3

Structures of Mediation: A Formal Approach to Brokerage in Transaction Networks

Roger V. Gould and Roberto M. Fernandez†*

The concept of brokerage has gained considerable attention in recent years, but few researchers have attempted to specify what the phenomenon is. In this paper, we develop a theoretical conception of brokerage behavior in social systems characterized by the exchange or flow of resources. Building on the idea that any set of actors can be partitioned in a meaningful way into a set of mutually exclusive subgroups, we show that such a partition generates five formally, analytically, and intuitively distinct brokerage types or roles. We construct quantitative measures of each of these five types for actors in social networks and for whole systems, and show that statistical inference can be used to test whether occupancy of a brokerage position is the product of a random distribution of exchange relations or the product of underlying social structure.

The authors thank Ken Dauber, Harry Ganzeboom, Paul Holland, Jim Shockey, Harrison White, and the anonymous reviewers for their helpful comments and suggestions. We also thank Joseph Galaskiewicz for permission to use his data.

*Harvard University
†University of Arizona

1. INTRODUCTION

Social scientists have shown in a variety of ways that centrality in networks of social relations is an important determinant of such phenomena as power and influence (Laumann and Pappi 1976), employment opportunities (Granovetter 1974), and the transmission of information (Weimann 1983). Recently, however, the work of a number of researchers (Cook 1982; Cook et al. 1983; Marsden 1982, 1983; Bonacich 1987) has begun to divert attention from network centrality as it has traditionally been defined. For example, Cook et al.'s (1983) experimental work on exchange in negatively connected networks indicates that highly central actors may be at a disadvantage in bargaining with other actors in only moderately central positions. Similarly, Marsden (1983) found in a simulation study based on Coleman's (1973) model of exchange systems that actors in monopoly positions of moderate centrality are at least as powerful as actors in central positions. To explain this apparent discrepancy between empirical studies and experimental and simulation results, Marsden (1982) proposed a revised model in which actors could broker exchanges between pairs of other actors in return for a commission. At the same time, a number of recent studies (Galaskiewicz 1979; Galaskiewicz and Krohn 1984; Gould 1989) have observed a relationship between perceived influence and the ability to broker negotiation or resource flows.

These and other empirical and theoretical studies (Blok 1974; Boissevain 1974; Knoke and Laumann 1982; Prensky 1986) have focused on brokerage as an important theoretical concept, but very little effort has been made to formulate a general, rigorous conception of the phenomenon or to make such a conception operational in empirical settings. In this paper, therefore, we propose a formal definition of brokerage in concrete social systems. We identify five qualitatively different mediation structures that emerge when actors in transaction networks are differentiated into nonoverlapping subgroups and show that these structures correspond to intuitive and theoretically meaningful brokerage roles. We then translate these abstract conceptions into a set of quantitative measures. After describing the technical underpinnings of the measures in detail, we demonstrate that statistical inference can be used to determine whether an actor's observed brokerage behavior is due to a chance distribution of exchange relations or to an underlying tendency that structures these relations in a particular way. We conclude with an illustrative application of the techniques to empirical data.

2. WHAT IS BROKERAGE?

Marsden (1982, p. 202) defines brokerage as a process "by which intermediary actors facilitate transactions between other actors lacking access to or trust in one another." Thus, any brokered exchange can be thought of as a *relation* involving three actors, two of whom are the actual parties to the transaction and one of whom is the intermediary or broker. While the central aim of Marsden's brokerage model is to show that brokers can gain power by charging "commissions" each time they facilitate an exchange, this is not an integral component of his definition of brokerage behavior, nor is it the only way in which brokers can obtain power. On the contrary: Ethnographic and other empirical literature is rife with examples of intermediaries whose reward for brokerage services is diffuse or even nonexistent (see, e.g., Blok 1974; Boissevain 1974; Evans-Pritchard 1940). Since the idea of a commission is thus conceptually and often empirically quite distinct from the idea of brokerage, we refer to an actor who facilitates transactions or resource flows as a broker whether or not the actor attempts to extract a direct reward.

An important factor that needs to be added to this conception, however, is the possibility that actors in a social structure are differentiated with regard to activities or interests, so that exchanges between some actors differ in meaning from exchanges between other actors. An obvious way to take such differentiation into account is to partition a system into a set of mutually exclusive (nonoverlapping) classes or subgroups of actors. For example, Gould (1989) has shown that brokerage between rival factions in community elites contributes to influence, while brokerage between elite members who are not political rivals does not. This implies that communication or resource flows within groups should in general be distinguished from flows between groups.

In the specific context of transaction networks, a further distinction needs to be made: If the subgroup affiliations of the transacting parties are relevant, then so is the affiliation of the broker. In political negotiations, a member of one party may approach someone in a rival party through an intermediary who belongs to the rival group; alternatively, he or she may attempt to go through a fellow party member. The brokers in these two situations are playing distinct *roles* (Rogers and Agarwala-Rogers 1976). In the first case, the broker acts as a *gatekeeper* for his or her party and can decide whether or not to grant access to an outsider. In the second case, the broker acts as a *representative* for a fellow party member and attempts to establish contact with an outsider. More generally, a representative role is created when one or more members of a subgroup delegate one of their own to communicate information to, or negotiate exchanges with, outsiders. In contrast, gatekeeping occurs when an actor selectively grants outsiders access to members of his or her own group. Other examples of gatekeepers are personnel or recruitment officers and journal editors (see Merton 1973).

More systematically, we can identify exactly five structurally distinct types of brokers (or equivalently, five types of brokerage relations) that follow from a partitioning of actors into nonoverlapping subgroups (see Figure 1). First, all three actors may belong to the same group, so that the brokerage relation is completely internal to the group. Because this kind of exchange involves the services of an agent who is a member of the same group as the principals, an individual or organization who occupies this role can be seen as a *local broker* or *coordinator*. One example of a coordinator is the Federal Reserve Bank in a major city such as Boston or Atlanta, which serves as a kind of clearinghouse for all the private banks in its area. Since many smaller banks keep their funds on deposit with the Federal Reserve, transactions among these lesser institutions are frequently conducted through the central bank rather than directly.

In the second form of within-group brokerage, the two principals belong to the same subgroup while the intermediary belongs to a different group. Because the mediator in this type of transaction is an outsider, he or she is called a *cosmopolitan* or *itinerant* broker. A stockbroker is an example of this sort of mediator: Brokerage firms are generally set apart quite clearly from their clients, while buyers and sellers (other than institutional investors) make up an undifferentiated group from the broker's point of view and from their own.

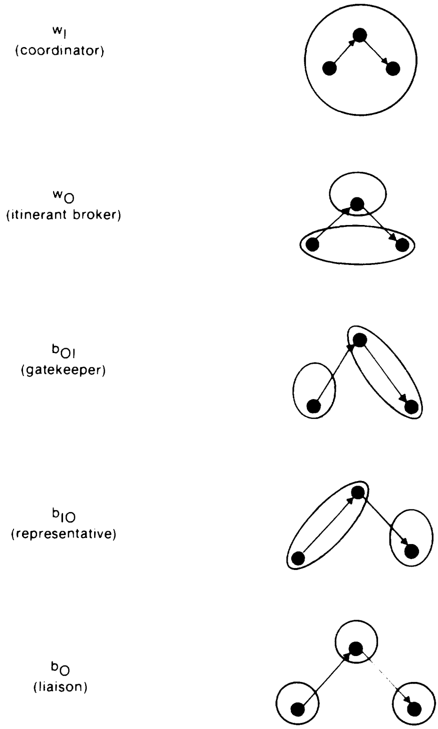

FIGURE 1 Graphic representation of the five types of brokerage relation. Solid points are actors; ellipses correspond to subgroup boundaries. The top point in each triad represents the broker.

The third and fourth types of brokerage roles are the gatekeeper and representative roles just discussed. The fifth type is another form of "between" flow, but in this case the broker is an outsider with respect to both the initiator of the brokerage relation and the receiver of the relation. We refer to a broker of this kind as a *liaison* in the sense that the actor's role is to link distinct groups without having prior allegiance to either (Weiss and Jacobson 1955). Agents in the publishing and entertainment industries are clear examples of liaison brokers: The actors whose transactions they mediate—writers and publishers in one case, performers and production companies in the other—are members of separate groups, and the agents belong to a third category.

The five brokerage types we have described represent specific structural positions or, alternatively, concrete social *roles* that actors can occupy in systems of exchange or networks of resource flows.

(Note, though, that while any given brokerage *relation* falls into only one of the five categories, individual *actors* can perform any combination of the corresponding roles simultaneously.) Our linkage of the term *position* with the term *role* (see White, Boorman, and Breiger 1976) reflects our conviction that brokerage is inherently and inextricably tied to structural position in transaction networks. Likewise, the interpretation we provide of each subtype is based on the structure of the brokerage relation and is consequently independent of the specific content of the transaction involved.

3. MEASURES OF BROKERAGE

Burt (1976) and Galaskiewicz and Krohn (1984) define brokers as actors who simultaneously send and receive resources from different parts of the network in which they are embedded. Both of these studies focus on the role of transmitter or broker as a position in a social network that is jointly occupied by a set of structurally equivalent actors; actors in this position are brokers insofar as they receive ties from one position (a *generator*, in Galaskiewicz and Krohn's terminology) and send ties to a different position (a *consumer*).

