Negotiated Exchanges in Social Networks*

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Abstract

Network exchange theory predicts relative profits from negotiations among actors in social exchange networks (Markovsky et al. 1993; Markovsky, Willer & Patton 1988). Here we extend the theory to allow exact predictions, rather than merely ordinal, for actors' exchange profits. This is accomplished by integrating two important factors. First, a resistance model predicts bilateral negotiation outcomes within a given set of network constraints. It does so by weighing actors' interests in gaining the best possible exchanges against their desires to avoid the worst. Second, the resistance model predictions are modified by actors' profit expectations. In particular, we incorporate two factors that affect such expectations, both common features of ongoing exchange relations: the number of other actors to whom one is directly connected in the network, and the likelihood of one's completing exchanges with them. We derive hypotheses from the theory and test them in two very different experimental settings. We find that the theory's predictions are more accurate than those of previous versions of the theory and those of five alternative theories.

Social exchange theory grew from the application of the economic theory of exchange to social relationships. Sociology focuses on a problematic area for economic theory: the exchange of valued objects in relatively small groups, where actors seek to settle on one optimal outcome out of a range of possibilities. How can we predict that outcome? And how are such outcomes affected by social structure? Homans (1958, 1974) suggested that principles of behaviorist psychology would help to answer these questions. Blau's (1964) approach used rational choice and utility theory. Theoretical work on the problem since then has largely developed from one or the other perspective, sometimes combining the two.

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Both Homans and Blau illustrated their ideas in the context of dyadic relationships. In work settings, for instance, an exchange may entail conferring some reward in return for a costly act. Giving prestige in return for expert help is a common example. Some of these illustrations were quite ingenious. Their very ingenuity, however, convinced critics that the social exchange perspective was tautological and scientifically vacuous. It seemed that any outcome could be explained by a judicious identification of the costs and rewards. This criticism was difficult to overcome as long as the theoretical context remained the isolated dyad. The key to theoretical advance in social exchange was to focus on the embeddedness of dyadic relations in broader contexts. The conceptual horizon has since expanded to incorporate broader relational structures. As a result, social networks have become the focus for rigorous tests of developing theories. These developments were led by Emerson's (1962) seminal work on power-dependence theory. He was the first to suggest specific ways to extend a model of dyadic exchange to larger networks of exchange relations (Emerson 1972). Emerson and colleagues (Cook et al. 1983) later introduced the concept of vulnerability, a measure that predicted which positions in a network structure had power. Vulnerability was based on the idea that some network positions are more important than others in determining the flow of resources through a network. If by removing itself from an exchange a position could reduce the total resources available in a network, then that position had power. The amount of power depends on the disruption in resource flow.

The pace of research on structural power in social exchange networks quickened soon thereafter, spurred by Willer's (1986) critique of the 1983 vulnerability model and a reply by the power-dependence group (Cook, Gillmore & Yamagishi 1986). It was another two years before an alternative formulation was developed that offered better predictions — the network exchange theory of Markovsky, Willer, and Patton (1988). To predict relative power levels for positions in exchange networks, it provided a graph-theoretical power index (GPI) based on a network path-counting algorithm. The theory challenged some basic assumptions of power-dependence theory and withstood critical tests that corroborated GPI predictions and falsified those from the vulnerability model of power-dependence theory.

In 1990 comments and responses pointed out limitations of the GPI (Markovsky, Willer & Patton 1990; Yamagishi & Cook 1990). Soon thereafter, Markovsky (1992) introduced a further refinement, just as power-dependence researchers replaced vulnerability with a completely new algorithm (Cook & Yamagishi 1992). At the same time, three new theories were introduced: Friedkin's (1992) expected value theory, Bienenstock and Bonacich's (1992) application of the "core" from game theory, and Skvoretz and Fararo's (1992) application of Coleman's (1990) rational exchange model. In the next year, Markovsky et al. (1993) identified a new class of structural dynamics and additional refinements in the network exchange theory. Most recently, Skvoretz and Willer (1993) tested the first ratio scale predictions from four theories on a variety of networks. Now, it seems, theoretical developments that once required half a decade occur within a year's time.

Central to theoretical development today is a class of networks in which subtle power differences occur. This phenomenon is known as weak power. In these weak power networks, some positions may have advantages over others in acquiring resources through exchange. However, unlike the advantages in strong power networks, advantages in weak power networks are not progressive. Over a series of exchanges, a strong power advantage eventually results in one exchange partner receiving nearly all available resources. Weak power is limited in range and magnitude. This necessitates theoretical refinement because adequate assessment of power differences between positions in weak power structures requires more precise predictions of exchange rates at equilibrium.

