Many donations	.399	−.208	−.192
Panel C			
Y_1 = CONTRIBS 80 × Y_1X_B = CONTRIBS 80* NPO NETS			
Y_1 = Small			
Y_1X_B =			
None or few donations	.369	−.271	−.098
Many donations	−.369	.271	.098
Y_1 = Large			
Y_1X_B			
None or few donations	−.369	.271	.098
Many donations	.369	−.271	−.098

terms: $A_T \times X_S Y_1$ (Panel A), $Y_1 \times X_S Y_1$ (Panel B), and $Y_1 \times Y_1 X_B$ (Panel C). The first two terms are associated with model H_4 and involve the multiplicative variable $X_S Y_1$, indicating the extent to which a giving officer knew officers in other firms that contributed to a nonprofit in 1980. The last is associated with model H_6 and involves the multiplicative term $Y_1 X_B$.

Panel A in Table 5 shows that the influence of $X_S Y_1$ on Y_2 is different depending on whether corporation *i* had higher or lower earnings in 1984. If a company had higher earnings, it tended to fund nonprofits that received support from companies whose officers were in the network of its giving officer. If the company had weaker earnings, it tended to support nonprofits that received support from companies whose officers were *not* in the network of the firm's giving officer.

The second statistically significant interaction term also involves $X_S Y_1$. Panel B in Table 5 shows that the influence of $X_S Y_1$ on Y_2 is different depending on whether the firm made a larger or smaller gift to the NPO in 1980. If the firm gave only a small gift or no gift in 1980, it tended to support those nonprofits in 1984 that received gifts in 1980 from firms whose officers were in the network of its giving officer. If it made a large gift to the NPO in 1980, it tended to fund NPOs in 1984 that received gifts in 1980 from firms whose officers were *not* in the network of its giving officer. It thus imitated peers when it had no prior experience with an NPO, but ignored what peers did if it had already funded an NPO.

The last statistically significant interaction term involves Y_1 and the multiplicative variable $Y_1 X_B$, from model H_6. Panel C in Table 5 shows that the effect of $Y_1 X_B$ *on* Y_2 depends on the size of the gift in 1980 (Y_1). In the case where a donor made no (or only a small) gift to the NPO in 1980, nonprofits received a medium-size gift from the donor in 1984 if their directors sat on boards of NPOs that received funding from the donor in 1980 and nothing (or a small gift) if their directors sat on boards of NPOs that received no funding from the donor in 1980. Thus if the NPO had not been funded before (or funded only minimally), mimicry was a factor in its receiving funding in 1984. In contrast, where a donor made a large gift to the NPO in 1980, nonprofits received a small (or no) gift from the donor in 1984 if directors sat on boards of nonprofits that received donations from the donor in 1980 and a medium-size gift if their directors sat on boards of NPOs that received no gifts from the donor in 1980. However, regardless of whether the gift to the NPO in 1980 was large or small, $X_1 X_B$ had no effect on NPOs receiving large gifts in 1984.

DISCUSSION AND CONCLUSIONS

The goal of this paper was to see if mimetic processes, as described in DiMaggio and Powell (1983), had any effect on the corporate contributions of firms in the Minneapolis-St. Paul metro area. Within the larger framework of the study of organizational decision making, we wanted to assess the importance of these processes when management has to make decisions under conditions of unusual uncertainty. We argued that, under these conditions, organizations would likely mimic the behavior or adopt the preferences of elites and other organizations in their environment.

Mimetic Processes

Our findings show that networks are critical to mimetic processes. This paper clearly demonstrates that organizational actors are more likely to mimic those organizations to which they have some interpersonal tie via boundary-spanning personnel such as giving officers and CEOs. An organization may mimic those that it thinks are particularly successful, but more likely it will mimic those organizations that it trusts. As Granovetter (1985) noted, interpersonal networks in highly competitive organizational fields are important mechanisms to sort out trustworthy information. While environmental conditions create the uncertainty that motivates organizational mimicry, it is the network ties of boundary-spanning personnel that tell us whom they will imitate and thus how they will behave.