We believe that this method of identifying brokers is unsatisfactory for several reasons. First, it assumes unreasonably that brokers are present in a system of transactions or resource flows only to the extent that they can be aggregated into sets of equivalent actors. We maintain, in contrast, that any social system can contain numerous brokers, none of whom need be structurally equivalent to any other actor in the network. Identification of brokerage roles and the actors who occupy these roles should not be dependent on a prior condensation of a network into structurally equivalent blocks.

Second, because this method ignores the exact pattern of flows and looks only at overall volumes (except to ensure that actors are not brokers unless their position sends to and receives from different blocks), any information about the kind of brokerage an actor performs is thrown away. For instance, there is no way to tell from this method whether an actor brokers primarily for others in his or her own group or for outsiders; nor is it possible to distinguish any single actor from others in the same jointly occupied position.

Most importantly, a method based on aggregate flows fails completely to consider whether the senders and receivers of these flows have any direct relations. Since the whole point of brokerage is to create an indirect relation where no direct relation exists, it is absolutely essential to address this question. Because Burt's and Galaskiewicz and Krohn's conceptions ignore this issue, they cannot fairly be interpreted as measures of brokerage at all (which may explain why Galaskiewicz and Krohn substitute the term *transmitter* for Burt's term *broker*).

A more natural way to measure brokerage is through the graph-theoretic centrality measure known as betweenness (Bavelas 1948; Freeman 1977, 1979). Generally speaking, betweenness-based measures count the number of paths between other actors that a given actor lies on; they therefore express the extent to which the connectivity of a network depends upon the actor in question.

Nevertheless, there are several potential difficulties with using betweenness as a measure of an actor's ability to broker exchanges between others. For example, it takes geodesics (shortest paths) of any length into account and treats them equally (although the measure can be modified by weighting long paths less heavily than short ones). In other words, in a network with many actors, geodesics involving extremely long chains of intermediaries may contribute substantially to an individual's betweenness score; in fact, such paths may actually make up most of an actor's score. This would not be a problem except that long paths do not seem, either empirically or intuitively, to play a very important role in purposive social interaction. Experiments on the small-world problem strongly suggest that paths between individuals who are not directly linked tend to be quite short, when they are completed at all. For instance, Travers and Milgram (1969) reported that 29 percent of started chains actually reached their targets and that the vast majority of these required six intermediaries or fewer. If paths between individuals who do not even know each other tend to be this small, one must conclude that actors who are aware of each other and who are attempting to communicate or exchange resources should be able to reach each other in even fewer steps. Even if paths of greater length exist, it is unreasonable to assume that people are generally capable of tracing these paths out in practice.

In this paper, consequently, we deal only with forms of brokerage that involve a single intermediary. Though some forms of exchange may be brokered along paths of length greater than two, these paths will appear in the kinds of relational systems we propose to analyze as aggregations of the basic two-step brokerage process. For example, a brokered information flow that passes through three intermediaries (a path of length four) is indistinguishable in a binary information network from a series of three brokered exchanges. Even though the two situations may be analytically distinct, for the purposes of measurement they are substantially the same. The brokerage measures we propose and formalize in the following section therefore exclude from consideration all paths of length greater than two.[1]

3.1. *A Formal Approach to Brokerage*

In light of the foregoing discussion, we define brokerage in the following way. In a graph representing the nonsymmetric binary relation R, j is said to broker between i and k if and only if

$$iRj,\ jRk, \text{ and } i\bar{R}k,$$

where iRj indicates that i is tied to j by the relation R, and $i\bar{R}k$ is the negation of iRk. Stated less formally, i is tied directly to j, j is tied directly to k, and i is not tied directly to k.[2] (The statement

[1] We do not mean to suggest that centrality measures that take account of longer paths should not be used. On the contrary, there are many social processes in which paths of length three or greater are equally important: These include diffusion processes (Coleman, Katz, and Menzel 1966), river transportation (Freeman 1979), telecommunications systems, and others. The salience of two-step paths emerges when the relations involve *brokered* flows or transactions, that is, when the intermediary acts as an agent for the sender of the relation.

[2] We assume a single binary relation for the sake of simplicity, but it is possible to extend this conceptualization to take account of multiple relations and the volume of network flows. For example, if i sends ten pieces of information per unit time to j and j sends only four to k, we can treat the size of the j-k flow as the upper limit or carrying capacity for j's brokerage of i and k. This brokerage relation would be worth four times as much in computing j's score as a brokerage relation in which the carrying capacity was only one unit.

that j brokers between two other actors says nothing about whether there are other actors who also broker for this pair.) For any ordered triple of actors i, j, and k, we denote the condition in which j brokers i and k by the symbol ijk. Note that if ijk is true, ikj cannot be true, since there is a direct tie from i to j and no direct tie from i to k. Thus, ijk represents an intransitive triple (Holland and Leinhardt 1970, 1975, 1978).[3] Holland and Leinhardt have developed elaborate test statistics for detecting intransitivity in social networks, but we do not use them here for several reasons. First, these techniques are exclusively geared to global triad counts, whereas we are equally interested in individual-level tendencies to participate in intransitive triples. Second, Holland and Leinhardt's methods do not allow the identification of subgroups, which our five brokerage types require. Finally, their measures of intransitivity do not take into account the difference between a brokerage relation (ijk) and a brokered pair (see below), making it difficult to determine the extent to which pairs of actors are linked by more than one broker. Achieving all of this simultaneously requires a substantial departure from earlier work.

We can now give a simple definition of an actor j's total brokerage activity in a network with N actors or nodes. This measure, which we write as t_j, is the number of ordered pairs (i,k) in the network for which the condition ijk holds. The maximum possible score j can have is just the number of ordered pairs of actors in the network that do not include j, which is equal to $(N-1)(N-2)$. This is the value t_j would have if j were the center of a star graph, that is, if j were directly and reciprocally tied to every other actor and no other actors were tied directly to each other. This is, of course, the maximum possible betweenness score as well (see Freeman 1977; Gould 1987).

[3] Holland and Leinhardt's approach was designed to test predictions based on balance theory in affective networks. According to balance theory, intransitive triads should occur in affective networks only at below-chance levels. From this perspective, by studying whether ijk relations appear at above-chance levels, we measure departures from transitivity. While we owe much to their approach, our theoretical concerns are quite different from Holland and Leinhardt's in that we do not think that the brokerage concept makes sense in the context of affective relations; we would apply our techniques only to exchange or transaction networks.

Following Freeman's strategy, we can modify the brokerage measure to reflect the extent to which j is in control of the two-step link between any given i and k. That is, if j is the only intermediary between the two actors, he or she completely controls any flow from i to k, whereas j only partially controls this flow if there are other intermediaries. Accordingly, if there are g_{ik} two-step paths from i to k, and if j lies on one of them, the contribution to j's partial brokerage score from the (i,k) pair is $1/g_{ik}$. An actor j's overall partial brokerage level, t_j^*, is then the sum of his or her partial brokerage scores for all of the ordered pairs of other actors in the network. Since the maximum contribution to j's partial brokerage from any one pair is 1 (when $g_{ik} = 1$), the maximum partial brokerage score is again $(N-1)(N-2)$.

Which of these two forms of the brokerage measure should be used depends, of course, on the substantive context. If the researcher is interested in the number of brokerage relations an actor is capable of mediating, the appropriate measure is the absolute number of paths on which the actor lies; this corresponds to the individual's total capacity for brokerage. If, on the other hand, the central issue is the degree to which the actor actually controls brokerage relations in the network, then the appropriate measure is the partial score.[4] (In the discussion that follows, we refer to t_j, the simple number of pairs for whom j can broker, as j's raw brokerage, and to t_j^* as his or her partial brokerage.)

In accordance with the theoretical discussion above, we now add a crucial refinement to the brokerage measure by taking into account the possibility of partitioning any network into a set of disjoint subgroups. (Formally, we write $m_i = m_j$ when i and j belong

[4] It should be stressed that although we refer to the techniques outlined here as measures of brokerage, they do not necessarily measure the amount of brokerage an actor *actually performs*. Rather, they measure an aspect of an actor's structural position, namely, the extent to which the actor is capable of linking others in an indirect social relation or, equally importantly, of preventing such a link from being forged. Occupancy of such a position is, in our view, a necessary but not sufficient condition for actual brokerage behavior. While it would be interesting to know how likely actors are to engage in the brokerage activity of which they are structurally capable, this is an empirical question that needs to be explored in a variety of social systems. Our goal in this paper is to provide the tools to answer such questions.

to the same subgroup, and $m_i \neq m_j$ when i and j belong to different subgroups.)[5]

Because the notion of partitioning a network into disjoint subgroups is fundamental to our approach to brokerage, it is important to discuss the grouping criteria. The subgroup criteria need not be restricted to those found by analyzing the network data themselves. While it may be important to locate actors who mediate between sociometrically defined cliques or structurally equivalent blocks, it may also be useful to partition actors by attributes, such as interests or activities (see Gould 1989). In the empirical analyses we present below, we use a categorical rather than sociometric partition to demonstrate how our brokerage measure permits the combination of attribute data with structural analysis. In general, of course, the subgroup partition needs to be informed by substantive judgement. The appropriate grouping criterion depends on the goals of the actors in the given context and on the particular functions of the brokerage relation, e.g., conflict mediation, negotiation, information diffusion. If the broker functions to resolve conflict in an oppositional structure, then the most illuminating grouping criterion is the interests of the opposed parties. On the other hand, if the broker is seen as a diffuser of information bridging otherwise disconnected groups (e.g., Weiss and Jacobson's [1955] liaison), then it might be appropriate to adopt some sociometric criterion to group actors.