Network exchange theory (Markovsky, Willer & Patton 1988) and its weak power extension (Markovsky et al. 1993) generate ordinal predictions for profits accruing from exchanges among negotiating actors in social networks. The theory is supported primarily by data from experiments in which actors have full information about the shape of the network and know the offers and agreements of all other actors (Skvoretz & Willer 1991).[1] Though the theory is well supported by empirical tests, we make two improvements in the present research. First, we make the theory more precise: By taking into account actors' expectations, we generate ratio-scale predictions. Our refinement predicts exact exchange outcomes. Second, we make the theory more general: We test the theory in a new restricted information setting. Correct predictions for this setting mean we expand the theory's domain of applicability. The theory could then potentially subsume within its scope more social settings in the field — buying a house, for example. When negotiating for a house, a buyer may have little information about the profit her offer will provide the seller and little information about the number and nature of the seller's alternative offers.

Below we review network exchange theory and then describe a new integration of two previous lines of theorizing: the graph-theoretic power index (GPI) for network structures and the resistance model for bilateral negotiations. The extended theory also incorporates biases in actors' expectations induced by the number of their direct ties to other network positions. We first test this new version of the theory against five alternatives with data from full information experiments on four different exchange networks. Finally, the generality of the theory is tested by replicating one of the networks under a new restricted information setting.

Network Exchange Theory

Network exchange theory uses GPI to predict power and profit rankings in exchange networks. Its scope includes networks in which actors in directly connected positions engage in a series of negotiations over divisions of resource pools. Most interesting are networks in which prevailing structural conditions prevent some actors from exchanging at certain times. Such conditions foster power.

GPI: DETECTING STRONG POWER DIFFERENCES

Network exchange theory assumes that GPI can predict power and profit rankings in exchange networks by detecting a position's structural advantage or disadvantage. Here we present an intuitive explanation of how and why it works. The appendix to this article provides a more rigorous treatment.

GPI is calculated by counting paths out from a position in a network. It adds odd-length paths, which are advantageous, and subtracts even-length paths, which are disadvantageous. Odd lengths are advantageous because it means a position has alternatives or a partner's alternatives have alternatives and so on. For example, consider a simple network, three actors connected in a line: A-B-C. Actor A may exchange with B and B with C, but A may not exchange with C. If all actors may exchange only once in a round of bargaining, B gains power because the other actors compete for the single available exchange opportunity with B. We say that B has two 1-paths while A and C have only one. Even-length paths are disadvantageous because it means that a position's potential partners have alternatives that vie with A for exchange with the partners. Actor A has a 2-path through B to C. This is disadvantageous and subtracts from A's GPI score. It means that B has an alternative to exchange with A. Actor B has no 2-paths. Thus the GPI index for the positions in the three-actor line network are 0-2-0. B will have an overwhelming advantage in this network because B has a higher GPI score than A and C. We say that B has a strong power advantage.

Power changes dramatically with the addition of another actor to the above network, making a four-actor line, A-B-C-D (Willer & Patton 1987). Actor A now has a 1-path, a 2-path, and a 3-path. Its GPI score is 1. Actor B now has two 1-paths and one 2-path. Its GPI score is also 1. GPI predicts no strong power advantage for B in the four-actor line network. The reason for this is that the addition of a fourth actor gave A an additional, advantageous, odd-length path, and the addition also gave B an additional disadvantageous even-length path.

GPI extends this analysis to exchange networks of any size and density of relations by counting only nonintersecting paths leading away from a position. Only nonintersecting paths are counted because intersecting paths do not seem to change fundamental power relations in a network. For example, suppose we add a fourth actor, Z, to the three-actor line A-B-C. Actor Z is connected only to B. Actor A now has two disadvantageous 2-paths, one through B to C and one through B to Z. But because these 2-paths intersect at B, the additional disadvantageous 2-path makes no qualitative difference in A's relationship with B. B is still A's only possible exchange partner and B still has an alternative to exchanging with A. GPI ranks the two actors as in the three-actor line. B has a strong power advantage over A, but now GPI scores are more extreme. The GPI score for B is 3 because of the additional 1-path, while for A the GPI score remains 0.

GPI assumes that actors seek exchange with a potential partner who has a larger GPI only if no weaker alternative exists. (Here "to seek exchange" means to make competitive offers, a situation determined only by structural conditions.) Analysis of the Stem network (Figure 2) shows that both C_1 and C_2 have

GPI scores of 1. They will seek exchange with each other but not with B who has a GPI score of 2. The theory assumes that when this happens, GPI is recalculated among the resulting subnetworks of actors who mutually seek exchange. Two subnetworks in the Stem, A-B and C_1-C_2, result; all positions now have a GPI score of 1. No position is predicted to have an overwhelming power advantage in the Stem.

LIKELIHOOD OF EXCLUSION IN WEAK POWER NETWORKS

Markovsky et al. (1993) identify two kinds of power in exchange networks — strong and weak — distinguished by their structural bases and their consequences for exchange profits. The source of power in the two types of network is identical, however: exclusion from exchange. In strong power networks, one or more actors are excluded in every round of exchange by one or more others who, under given structural arrangements, need never be excluded. A position's GPI score encodes its potential to be excluded (or to exclude) relative to its partners. Immediate ties to partners — 1-paths — provide alternatives that enhance a position's potential to exclude or avoid exclusion. This holds for all paths of odd length. But partners' immediate ties to others — 2-paths — provide one's partners with alternatives to oneself and thus decrease a position's potential to avoid exclusion or to exclude. This holds for all paths of even length.