Our empirical investigation aimed at identifying the variables that most influenced corporate giving at the dyadic level in 1984. Throughout the paper, we controlled for both the size of a gift that firm *i* made to firm *j* in 1980 and the 1984 pretax net income of firm *i*. This enabled us to identify the factors influencing *changes* in funding patterns. Although 1980 funding was an important predictor of 1984 funding, we found a number of statistically significant effects among our network variables. This indicates that there was considerable instability in this relational system. This, we believe, was due to the mimetic processes operative in this interorganizational field.

Model H_1 hypothesized that the size of a gift in 1984 from firm *i* to nonprofit *j* would be a function of how highly the giving officer in firm *i* regarded the nonprofit in 1980 and how highly the corporate philanthropic elite regarded the nonprofit in 1980. In model H_2 we hypothesized that the size of a gift would be a function of what the philanthropic elite thought of the nonprofit *and* whether the company's CEO was in the same social circles as the local elite. In model H_3 we hypothesized that the size of a gift in 1984 from firm *i* to nonprofit *j* would be a function of whether the giving officer in firm *i* knew several other officers in the community who regarded the nonprofit highly.

The results showed that only the attitudes of the elite toward the nonprofit in 1980 had any effect on funding in 1984. The impact of the other preference variables was marginal, at best. Thus, it does not appear that companies gave more to an NPO in 1984 simply because officers known by their staff, or philanthropic leaders known by their executives, thought highly of the organization in 1980.

These results are important for two reasons. First, the fact that the opinions of local business leaders should influence allocations of corporate contributions is consistent with Galaskiewicz's (1985b) findings for the 1980 corporate contributions data. However, it does challenge his assertion that the impact of the "old" philanthropic leaders would weaken over time. The fact that preferences expressed in 1980 would carry any weight in 1984 suggests that the opinions of these philanthropic leaders were still critical guideposts to corporate philanthropists. Second, because the ties between company executives and the local elite were unimportant in explaining who funded whom, it appears that the impact of the elite's values was not due to direct solicitation but to the respect that firms held for these individuals' opinions. This suggests that actors in an organizational field can be influenced by others *without* networks being operative.

Models H_4, H_5, H_7, and H_8 postulated that companies would mimic those firms to which they were linked through giving officers and the CEO. Models H_6 and H_9 postulated that nonprofits would receive funds from companies that funded nonprofits to which they were linked. In general, we found that companies gave significant amounts to nonprofits in 1984 if giving officers knew officers in other firms that gave significant amounts in 1980 or if giving officers were indirectly linked to officers whose firms gave significant amounts to the nonprofits in 1980. We also found that companies gave significant amounts to nonprofits in 1984 if CEOs were in clubs or on boards with CEOs whose firms gave significant amounts in 1980 or if CEOs were indirectly linked to CEOs whose firms gave significant amounts to nonprofits in 1980. We interpreted these findings as telling us that corporate contributors were watching their peers and following suit. Giving officers and CEOs apparently looked at what others were doing—at their acquaintances and the acquaintances of their acquaintances—and encouraged their firm to follow suit. If others think highly enough of a NPO to fund it, so should they.

The same mimetic processes were operative for nonprofits. We found that nonprofit organizations received more money from firms in 1984 if their directors sat on the boards of nonprofits that received substantial funding from those firms in 1980. An NPO also received more money in 1984 if it was indirectly interlocked to nonprofits that received funding in 1980. These findings suggest that nonprofit administrators learned about prospective funders from their directors who saw firms funding other nonprofits or heard about funders while interacting with board members of another nonprofit. Evidently, administrators followed up on these "tips" and solicited the firm as well, resulting in a gift at time 2.