Identification of subgroup memberships for all three parties in a brokerage relation generates the five structurally distinct forms

[5] Fienberg and Wasserman (1981) and Fienberg, Meyer, and Wasserman (1985) have developed elaborate techniques for analyzing dyadic—that is, direct—relations in partitioned networks, with an emphasis on comparing subgroups' propensities to send or receive ties. Similarly, Snijders and Stokman (1987) have extended Holland and Leinhardt's (1970, 1975, 1978) triad approach by describing the statistical distribution of triads in which two actors belong to one subgroup and the third belongs to a different group. Our work differs sharply from that of Fienberg and Wasserman and Fienberg et al. in that we concentrate on *indirect* relations formed by ordered triples of actors, rather than on simple dyadic links considered one at a time. On the other hand, we diverge from Snijders and Stokman's work insofar as our research is concerned with individual-level measures in networks of resource flows, while theirs focuses on total counts of triad types in networks of affective relations.

of two-step brokerage shown in Figure 1. In the first type, all three actors belong to the same group ($m_i = m_j = m_k$). Because the two endpoints belong to the same group, we refer to this type of brokerage with the symbol w (for "within"); since the broker is *internal* to the group, we refer to this particular kind of within-group brokerage as w_I. An actor j's w_I score is written w_{Ij} and is defined as follows:

$$w_{Ij} = \sum_{i}^{N} \sum_{k}^{N} w_I(ik), \qquad (i \neq j \neq k), \tag{1}$$

where N is the number of actors in the network, and $w_I(ik)$ equals 1 if ijk is true and if $m_i = m_j = m_k$, and 0 otherwise.

In the second type, the two endpoints belong to the same subgroup and the intermediary belongs to a different group ($m_i = m_k \neq m_j$). This is the second kind of within-group flow; since the broker is now *outside* the group, we denote this type of brokerage relation by the symbol w_O. (The formulae for this score and for the three scores to follow are written analogously to (1) above.) Actors who occupy this position are cosmopolitan or itinerant brokers.

When the endpoints belong to two different subgroups, a brokered transaction from one actor to the other constitutes a between-group flow; the subtypes in this second general class of brokerage relations thus share the symbol b. When the broker belongs to the same subgroup as the initiator of the relation ($m_i = m_j \neq m_k$), the flow stays within the initial subgroup on the first step and leaves the group only after passing through the broker. Since the brokerage occurs from the inside out, we refer to this type of relation as b_{IO} or representative brokerage.

In the fourth type, the broker is a member of the same subgroup as the receiver of the indirect relation; that is, the initial tie comes from an outsider and enters the receiver's subgroup before being passed along by the broker ($m_i \neq m_j = m_k$). Since this gatekeeping form of brokerage starts from the outside and is mediated by an insider, we denote this relation b_{OI}.

Finally, when all three actors being to different groups, the path is a between-group flow mediated by a member of a third group ($m_i \neq m_j \neq m_k$). We write this form of brokerage relation as b_O, because everyone involved is an outsider with respect to everyone else. This type of broker was defined above as a liaison.

This classification of the forms of brokerage relations is an exhaustive listing of the possible types of two-step paths on which any actor may lie, and it is thus an exclusive and exhaustive partition of any actor j's total raw brokerage score t_j. Consequently, it is clear that

$$t_j = b_{Oj} + b_{IOj} + b_{OIj} + w_{Oj} + w_{Ij} \tag{2}$$

for any point j in any network; that is, an actor's total raw brokerage measure is equal to the sum of its five component measures. Moreover, j's partial score for each of these types of brokerage may be computed analogously to t_j^*, defined above. For example, j's partial brokerage for ordered pairs of actors (i,k) in which i is always an actor in j's group, and in which k is always an actor outside j's group (denoted by b_{IOj}^*), is given by

$$b_{IOj}^* = \sum_i^N \sum_k^N \frac{b_{IO}(ik)}{g_{ik}}, \quad (i \neq j \neq k,\; g_{ik} \neq 0), \tag{3}$$

where g_{ik} is the number of two-step paths between i and k, N is again the number of actors in the network, and $b_{IO}(ik)$ is equal to 1 if ijk is true and if $m_i = m_j \neq m_k$, and 0 otherwise. We can write a statement similar to (2), equating t_j^* with the sum of the five types of partial brokerage measures b_O^*, b_{IO}^*, etc.

Since every actor in a network has a score on all five types of brokerage (which may of course be zero), the network as a whole can be characterized in the same terms. For example, if we were to sum every actor's b_O score in a given network, we would have the total number of ordered triples (i,j,k) in the network whose members belong to three different groups and for which the condition ijk holds—in other words, the number of b_O brokerage relations in the network. This global feature of the network, written B_O, is therefore defined as

$$B_O = \sum_j^N b_{Oj}. \tag{4}$$

Similarly, if we were to sum every actor's b_O^* measure, we would obtain the number of pairs of actors belonging to different groups whose indirect link is mediated by a member of a third group. This network-level score, which we write as B^*_O, need not be an integer, because some pairs may be mediated partly by outsiders (b_O) and partly by insiders (b_{IO} and b_{OI}); these pairs each contribute less than a full point to the global B^*_O score. Therefore, like the individual measures of which it is the sum, B^*_O is a partial measure. B_O is thus the global raw measure for b_O brokerage in the network. Clearly, as with the individual scores, the global total brokerage measures T and T^* are equal to the sums of the five types of global raw and global partial brokerage measures, respectively.

An obvious problem with these measures is that their values depend on the size of the network being examined and on the subgroup partition being used. For example, an actor in a subgroup with twenty members has many more opportunities for w_I brokerage than an actor in a subgroup with only three members, because there are many more w_I paths on which the first actor might lie. What we need is a method that standardizes an individual's scores in such a way that they can be compared with the scores for any other actor in a different part of the same network or in a completely different network. Accordingly, in the next section we develop a test statistic that will tell us not only whether one actor's score is larger than the score of another, but also exactly how much larger or smaller this score is than the score one would expect under a chance model.

4. STATISTICAL TESTS FOR BROKERAGE MEASURES

We begin with a simple null model for a random network with N actors or nodes and K disjoint subgroups. In the discussion to follow, n_i is the number of actors in the ith subgroup, so that

$$\sum_{i}^{K} n_i = N. \tag{5}$$

We assume that all ordered pairs of actors (i,j) in the network have a fixed probability D of being linked by a directed tie, and that this probability is independent of whether any other dyad in the network is linked. If the symbol ij is taken to mean that i is tied directly to j, then the independence assumption is equivalent to saying that $p(ij|kl) = p(ij) = D$. We further assume that the independence condition holds even if the dyads share one or both actors. That is, $p(ij|ik) = p(ij)$ and $p(ij|ji) = p(ij)$ (see Katz and Powell 1954; Frank 1980).

To apply the null model, we simply interpret the number of links in an observed network as an *estimate* of the expected number of links in the network; that is, if there are q observed directed ties in a network with N actors, we use the density, $q/(N(N-1))$, as an estimate of the underlying parameter D. Thus, the number of links in the random network has a binomial distribution (given the independence assumption) with the probability of an event equal to D and the number of trials equal to $N(N-1)$.

The assumption of independent occurrence of links entails several important divergences from the random models used by Holland and Leinhardt (1970, 1975, 1978, 1981; see also Fienberg and Wasserman 1981; Fienberg et al. 1985). First, we are fixing not the total number of links in the network but rather the probability that any given ordered pair will be linked. Second, we do not take account of tendencies toward reciprocity or the variance in indegree and outdegree. The τ test statistic developed by Holland and Leinhardt (1970) and related tests for social structure using the triad census have usually used the $U|m,a,n$ distribution, which constrains the random network to contain the same number of mutual, asymmetric, and null dyads as the observed network under study. Their primary rationale for using this conditional distribution is their claim, based on "intuition and substantive theoretical consideration" (1981, p. 35), that affective social relations tend to exhibit a tendency toward mutuality. Similarly, the p_1 distribution conditions on each actor's indegree and outdegree (and on general tendencies toward reciprocity) on the grounds that most networks contain actors with different levels of "attractiveness" and "expansiveness."

Although p_1 is generally considered the state of the art in null models for social networks, we are reluctant to accept it uncritically as a baseline in the context of brokerage. While it is certainly true that actors with high indegrees and outdegrees tend, *ceteris paribus*, to exhibit higher brokerage levels than actors with low indegrees and outdegrees, it is by no means clear that these influences should therefore be controlled out of the expected values for our brokerage measures. An actor who wants to occupy a structural position with a high potential for brokerage may choose to maximize his or her interactions with other actors. Standardizing on variations in indegree and outdegree when calculating such an actor's brokerage level would obscure this aspect of the brokerage role and allow the researcher to measure only the extent to which pairs of actors linked by the actor were not linked directly—a contingency over which the focal actor may have little or no control. Since we view brokerage not as an activity thrust upon actors in social systems by chance or accident but rather as a role that may be purposively sought or avoided, we believe that it would be misleading to condition our null model on the differential tendencies of actors to interact in a network.

The question of reciprocity or mutuality is not so clearcut, however. In the simple case of complete reciprocity, statistical inference based on the null model presented above would be misleading, because the *i-j-k* triplet would be completely dependent on the *k-j-i* triplet: The condition *ijk* would imply *kji* and would increase the probability that other triplets involving the *k-j* and *j-i* ordered pairs were brokerage relations. Conversely, in a completely asymmetric network (no reciprocated links), *ijk* would always imply $\sim kji$. While these additional dependencies would not change the expected values of the various brokerage measures, they would affect the variance of the measures. (For example, the variance of individual measures would be doubled in symmetric networks and reduced by an amount proportional to $D^4(1 - D)^2$ in asymmetric networks.) Since tendencies toward mutuality are just as likely to result from normative considerations—or even from the operational definition of the relation being studied—as from the voluntaristic behavior of actors in a social system, one should control for the influence of reciprocity when comparing different networks.

Our point, in short, is that the choice of an appropriate null model depends on the social context, the type of relation involved, and the specific substantive questions the researcher is interested in. No model should be adopted naïvely—and it is no less naïve to assume that indegree and outdegree *are* independent of brokerage activity than to assume that they are not. Accordingly, the expected values and variances we derive here are based on a null model in which no deviations from pure randomness are assumed. (In other words, we adopt a baseline that treats the difference between two actors in brokerage activity as interesting even if this difference is purely the result of a difference in the number of ties sent or received.) However, for researchers interested in using more complicated null models, such as p_1, we have developed software that estimates the appropriate means and variances directly.

Given this null model of the distribution of links in a random network of size N and density D, the first step in determining the expected values of our brokerage measures is to identify the probability that any ordered triple (i,j,k) will exhibit the brokerage relation ijk. Since the null model assumes independence of dyads, this probability is given by

$$\begin{aligned} p(ijk) &= p(ij) \times p(jk) \times (1 - p(ik)) \\ &= D^2(1-D), \end{aligned} \tag{6}$$

which is simply the probability that i is tied to j, j is tied to k, and i is not tied directly to k. The expected value of any raw brokerage score, whether global or individual, is simply the product of this quantity and the number of possible ordered triples for which the brokerage condition could hold. Thus, the expected value of the total global brokerage score T is given by the equation

$$E(T) = D^2(1-D) \times N(N-1)(N-2), \tag{7}$$

because $\binom{N}{3}(3!) = N(N-1)(N-2)$ is the total number of ordered triples of actors in a network of size N. Similarly, an actor's expected total raw brokerage score is

$$E(t_j) = D^2(1-D) \times (N-1)(N-2), \tag{8}$$

since there are $(N-1)(N-2)$ ordered pairs of other actors for whom j might broker.

The derivations of the expected values for the five brokerage subtypes take exactly the same form for global and individual measures; that is, the expectations are found in each case by multiplying the probability of any given brokerage relation by the number of possible brokerage relations. The formulae for the expected values of individual and global raw scores are reported in Tables 1 and 2. Computer routines for calculating these expected values are also available from the authors.

TABLE 1
Expected Values and Variances for Individual Raw Brokerage Measures for an Actor in Group j

b_O	$E(b_O)$	$= (D^2(1-D)) \times \sum_i^K \sum_k^K n_i \times n_k$	$(i \neq j \neq k)$
	$\text{var}(b_O)$	$= E(b_O)\times(1-D^2(1-D))$	
		$+ 4\sum_i^K n_i \times \left[\frac{N-(n_i+n_j)}{2}\right] \times \left[D^3(1-D)^3\right]$	$(i \neq j)$
b_{IO} and b_{OI}	$E(b_{IO})$	$= E(b_{OI}) = (D^2(1-D)) \times \left[(N-n_j)(n_j-1)\right]$	
	$\text{var}(b_{IO})$	$= \text{var}(b_{OI}) = E(b_{IO})\times(1 - D^2(1-D))$	
		$+ 2\left[(n_j-1) \times \left[\frac{N-n_j}{2}\right] + (N-n_j) \times \left[\frac{n_j-1}{2}\right]\right] \times \left[D^3(1-D)^3\right]$	
w_O	$E(w_O)$	$= (D^2(1-D)) \times \sum_i^K n_i(n_i-1)$	$(i \neq j)$

	$\mathrm{var}(w_O)$	$= E(w_O)\times(1 - D^2(1-D)) + 2\sum_i^K n_i(n_i-1)(n_i-2) \times \left[D^3(1-D)^3\right]$	$(i \neq j)$
w_I	$E(w_I)$	$= (D^2(1-D)) \times \left[(n_j-1)(n_j-2)\right]$	
	$\mathrm{var}(w_I)$	$= E(w_I) \times (1 - D^2(1-D)) + 2(n_j-1)(n_j-2)(n_j-3) \times \left[D^3(1-D)^3\right]$	
t	$E(t)$	$= (D^2(1-D)) \times \left[(N-1)(N-2)\right]$	
	$\mathrm{var}(t)$	$= E(t)\times (1 - D^2(1-D)) + 2(N-1)(N-2)(N-3) \times \left[D^3(1-D)^3\right]$	

Note. As in the text, n_j refers to the number of actors in the jth subgroup. Thus, indices reflect summation across subgroups, not across actors.

TABLE 2
Expected Values and Variances for Global Raw Brokerage Measures

B_O	$E(B_O)$	$= (D^2(1-D)) \sum_i^K \sum_j^K n_i n_j (N-(n_i+n_j))$	$(i \neq j)$
	$\mathrm{var}(B_O)$	$= E(B_O) \times (1 - D^2(1-D)) + \sum_i^K \sum_j^K \sum_k^K n_i n_j n_k \times \Big[\big[4(N-n_j) - 2(n_i+n_k+1)\big] \times D^3(1-D)^3 - \big[4(N-n_k) - 2(n_i+n_j+1)\big] \times D^4(1-D)^2 + \big[N - (n_i+n_k+1)\big] \times D^5(1-D) \Big]$	$(i \neq j \neq k)$
B_{IO} and B_{OI}	$E(B_{OI})$	$= (D^2(1-D)) \times \sum_i^K n_i(N-n_i)(n_i-1)$	
	$\mathrm{var}(B_{IO})$	$= \mathrm{var}(B_{OI}) = E(B_{IO}) \times (1 - D^2(1-D)) + \sum_i^K n_i(N-n_i)(n_i-1) \times \Big[\big[(N-3) \times D^3(1-D)^3\big] + \big[(n_i-2) \times D^5(1-D)\big] \Big]$	
W_O	$E(W_O)$	$= (D^2(1-D)) \times \sum_i^K n_i(N-n_i)(n_i-1)$	
	$\mathrm{var}(W_O)$	$= E(W_O) \times (1 - D^2(1-D))$	

$$+\sum_{i}^{K}\sum_{j}^{K} n_i n_j (n_i-1) \times \left[\left[(2n_i+2n_j-6) \times D^3(1-D)^3\right] + \left[(N-n_i-1) \times D^5(1-D)\right]\right] \qquad (i \neq j)$$

W_I

$$E(W_I) = (D^2(1-D)) \times \sum_{i}^{K} n_i(n_i-1)(n_i-2)$$

$$\mathrm{var}(W_I) = E(W_I) \times (1 - D^2(1-D))$$

$$+\sum_{i}^{K} n_i(n_i-1)(n_i-2) \times \left[\left[(4n_i-10) \times D^3(1-D)^3\right] - \left[4(n_i-3) \times D^4(1-D)^2\right] + \left[(n_i-3) \times D^5(1-D)\right]\right]$$

T

$$E(T) = (D^2(1-D)) \times N(N-1)(N-2)$$

$$\mathrm{var}(T) = E(T) \times (1 - D^2(1-D))$$

$$+ N(N-1)(N-2) \times \left[\left[(4N-10) \times D^3(1-D)^3\right] - \left[4(N-3) \times D^4(1-D)^2\right] + \left[(N-3) \times D^5(1-D)\right]\right]$$

Although each ordered triple of actors (i,j,k) is treated here as a Bernoulli trial with $p = D^2(1-D)$, the full score is not distributed as an ordinary binomial random variable because the trials are not independent. This is easy to see because, for example, the distinct events *ijk* and *ijl* share the subevent *ij*. Consequently, $p(ijl|ijk) \neq p(ijl)$. Moreover, as noted earlier in the definition of the condition *ijk*, $p(ikl|ijk) = 0$ because i cannot be tied directly to k if *ijk* is true. Thus, the variances of the brokerage measures in this null model include terms for the covariances of the ordered triples that constitute the trials. For example, the variance of b_O for any actor in group j is given by

$$\operatorname{var}(b_O) = E(b_O)(1-p) + 4\sum_{i}^{K} n_i \left[\frac{N-(n_i+n_j)}{2}\right] \times \left[D^3(1-D)^3\right], \quad (i \neq j), \tag{9}$$

where p is the probability of any brokerage relation, $D^2(1-D)$, K is again the number of subgroups, and n_i is the number of actors in the ith subgroup. These variances are also reported in Tables 1 and 2.