However, since there were statistically significant interaction effects, we must qualify some of our findings. First, more profitable donors gave a great deal of money to nonprofits that received support in 1980 from firms whose officers were in direct contact with their giving officer. Less profitable donors gave a larger amount of money to nonprofits that received support in 1980 from firms whose giving officers were *not* in direct contact with their giving officer. The network variable had no effect on smaller gifts in 1984. The second interaction term told us that our network variable had an effect only if the firm had *not* made a gift or only made a small gift in 1980 to the nonprofit. If the firm made a large gift to the NPO in 1980, the giving pattern of those in their officers' network had a negative effect on the likelihood of their funding the NPO at time 2.

Both findings make sense. First, more profitable firms supported the same NPOs as peers, while less profitable firms mimicked the giving patterns of the more profitable firms. In both cases there is mimicry. In the first case, firms are mimicking those to whom they have ties; in the second case, firms are mimicking those whom they know only at a distance. Evidently, less profitable firms supported NPOs that more profitable firms were funding, even though they had no ties to them. Second, when a firm considers funding nonprofits it has not funded previously, it will support those that have been supported by the firm's peers in the past. If a firm is considering nonprofits it has funded previously, it will probably fund these NPOs again, even though peers are not funding them. We would argue that peer influence is important under conditions of uncertainty but is less important when a donor has some experience with the organization.

The third interaction term told us that networks among nonprofits had an effect only on small and medium-size gifts and only if the firm made no donation, or just a small donation to the nonprofit in 1980. If the nonprofit received a substantial gift from the firm in 1980, it was more likely to receive a medium-size gift in 1984 if *fewer* network contacts received gifts and a smaller gift if many network contacts received gifts from the donor. The network variable had no effect on larger gifts in 1984. This finding suggests that mimetic processes are important, but only if the firm did not fund the nonprofit before and only if we look at small and medium-size gifts. Apparently, nonprofits can successfully approach *new* funders that support friends in their network if their request is small. Here, networks work when the stakes are low and the firm has little firsthand knowledge of the nonprofit.

Obviously our analyses could be extended in any number of different ways. For instance, we could focus more attention on the nonprofit organizations in the sample. For the most part, this paper deals only with things happening in the business community. We could look at changes in nonprofits' clientele, numbers of professional staff members, and fund-raising practices. We could also see if NPOs lost government funding during the period from 1980 to 1984. These variables could influence the "attractiveness" of an NPO to corporate funders. Space limitations made it impossible to incorporate them into our models.

More importantly, this research needs to be replicated in different community settings and in different historical contexts. We are hesitant to generalize our findings beyond Minneapolis-St. Paul. Twin Cities' firms have a national reputation for their contributions to charity, and all the efforts to promote corporate philanthropy in the Twin Cities may have invigorated networking among giving officers and CEOs. Furthermore, the period we studied—1980 to 1984—was an era of government retrenchments and cutbacks. Both nonprofits and corporations were working under very stressful conditions, and the latter were under considerable pressure to "make-up" for government cutbacks. We are not sure how this particular historical context influenced our findings. If anything, it may have made corporations more conscientious, given that the public was closely scrutinizing their activities. If so, corporations had to be especially sure about the new nonprofits they funded, and the networks of both giving officers and CEOs would then become more important for obtaining information on prospective donees.

Despite these limitations, we believe that our findings add to the literature on strategic decision making in several ways.

First, our results strongly suggest that so-called institutional processes are critical in explaining organizational behavior, as suggested by DiMaggio and Powell (1983). Our research suggests that when faced with uncertainty, decision makers will mimic the behavior of other actors in their environment. If clear criteria do not exist, decision makers will try what others have done and have found to work. Second, social networks are important in determining which actors decision makers will imitate. There are several possible options that decision makers can pursue under conditions of uncertainty; there are several models that they can adapt. We have argued and shown that decision makers will mimic the behavior of those in their networks, those whom they know and trust.