The expected value of an actor's partial brokerage is equal to the expected raw brokerage divided by the expected number of two-step paths between any pair of actors. Consequently, the variance of partial brokerage values equals the variance of the raw scores divided by the square of this expected number of paths. The appropriate formulae for all five types appear in Table 3.

The expected values of the global partial scores can also be calculated exactly, since these scores correspond simply to the number of ordered pairs of actors who are linked indirectly by intermediaries in particular subgroups. Thus, for example, a network's global partial score W_O^* is the number of pairs of actors in the same group who are linked by members of another group; or to be more precise, since the same pair of actors can be linked simultaneously by insiders and by outsiders, we should interpret W_O^* as the sum of the *fractions* of pairs who are brokered in this manner. To calculate expected values for these measures, then, we need to know the probability that any ordered pair of actors will

TABLE 3
Expected Values and Variances for Individual Partial Brokerage Measures

b_O^*	$E(b_O^*)$	$= E(b_O) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]$
	$\mathrm{var}(b_O^*)$	$= \mathrm{var}(b_O) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]^2$
b_{IO}^* and b_{OI}^*	$E(b_{IO}^*)$	$= E(b_{OI}^*) = E(b_{IO}) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]$
	$\mathrm{var}(b_{IO}^*)$	$= \mathrm{var}(b_{OI}^*) = \mathrm{var}(b_{IO}) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]^2$
w_O^*	$E(w_O^*)$	$= E(w_O) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]$
	$\mathrm{var}(w_O^*)$	$= \mathrm{var}(w_O) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]^2$
w_I^*	$E(w_I^*)$	$= E(w_I) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]$
	$\mathrm{var}(w_I^*)$	$= \mathrm{var}(w_I) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]^2$
t^*	$E(t^*)$	$= E(t) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]$
	$\mathrm{var}(t^*)$	$= \mathrm{var}(t) \times \left[\frac{1-(1-D^2)^{N-2}}{D^2(N-2)}\right]^2$

be brokered by at least one other actor—that is, the probability for any pair (i,k) that there is some j such that ijk is true.

This probability can easily be derived as follows. The probability that i is not tied directly to k is just $(1-D)$, and the probability that any actor j does not link i to k is simply $(1-D^2)$. Since there are $N-2$ j's in a network with N actors who might link i to k, the probability that i is *not* tied indirectly to k by anyone is $(1-D^2)^{N-2}$. Consequently, the probability that i is indirectly tied to k by a two-step path but is not directly tied to k, which we denote by $p(i2k)$, is

$$p(i2k) = \left[1 - (1-D^2)^{N-2}\right] \times (1-D). \tag{10}$$

In other words, there is a two-step path from i to k that is not "short-circuited" by a direct link from i to k.

It is now clear that the expected value of T^* is simply $p(i2k)$ multiplied by the number of ordered pairs (i,k) in the network. That is,

$$E(T^*) = p(i2k) \times N \times (N-1). \tag{11}$$

Expected values of the five subtypes are calculated in an analogous manner, although the expressions are slightly more complex because the brokerage of i and k may fall into three parts (b_O,b_{IO}, and b_{OI}) when i and k belong to different groups and into two parts (w_O and w_I) when they belong to the same group. These expected

TABLE 4
Expected Values for Global Partial Measures

B^*_O	$E(B^*_O)$	$= \sum_i^K \sum_j^K \frac{N-(n_i+n_j)}{N-2}\left[(1-(1-D^2)^{N-2}) \times (1-D)\right] \times n_i n_j$
B^*_{IO} and B^*_{OI}	$E(B^*_{IO})$	$= E(B^*_{OI})$ $= \sum_i^K \sum_j^K \frac{n_i-1}{N-2}\left[(1-(1-D^2)^{N-2}) \times (1-D)\right] \times n_i n_j$
W^*_O	$E(W^*_O)$	$= \sum_i^K \frac{N-n_i}{N-2}\left[(1-(1-D^2)^{N-2}) \times (1-D)\right] \times n_i(n_i-1)$
W^*_I	$E(W^*_I)$	$= \sum_i^K \frac{n_i-2}{N-2}\left[(1-(1-D^2)^{N-2}) \times (1-D)\right] \times n_i(n_i-1)$
T^*	$E(T^*)$	$= \left[(1-(1-D^2)^{N-2}) \times (1-D)\right] \times N(N-1)$

values are reported in Table 4. Unfortunately, we are unable to derive the variances for these global partial measures; nevertheless, they can be estimated using a computer simulation procedure available from the authors.

We can now standardize any actor's brokerage position using a test statistic of the form

$$\beta = \frac{b - \mu_b}{\sigma_b}, \tag{12}$$

where b is any of the brokerage scores defined above, μ_b is the expected value of b, and σ_b is the standard deviation of b under the null model. For sufficiently large networks (about 15 actors for global scores, 30 for individual scores except when the density is very low), it is reasonable to assume that this test statistic has the standard normal distribution. The defensibility of the normality assumption is discussed by Holland and Leinhardt (1978, 1970) for triad counts, which are closely related to the counts of ordered triples used in these calculations; moreover, computer simulations (see Figure 2; detailed results are available from the authors) provide strong evidence that these measures are normally distributed in random networks of sufficient size.[6]

For global brokerage measures, this statistic is comparable to the various tests for social structure developed by Holland and Leinhardt (1970, 1978). Just as a statistically significant value of τ indicates that a network exhibits an overall tendency toward transitivity, a significant positive value of β for the partial global measure B_O^* shows that actors in the system have a tendency to participate in brokerage relations in which all three parties belong

[6] Note that regardless of the size of the network, w_I scores for actors whose subgroups are very small are *not* normally distributed. Also, for networks of a given size, the distribution is not invariant under changes in the density D: For extreme values of D, β's distribution may be skewed. Thus, it is generally a good idea to examine the distribution of a measure before using normal probabilities to test hypotheses about it. As we noted above, researchers can directly estimate the probability distributions for any of the measures using computer simulation techniques. We suggest that this be done when the expected value is less than twice the magnitude of the standard deviation, but researchers who are skeptical of the normality assumption can use the same procedures to estimate probabilities in any network. Thus, the assumption of normality is in no sense essential to the use of statistical inference in analyzing brokerage scores.

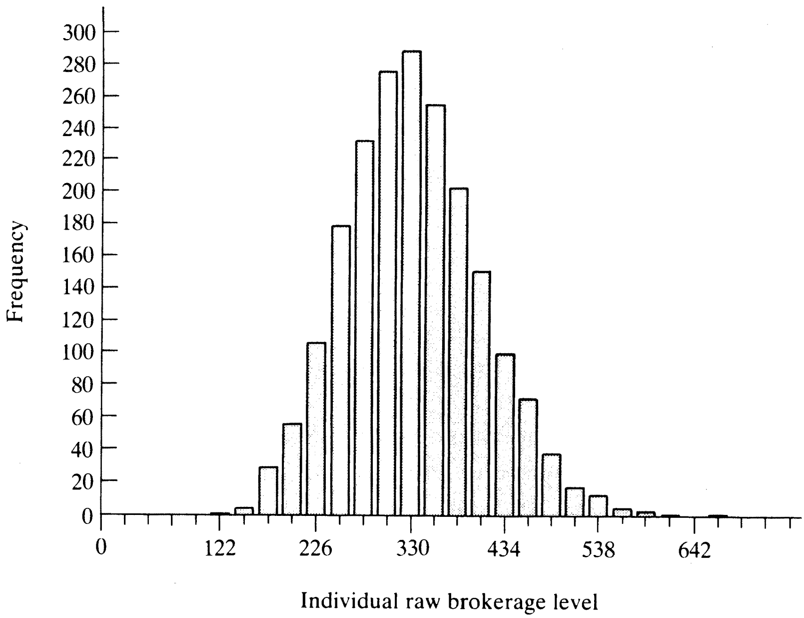

FIGURE 2 Frequency distribution of t (total raw brokerage) for an actor in a random network with N=60, D=0.4 (2,000 sampled graphs).

to different subgroups. Conversely, a significant negative value suggests that actors avoid entering into brokerage relations of this type, either by pursuing direct relations with the target or by foregoing the indirect relation entirely. Therefore, we can use β to make inferences about single social systems or to compare different systems in terms of their reliance on various types of brokered transactions. At the individual level of analysis, researchers can use β to compare the brokerage roles of two actors from different networks or from the same network. Since β standardizes every individual score on the basis of its expected value *and* variance, actors can be compared even when the systems they are involved in have very different global characteristics.

More importantly, β can be used at the individual level literally to test for an actor's *role* in a specific social system. Since the five types of brokerage roles described here are measured as continuous variables, any actor can simultaneously occupy all five roles to varying degrees. The virtue of statistical tests for these individual scores, then, is that they allow the researcher to evaluate the relative significance of each type in determining the structural role the actor plays. For instance, one actor in a social system may have fairly high partial scores on all five brokerage measures when compared with other actors in the same system, leading the analyst to believe that this actor occupies a general brokerage position; but if the β test statistic shows that only one or two of these apparently high scores are statistically significant, the researcher would conclude that the actor's role should really be characterized only in terms of these particular forms of brokerage. A positive and statistically significant value of β for an individual actor can consequently be interpreted to mean that the actor occupies a certain brokerage position by virtue of a systematic structuring of relations in his egocentric or local network rather than by random assignment of these relations to dyads in the network.

Note that such a result (for example, a statistically significant value of b_{IOj} for actor j) is quite possible even when global measures of brokerage do not reveal any systematic social structure. In other words, actors may be able to structure their own relations to guarantee significant brokerage roles even though the system as a whole conforms to the chance model of social networks. Statistical tests for individual measures of brokerage are consequently mathematically and qualitatively distinct from tests for structure in an overall network (as exemplified by Holland and Leinhardt's τ [1978, 1970] and similar measures). To our knowledge, β is unique in that it is the only test statistic that has been proposed for an *individual*'s structural position.

5. BROKERAGE ROLES IN TOWERTOWN: A CASE STUDY

Galaskiewicz (1979) conducted an extensive study of resource flows in a network of 73 organizations in Towertown, a medium-sized city in Illinois. Detailed descriptions and analyses of the social structure and political processes of this community can be found in Laumann, Marsden, and Galaskiewicz (1977), Galaskiewicz (1979), and Galaskiewicz and Krohn (1984); we employ data from this study simply to demonstrate how our techniques can be used to draw conclusions about the roles and positions actors occupy in transactional networks.

The network data we use consist of the responses of 73 organizational representatives to questions about which other organizations they were likely to rely on for "information regarding community affairs," and conversely about which groups were likely to receive such information from the respondent's organization (Galaskiewicz 1979, p. 173). The sociomatrices constructed from these two questions (the "send" matrix and the transpose of the "receive" matrix) were unioned on the assumption that a tie existed even if one organization failed to report it, yielding a nonsymmetric 73×73 matrix representing information flows among organizations in Towertown.

We partitioned this set of actors into three subgroups according to activity or function criteria. The first subgroup consists of 23 businesses and professional associations, comprising all of the private, profit-oriented organizations in the study. The second subgroup consists of the 25 government agencies in Towertown and the surrounding county. Finally, we assigned to the third group the 25 clubs, churches, voluntary organizations, and social service groups in the city. Thus, the partition divides the 73 actors roughly into for-profit, public, and nonprofit organizations.[7]

Standardized partial scores on the five types of brokerage and the total measure t^* are reported for all 73 organizations in Table 5. Looking first at the total scores, we observe that fully 41 of the organizations in the network exhibit brokerage behavior at *less* than chance levels (assuming a normal distribution, we use $|\beta| > 1.96$ as our statistical test), while 10 of the actors have total partial scores that significantly exceed chance. In a completely random network, only 5 percent of the actors should have scores

[7] We choose a partition based on profit orientation because we believe that such a division is likely to reflect interest groups. It is important to choose a partitioning scheme that is relevant to the actors in the system or at least to the research question; without this restriction, the substantive interpretations of our five types of brokerage would make little sense. While Galaskiewicz's (1979) classification of the organizations into economic, problem-solving, and service organizations would make sense for this analysis, we felt that our partition based on imputed interests would yield substantively more interesting results.

TABLE 5
Standardized Partial Brokerage Scores (β) for 73 Organizations in Towertown

Organization	b_O^*	b_{IO}^*	b_{OI}^*	w_O^*	w_I^*	t^*
Subgroup 1						
Towertown Newspaper	22.523	4.557	5.863	19.058	−0.401	15.778
WTWR Radio	50.342	36.341	36.494	44.281	18.771	55.724
Chamber of Commerce	1.938	10.675	4.962	1.670	15.981	9.034
Towertown Bus. Assoc.	−0.171	−1.005	−1.013	−0.166	−1.427	−1.019
Bankers' Assoc.	−2.673	−2.128	−2.128	−2.680	−1.766	−3.316
1st Towertown Bank	0.027	2.047	3.375	−0.271	3.907	2.413
Towertown S & L	1.856	2.733	1.927	3.798	0.993	3.398
Bank of Towertown	−1.719	−0.907	0.921	−2.205	1.705	−0.866
2nd Towertown Bank	−2.599	−2.102	−2.114	−2.680	−1.766	−3.280
Brinkman Law Firm	−2.383	−0.577	−0.444	−1.631	2.312	−1.144
Cater Law Firm	−2.463	−1.815	−1.656	−2.599	−1.766	−2.965
Lenhart Law Firm	−2.187	−0.782	−1.136	−0.989	−1.158	−1.789
County Bar Assoc.	−2.659	−1.921	−2.002	−2.657	−1.493	−3.146
Board of Realtors	−1.875	−0.102	−1.913	−1.999	−1.234	−2.034
Farm Equipment Co.	−2.174	−1.293	−0.715	−2.120	0.541	−1.855
Clothing Mfg. Co.	−2.652	−1.760	−1.813	−2.607	−1.733	−3.053
Farm Supply Co.	−1.661	−0.389	−1.383	−1.963	−0.658	−1.780
Mechanical Co.	−2.676	−2.115	−2.116	−2.630	−1.733	−3.288
Elec. Equipment Co.	−2.281	−1.502	−1.922	−2.075	−1.408	−2.681
Metal Products Co.	−1.882	−1.221	−1.308	−2.107	−0.600	−2.132
Music Equipment Co.	−2.676	−1.803	−2.122	−2.654	−1.431	−3.141
County Medical Soc.	−2.675	−2.074	−2.110	−2.680	−1.720	−3.284
Cnty. Hlth. Serv. Ctr.	−0.274	−0.833	0.285	−1.106	−0.706	−0.708
Subgroup 2						
City Council	0.625	4.567	4.438	2.602	6.261	5.195
City Manager	11.235	10.496	11.917	8.312	8.547	14.828
School Board	2.581	3.597	1.537	1.680	1.278	3.206
State University	4.220	2.029	2.629	3.361	−0.187	3.686
County Board	−0.658	−0.622	0.036	−1.244	−0.350	−0.797
State Employment Serv.	−1.369	−0.313	0.201	−2.077	3.107	−0.397
Mental Health Ctr.	−2.051	2.117	−1.408	−1.967	3.549	−0.193
Fire Department	−2.481	−1.830	−1.877	−2.469	−1.531	−2.952
Human Rel. Comm.	−0.759	−1.427	−0.506	−1.194	−1.446	−1.487
Mayor's Office	−1.128	−0.376	−0.903	−1.385	−0.840	−1.302
Police Department	−2.382	−1.607	−1.138	−2.058	−0.983	−2.375
Sanitary District	−2.458	−1.779	−2.099	−2.570	−1.276	−2.983
Streets & Sanitation	−2.624	−2.168	−2.133	−2.609	−1.747	−3.277