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APPENDIX

The statistical model on which our methodology is based first appeared in Holland and Leinhardt (1981) and Fienberg and Wasserman (1981a). This model, termed p_1, is designed for binary, single relational data and postulates a log-linear model for the dyadic probabilities. It is fit using a standard iterative proportional fitting algorithm (Fienberg and Wasserman, 1981b; Wasserman and Weaver, 1985) or a Newton-Raphson algorithm (Haberman, 1979). A brief introduction to the model is given in the Appendix to Galaskiewicz et al. (1985). Since 1981, p_1 has been extended in many ways, in particular to multiple relational data sets including actor-attribute information. Here, we briefly review this extension and discuss how one can further generalize these ideas to predict one relation from the others.

The statistical aspects of our methodology for multiple relational data are described in Fienberg, Meyer, and Wasserman (1985). These authors gave a solution to the problem of simultaneous analysis of several relational variables. Wasserman and Iacobucci (1986) extended the solution to nonbinary, discrete-valued relational variables, and Wasserman (1987), focusing on two relational variables, discussed a logit model for predicting one of the relations from the other. Iacobucci and Wasserman (1987) provided a detailed, nontechnical introduction to these ideas. Of particular interest to us are models for sequential or longitudinal network data described in Wasserman and Iacobucci (1988b).

The primary relational variable of interest to us yields a rectangular two-way matrix Y_2, since the *sending* actors (the corporations or the rows of the matrix) differ from the *receiving* actors (the nonprofits or columns). The relational variable Y_1 is also rectangular, as well as X_R, the OFFICER PREF predictor variable. In addition to these three rectangular network variables, we used several attribute variables, two for the corporations and one for the nonprofits: A_N (ELITE PREFS) is a nonprofit-attribute variable and A_C (PROX TO ELITE) and A_T (PRETAX 84) are corporation-attribute variables. We also used several corporation-by-corporation square network variables (X_C, CEO NETS, and X_S, OFFICER NETS), and one nonprofit-by-nonprofit square network variable (X_B, NPO NETS). As mentioned in the text, the square network X variables were combined with Y_1 to yield a number of direct and indirect process variables that are substantively interesting predictor variables. These new combination variables were used instead of the original X variables in our models. This has the effect of making all of the "model predictor" relational variables rectangular (matrices of size 75×198). There are thus two kinds of variables in the models—rectangular (75×198) relational variables and attribute variables for either the rows ($R = 75$) or columns ($C = 198$). One of the relational variables, Y_2, is always the *response* relational variable. The models seek to predict Y_2 by functions of subsets of the attribute and relational predictor variables.

Following Wasserman and Iacobucci (1988b), let us assume we have T rectangular relational variables, $Z_1, Z_2, \ldots, Z_T$. We further assume these variables can take on any value from the set $(1, 2, \ldots, C)$. If $C = 2$, we have binary relations. We also have a number of attribute variables. Attributes such as sex, race, club memberships, or attitudes can be used to partition the actors into two sets of subgroups (one for the corporations and another for the nonprofits) such that all actors in a specific subgroup are assumed to be stochastically equivalent, as defined by Wasserman and Anderson (1987). We will let T be arbitrary and ask how well we can model or predict Z_T as a function of $Z_1, Z_2, \ldots, Z_{T-1}$ and the attribute variables, although we can just as easily predict any one of the T relational variables as a function of some subset of the others.

Our approach centers on linear models for logits, or log odds ratios (Haberman, 1978, 1979; Fienberg, 1980), derived from the state of the dyad (involving a specific corporation and a specific nonprofit) as measured on the response variable (the value of the donative transfer in 1984). These logit or multinomial response models are then fit to a contingency table that cross-tabulates the attribute variables and the relational variables, using a standard log-linear model. Consider the following log odds ration:

$$\tau_{ij}(Z_T; Z_1, Z_2, \ldots, Z_{T-1}) = \log \frac{P\{Z_{ijT} = z_{ijT} \mid Z_{ij1}, Z_{ij2}, \ldots, Z_{ijT-1}\}}{P\{Z_{ijT} = 1 \mid Z_{ij1}, Z_{ij2}, \ldots, Z_{ijT-1}\}} \quad \text{(A1)}$$