Continued overleaf

TABLE 5 *continued*

Standardized Partial Brokerage Scores (β) for 73 Organizations in Towertown

Organization	b^*_O	b^*_{IO}	b^*_{OI}	w^*_O	w^*_I	t^*
Park District	−1.880	−1.002	−1.448	−0.454	−1.568	−1.804
Zoning Board	−2.557	−2.162	−2.072	−2.543	−1.853	−3.238
State Highway Auth.	−2.587	−2.158	−2.029	−2.456	−1.853	−3.206
Towertown High School	−0.958	−1.301	−1.252	−1.413	−1.376	−1.803
Towertown Comm. Coll.	−2.399	−1.425	−1.687	−2.308	−1.334	−2.643
St. Dept. of Pub. Aid	−2.318	−1.578	−1.423	−2.328	−0.051	−2.339
Cnty. Housing Auth.	−2.266	−1.039	−1.334	−2.295	0.757	−1.943
Towertown Youth Serv.	−1.761	−0.179	1.396	−1.064	1.806	−0.026
Towertown Hospital Bd.	−1.387	−1.656	−0.821	−1.799	−1.417	−2.013
Towertown Public Hosp.	−0.945	0.112	−0.112	−1.839	0.818	−0.615
Cnty. Mental Hlth. Bd.	−2.142	−1.798	−1.371	−2.440	−1.350	−2.629
Cnty. Board of Health	−2.262	−1.597	−1.743	−2.377	−0.999	−2.636
Subgroup 3						
Family Services	14.659	7.168	5.784	9.852	2.035	11.716
Democratic Committee	−2.624	−2.148	−2.165	−2.619	−1.726	−3.280
Republican Committee	−2.624	−2.148	−2.140	−2.609	−1.726	−3.269
League of Women Voters	−0.236	−0.915	0.334	0.168	−1.014	−0.417
Farm Bureau	−0.506	2.034	2.593	−0.824	1.577	1.525
Munic. Empl. Union-1	−2.550	−1.538	−1.550	−2.585	−1.853	−2.854
Munic. Empl. Union-2	−1.220	1.017	1.892	−2.075	3.370	0.735
Teachers' Union	−2.624	−1.907	−1.862	−2.619	−1.641	−3.077
Central Labor Union	−2.624	−2.158	−2.178	−2.619	−1.508	−3.246
Kiwanis Club-1	−2.487	−2.069	−2.043	−2.543	−1.686	−3.144
Kiwanis Club-2	−2.519	−2.126	−1.818	−2.538	−1.614	−3.080
Rotary Club	−1.707	−1.682	−2.100	−2.064	−1.808	−2.701
Lions Club	−2.426	−1.886	−2.106	−2.332	−1.787	−3.047
United Fund	−1.354	−1.387	−1.588	−1.760	−1.278	−2.137
Towertown PTA	−2.464	−1.966	−1.820	−2.347	−1.691	−2.972
Assoc. of Churches-1	−2.590	−2.044	−1.511	−2.576	−0.675	−2.795
Assoc. of Churches-2	−2.298	−0.146	0.419	−2.028	2.635	−0.607
St. Hilary's Church	−1.824	−1.809	−1.979	−2.154	−1.818	−2.763
1st Baptist Church	−2.286	−1.428	−1.700	−2.110	−1.353	−2.565
1st Church of Light	2.443	−0.010	−0.054	1.271	−0.751	0.877
1st Congreg. Church	−1.876	−1.745	−1.502	−2.267	−1.818	−2.622
1st Methodist Church	−2.540	−2.007	−1.943	−2.591	−1.462	−3.073
Unity Lutheran	−2.347	−2.010	−2.034	−2.470	−1.790	−3.080
Univ. Methodist Church	−2.624	−2.123	−2.147	−2.619	−1.747	−3.270
YMCA	−2.041	−0.838	−1.617	−2.297	−0.400	−2.131

at these extremes; thus, we should reject the null hypothesis of a random network.[8] Substantively, this result suggests that the network of information flows in Towertown disproportionately assigns the structural position of intermediary or broker to only a few actors, while a considerable number of organizations either actively avoid playing this role or are prevented from occupying intermediary positions for other reasons. This observation is consistent with Galaskiewicz's (1979, p. 75) finding that organizations "engaged in general community problem solving" act as integrators in the Towertown information network, while other actors tend to occupy more peripheral positions. Similarly, Galaskiewicz and Krohn (1984) located a small set of organizational actors whose structural position suggests that they share an interest in coordination and community organization.

Turning now to the actors themselves, we see that the radio station occupies the position with by far the highest capacity for brokerage in this information network, followed at some distance by the city newspaper, the city manager's office, and the nonprofit Family Services organization. All of the actors with high total brokerage scores appear at or near the center of Galaskiewicz's (1979) smallest-space solution for the information network. In fact, all of these actors except for Family Services are included in what Galaskiewicz terms the integrators sector of the network; Family Services is located just outside of this sector.

Nevertheless, it would be a mistake to interpret these consistencies between our results and previous findings as an indication that these brokerage measures are simply another way of measuring centrality. Even though it is one of the most central

[8] Since the brokerage levels of two actors in the same random network are not in general independent, care must be taken when performing statistical inference on sets of actors. A rigorous test of whether the number of actors with extreme values is itself extreme must take into account the covariances of each actor's measure with every other. Because these covariances depend on the subgroup partition, we do not present a general formula here; nevertheless, they are easily calculated using the expected value formulae in Tables 1 and 3. Also, it can be shown that these dependencies approach zero as network size increases. In the analyses presented here, we focus on actors one at a time and consequently are not concerned with the joint occurrence of two or more actors' brokerage scores. We thus treat the measures as one would the standard errors for the parameter estimates in a regression equation: Each is examined as a separate event even though the events covary.

actors in Galaskiewicz's smallest-space depiction of the network, the mayor's office fails to show higher than chance levels on any of the five types of brokerage or on total brokerage; clearly, brokerage is not synonymous with centrality. (For empirical evidence that brokerage potential is actually a *better* predictor of influence than standard measures of centrality, see Gould [1989].)

Brokerage also differs from ordinary centrality in a more subtle way. While most of the organizational actors with high scores on t^* exhibit high brokerage activity on all five subtypes, indicating that they are brokers in the most general sense, each tends to peak on a different subtype. For instance, while the radio station's strongest brokerage position involves the liaison and itinerant broker roles, the chamber of commerce appears principally to occupy representative and coordinator positions (and does not exhibit higher than chance levels on either liaison or itinerant brokerage). The fact that this analysis can identify distinct structural roles among actors who occupy positions of roughly equal centrality shows that our brokerage measures are sensitive to differences in structural positions that are invisible to typical centrality measures. Consequently, while our analysis agrees with that of Galaskiewicz (1979) in identifying certain individuals as coordinators or brokers, it goes beyond the original analysis in outlining more precisely the *kinds* of brokerage each actor may perform.

The newspaper occupies liaison, representative, gatekeeper, and itinerant broker roles with respect to other organizations in the Towertown area, but it does not have any apparent tendency to transmit information within its own subgroup of for-profit organizations. In general, this means that the newspaper facilitates communication both *between* subgroups (such as information flows from businesses to government agencies, from social service organizations to businesses, from service organizations to government agencies, etc.) and *within* groups of which it is not a member.

Another organization in the network which exhibits a clear tendency to occupy one role but not another is the second municipal employees' union, which we assigned to the subgroup of voluntary and nonprofit organizations. While the union does not exhibit any general propensity to broker information flows, as shown by its nonsignificant total brokerage score, it nevertheless appears to act as a coordinator of communication for members of its own subgroup.

In contrast, its standardized score for w_O brokerage is significantly below chance levels, suggesting that the union is either unwilling or unable to aid government agencies or business concerns in their internal exchanges of information. The fact that all four unions in the network have significantly low w_O scores leads us to conclude that the occasionally confrontational activities of unions render them ineligible for the role of itinerant intermediaries, in part because they refuse to perform services of this kind for businesses and government organizations and in part because their sometime adversaries may not view them as trustworthy agents. Again, our result appears to reinforce Galaskiewicz's (1979) and Galaskiewicz and Krohn's (1984) analyses, both of which show the labor unions in Towertown as structurally equivalent actors occupying a fairly isolated position. Galaskiewicz and Krohn's principal components analysis of Towertown's money, information, and support networks places all four labor groups in the same structurally equivalent group with no other actors in the group, while Galaskiewicz's smallest-space solutions for the three networks consistently place the unions in the same sparsely populated sector of the social space. Clearly, the negative w_O scores for the unions are related to their isolation from other actors in the community.

Two final examples of organizational actors with specialized brokerage roles are the state university and the school board. Both of these organizations have significantly positive values of β for their overall partial scores (t^*), but neither has significantly positive values for all five subtypes. The university appears to be active as a liaison and itinerant broker for businesses and nonprofit firms and as a representative and gatekeeper for government agencies, but it is not especially likely to coordinate information flows within its own group. This may be a result of the university's reluctance, as an educational institution, to become too involved in local political issues; nevertheless, it seems to serve as an important conduit of information from public agencies to private ones, and vice versa.

Similarly, the school board does not occupy a significant place as a coordinator of information exchange in the government agency subgroup; nor is it in an especially strong position to act as a gatekeeper or an itinerant broker. As a much less visible organization than the university, the board is probably not approached as often by businesses or voluntary associations attempting to communicate with the government. Nevertheless, as the body in charge of the local educational system, it clearly has an audible voice in transmitting information from government agencies to the private sphere.

As a last illustration, global raw measures for the network are shown in Table 6 in both unstandardized and standardized form. These measures represent the total number of brokerage relations of each type that actually appear in the network (that is, the total number of ordered triples of each type for which the condition *ijk* holds). It is immediately clear that only two of the five types—B_{IO} and W_I—appear with frequencies significantly greater than chance, and that the total number of brokerage relations, while slightly higher than the expected number, is not significantly so. Although we have not reported them here, the global *partial* measures are within the chance range for all five types of brokerage and for the total, indicating that pairs of actors are about as likely to be brokered in this social system as in a random network. The significant values of B_{IO} and W_I suggest that actors in the system emphasize redundancy when searching for representatives and coordinators. In other words, organizations in Towertown tend to avoid depending on a small number of brokers when they attempt to communicate within their subgroups and when they use members of their groups to communicate with other groups. This suggests the intriguing possibility that such functions are too important to organizational actors to be entrusted to just

TABLE 6
Global Raw Measures for Towertown Information Network

	Total Number of Brokerage Relations (Unstandardized Global Measures)	Standardized Measures (β)
B_O	3,700	−0.4498
B_{IO}	4,138	2.7392
B_{OI}	3,963	1.7732
W_O	3,287	−1.5543
W_I	2,124	3.4913
T	17,212	1.1922

one or two others; organizations maintain numerous options to avoid developing severe dependencies on other actors in their own group. In contrast, the other three types may not be crucial enough to cause severe dependency when the services of only a few brokers are available; or, alternatively, because it may be too difficult to maintain multiple liaisons, gatekeepers, and outside brokers, organizations may be forced to rely on only a few.