defined for $z_{ijT} = 1, 2, \ldots, C$ (the maximum possible contribution category). Equation (A1) is predictive for a special function of the state of the dyad on relation T, conditional on the states of the dyad for the other T-1 relations. The logit function is frequently used in categorical data analysis and is discussed in detail by Cox (1970). We model the log of the odds of a gift at level $Z_{ijT} = c$ in 1984 to a gift at level 1, conditional on the relationships between corporation i and nonprofit j, as measured by the other T-1 relational variables. Technically speaking, this model simplifies to a difference in the logs of joint probabilities for all T dyad states, since the conditional probabilities are simple ratios of joint probabilities for the T dyad states to a common joint probability of the other T-1 dyad states.

The next step is to specify a log-linear model for the joint probabilities. We categorize the corporations into a finite number of categories as specified by the corporate attribute variables. If we have U such variables, we have a U-dimensional categorization. We do the same for the nonprofit variables, creating a V-dimensional categorization. We then form a $U + V + T$-dimensional contingency table, crossing the T relational variables with the subgroupings of the corporations and nonprofits. To fit logit models to the logits (A1), we fit log-linear models to this array. We must choose models that contain all parameters corresponding to main effects and interactions associated with corporate attributes $A_{C1}, A_{C2}, \ldots, A_{CU}$, nonprofit attributes $A_{N1}, A_{N2}, \ldots, A_{NV}$, and relations $1, 2, \ldots, T$-1, since we are statistically conditioning on all attributes and all other relational variables. This is analogous to multiple regression, where, to build a predictive model for a response variable, a data analyst will estimate a regression coefficient for all explanatory variables to be fixed.

The main technical difference between these predictive models and the associative models discussed by Fienberg, Meyer, and Wasserman (1985) and

Wasserman and Iacobucci (1988a) is that, for the former, one must assume the interaction among the $U + V + T$-1 explanatory variables must be included in the log-linear model. The attribute variables and the dyad states at times 1, 2, . . . , T-1 are explanatory variables for the response variable (the last variable of the array), specifying the relation T dyad state.

Examples of such predictive models are given in Wasserman (1987) for $T = 2$, and $U = V = 0$ and in Wasserman and Iacobucci (1988a) for $T = 3$ and general U and V. We refer the reader to these papers for details about models and parameters. To fit predictive models we use the standard theory for logit or multinomial response models (Fienberg, 1980: chap. 6; Agresti, 1984: chap. 6). The margins corresponding to the variables we are conditioning on are always included in the model. Any interaction of the response variable with some subset of the explanatory variables implies that a parameter subscripted by the product of the explanatory variables must be added to the predictive model. To allow these parameters to depend on the sending and/or receiving subgroups, the interactions should be crossed with variables 1 to U (for the corporations) and/or variables $U + 1$ to $U + V$ (for the non-profits).

One can now see how to determine how the state of the dyad on relation T depends on the other relational variables and the attribute variables. The interactions between the last variable of the data array and the other variables specify the extent of the dependence. Further, it is straightforward to do a series of conditional likelihood-ratio tests to evaluate statistically how the explanatory variables affect the response variable. The fits of these models and the conditional likelihood-ratio statistics that test whether specific parameters are zero are evaluated by referring such statistics to chi-squared distributions with the appropriate degrees of freedom. Such test statistics and associated p-values are reported in Tables 2 and 3. Parameter estimates, such as those in Tables 4 and 5, are estimated using maximum-likelihood theory and are usually given as output of computer programs that fit log-linear models using iterative proportional fitting or other algorithms. We refer the reader to Bishop, Fienberg, and Holland (1975) for technical details. We note that likelihood-ratio test statistics calculated by these programs are incorrect, since the data arrays modeled by the programs contain some duplicated and other doubled entries. It is straightforward to write a simple computer program to take the fitted and observed data arrays and calculate these statistics correctly (Fienberg and Wasserman, 1981a). We used GLIM 3.77 (Payne, 1985) to fit the models reported here.