6. SUMMARY AND CONCLUSIONS

This paper has formulated a rigorous theoretical conception of brokerage behavior in observable social structures. Beginning with the idea that brokerage in general involves the flow or exchange of resources from one actor to another via an intermediary, we showed that this simple structure (the three-person relation *ijk*) can be analytically decomposed into five distinct types, each of which corresponds to an intuitive, ideal-typical brokerage role. We then constructed a set of formal measures, which were shown to be isomorphic to the theoretical typology, both at the level of an entire network and at the level of individual actors. Finally, we derived the first two moments of these measures under a chance model of dyadic links and proposed a test statistic for evaluating the significance of each type of brokerage for whole social systems and for the actors they comprise.

Needless to say, one of the purposes of these brokerage measures is descriptive. Many researchers have used the brokerage concept, but usually in a rather diffuse and unanalyzed manner; thus, our aim in formalizing this idea and making it operational has been to provide an analytical tool that can be used to study brokerage directly. Rather than relying on subjective impressions that certain actors seem to occupy brokerage positions, researchers can apply our measures to determine exactly which actors do so, to what degree, and most importantly, in what form.

Nonetheless, we hope that this work will make a theoretical contribution as well. By identifying five qualitatively different roles, all of which have equal claim to the term *brokerage*, we have endeavored to add a degree of sophistication to conceptual discussions of brokerage behavior. In place of a somewhat nebulous but attractive idea, sociologists now have a rigorous theoretical language with which to discuss the role of brokers in interorganizational communication and exchange networks (Galaskiewicz 1979; Prensky 1986; Knoke and Laumann 1982), patron-client systems (Blok 1974), marketing channels (Reve and Stern 1979), and numerous other social settings in which actors engage in regular, patterned transactions.

In sum, it should be clear that we do not view brokerage simply as an inert epiphenomenon or artifact of social interaction. On the contrary, we expect researchers using our measures to explore the relationship of brokerage activity to various other phenomena of sociological interest, such as power, influence, collective behavior, and cultural diffusion. Moreover, like Aldrich (1982), we see brokerage not only as an explanatory variable but also as a phenomenon to be studied and explained in its own right. In other research, we have explored the determinants of individual brokerage roles in information flow networks in the national health policy domain (see Fernandez, Gould, and Prensky 1988). It is our hope that other researchers will employ the measures outlined here in the wide variety of fields in which brokerage has provoked interest.

REFERENCES

Aldrich, Howard. 1982. "The Origins and Persistence of Social Networks: A Comment." Pp. 281–93 in *Social Structure and Network Analysis*, edited by Peter V. Marsden and Nan Lin. Beverly Hills: Sage.

Bavelas, Alex. 1948. "A Mathematical Model for Group Structure." *Applied Anthropology* 7: 16–30.

Blok, Anton. 1974. *The Mafia of a Sicilian Village, 1860–1960.* New York: Harper and Row.

Boissevain, Jeremy. 1974. *Friends of Friends: Networks, Manipulators, and Coalitions*. Oxford: Basil Blackwell.

Bonacich, Phillip. 1987. "Power and Centrality: A Family of Measures." *American Journal of Sociology* 92: 1170–82.

Burt, Ronald S. 1976. "Positions in Networks." *Social Forces* 55: 93–122.

Coleman, James S. 1973. *The Mathematics of Collective Action*. Chicago: Aldine.

Coleman, James S., Elihu Katz, and Herbert Menzel. 1966. *Medical Innovation: A Diffusion Study*. Indianapolis: Bobbs-Merrill.

Cook, Karen S. 1982. "Network Structures from an Exchange Perspective." Pp. 177–99 in *Social Structure and Network Analysis*, edited by Peter V.

Marsden and Nan Lin. Beverly Hills: Sage.
Cook, Karen S., R. M. Emerson, M. R. Gillmore, and T. Yamagishi. 1983. "The Distribution of Power in Exchange Networks: Theory and Experimental Results." *American Journal of Sociology* 89: 275–305.
Evans-Pritchard, E. E. 1940. *The Nuer*. Oxford: Oxford University Press.
Fernandez, Roberto M., Roger V. Gould, and David Prensky. 1988. "Information Brokerage in the National Health Policy Domain." Paper presented at the annual meetings of the American Sociological Association, Atlanta.
Fienberg, Stephen E., Michael M. Meyer, and Stanley S. Wasserman. 1985. "Statistical Analysis of Multiple Social Relations." *Journal of the American Statistical Association* 80: 51–67.
Fienberg, Stephen E., and Stanley S. Wasserman. 1981. "Categorical Data Analysis of Single Sociometric Relations." Pp. 156–92 in *Sociological Methodology 1981*, edited by Samuel Leinhardt. San Francisco: Jossey-Bass.
Frank, Ove. 1980. "Transitivity in Stochastic Graphs and Digraphs." *Journal of Mathematical Sociology* 7: 199–213.
Freeman, Linton C. 1977. "A Set of Measures of Centrality Based on Betweenness." *Sociometry* 40: 35–41.
———. 1979. "Centrality in Social Networks: I. Conceptual Clarification." *Social Networks* 1: 215–39.
Galaskiewicz, Joseph. 1979. *Exchange Networks and Community Politics*. Beverly Hills: Sage.
Galaskiewicz, Joseph, and Karl R. Krohn. 1984. "Positions, Roles, and Dependencies in a Community Interorganizational System." *Sociological Quarterly* 25: 527–50.
Gould, Roger V. 1987. "Measures of Betweenness in Non-symmetric Networks." *Social Networks* 9: 277–82.
———. 1989. "Power and Social Structure in Community Elites." *Social Forces* (in press).
Granovetter, Mark S. 1974. *Getting a Job: A Study in Contacts and Careers*. Cambridge, MA: Harvard University Press.
Holland, Paul W., and Samuel Leinhardt. 1970. "A Method for Detecting Structure in Sociometric Data." *American Journal of Sociology* 70: 492–513.
———. 1975. "Local Structure in Social Networks." Pp. 1–45 in *Sociological Methodology 1976*, edited by David R. Heise. San Francisco: Jossey-Bass.
———. 1978. "An Omnibus Test for Social Structure Using Triads." *Sociological Methods and Research* 7: 227–56.
———. 1981. "An Exponential Family of Probability Distributions for Directed Graphs." *Journal of the American Statistical Association* 76: 33–50.
Katz, L., and J. H. Powell. 1954. "The Number of Locally Restricted Directed Graphs." *Proceedings of the American Mathematical Society* 5: 621–26.
Knoke, David, and Edward O. Laumann. 1982. "The Social Organization of National Policy Domains." Pp. 255–70 in *Social Structure and Network*

Analysis, edited by Peter V. Marsden and Nan Lin. Beverly Hills: Sage.

Laumann, Edward O., Peter V. Marsden, and Joseph Galaskiewicz. 1977. "Community Influence Structures: Extension and Replication of a Network Approach." *American Journal of Sociology* 83: 594–631.

Laumann, Edward O., and Franz U. Pappi. 1976. *Networks of Collective Action*. New York: Academic Press.

Marsden, Peter V. 1982. "Brokerage Behavior in Restricted Exchange Networks." Pp. 201–18 in *Social Structure and Network Analysis*, edited by Peter V. Marsden and Nan Lin. Beverly Hills: Sage.

———. 1983. "Restricted Access in Networks and Models of Power." *American Journal of Sociology* 88: 686–717.

Merton, Robert K. 1973. *The Sociology of Science*. Edited by Norman W. Storer. Chicago: University of Chicago Press.

Prensky, David. 1986. "Interorganizational Structure and Organizational Participation in a National Policy Domain." Ph.D. diss., University of Chicago.

Reve, Torger, and Louis W. Stern. 1979. "Interorganizational Relations in Marketing Channels." *Academy of Management Review* 4: 405–16.

Rogers, Everett M., and Rekha Agarwala-Rogers. 1976. *Communication in Organizations*. New York: Free Press.

Snijders, Tom A. B., and Frans N. Stokman. 1987. "Extensions of Triad Counts to Networks with Different Subsets of Points and Testing the Underlying Random Graph Distributions." *Social Networks* 9: 249–67.

Travers, Jeffrey, and Stanley Milgram. 1969. "An Experimental Study of the Small World Problem." *Sociometry* 32: 425–43.

Weimann, Gabriel. 1983. "On the Importance of Marginality: One More Step into the Two-Step Flow of Communication." *American Sociological Review* 47: 764–73.

Weiss, R.S., and Eugene Jacobson. 1955. "A Method for the Analysis of the Structure of Complex Organizations." *American Sociological Review* 20: 661–68.

White, Harrison C., Scott A. Boorman, and Ronald L. Breiger. 1976. "Social Structure from Multiple Networks: I. Blockmodels of Roles and Positions." *American Journal of Sociology* 81: 730–80.