The idea behind weak power is that no position can consistently exclude another without incurring costs to itself (Markovsky et al. 1993). In most weak power networks, either all positions are prone to exclusion or no position is necessarily excluded.[2] That is, for each position there is some outcome in which it is excluded from exchange or it is possible for all positions to be included in exchanges simultaneously. GPI registers these conditions by assigning the same score to all positions and thus predicts no strong power differences. However, GPI measures a position's susceptibility to exclusion on the basis of the pattern of ties alone. Markovsky and associates' (1993) weak power extension to network exchange theory takes account of other factors, in particular the pattern of activity in these ties that could induce differential susceptibility to exclusion.

In strong power networks, profit distributions approach maximum differentiation where the advantaged actors earns between 90% and 100% of available profit. In contrast, profits in weak power networks are more sensitive to actors' strategies, and profits from exchange stabilize well short of maximum differentiation. Generally, the advantaged actor in a weak power network earns between 51% and 75% of available profit. The different levels of profit differentiation between strong and weak power networks reflect the different bases for excludability — i.e., the pattern of ties versus the pattern of activity in those ties.

For example, the Stem is a weak power network. With strong power, profit distributions approach maximum differentiation. That is, if actors negotiate over the allocation of a resource pool containing *P* units, profits for high-power actors will approach *P* and those for low-power actors will approach zero. In contrast, profits in weak power structures are more sensitive to actors' strategies, and profits from exchange stabilize well short of maximum differentiation, e.g., at $(P/2) + 1$ for the advantaged actor, and $(P/2) - 1$ for the disadvantaged actor. In general, structurally disadvantaged actors face more exclusions from exchange than advantaged actors, and when excluded they respond by making offers that slightly favor actors in advantaged positions.

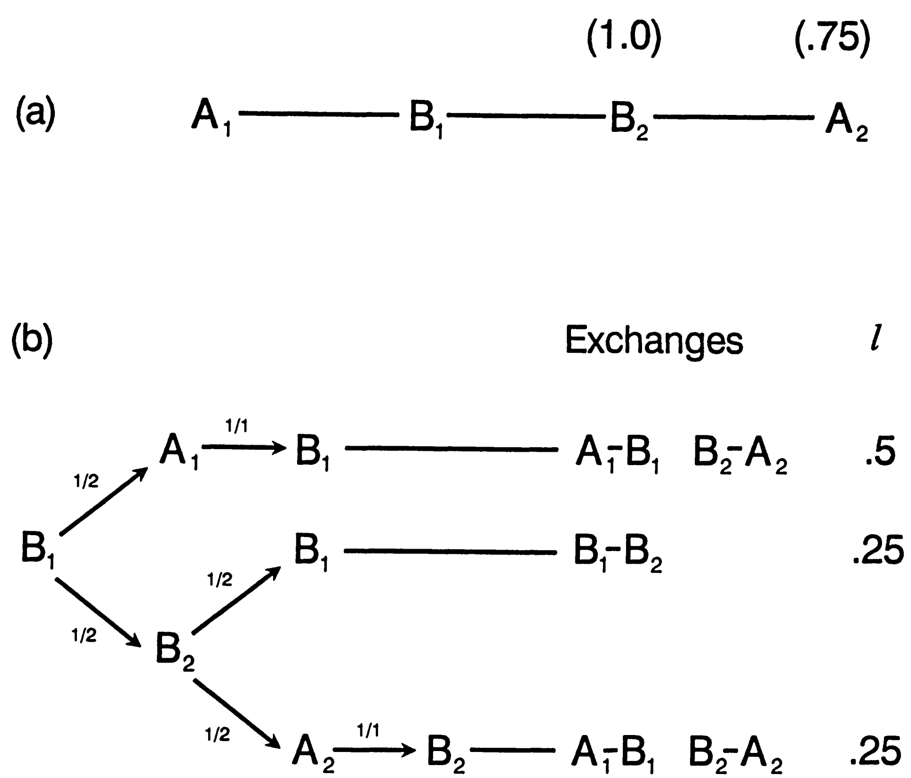
The Markovsky, Willer & Patton (1988) GPI model correctly identified strong power structures in all its tests. That is, (1) unequal GPI values correctly anticipated unequal profits, (2) such profit inequalities were relatively large, and (3) whenever profit levels were equal, then so were GPI values. However, Skvoretz and Willer (1991) found that actors' profits may differ even when their GPIs are equal. Prediction of these profit differences required a second step taken in Markovsky et al. (1993): When all GPIs are equal, each position's likelihood of being included in exchanges, l (or of being excluded, $1 - l$), is calculated under the assumption that actors have no preferences among partners.[3] Then, in an i-j relation, actor i has weak power over j only if GPI values are equal and if $l_i > l_j$ (see Appendix). Otherwise, $l_i = l_j$ and i and j are equal in power. Thus, likelihood of being included detects weak power in networks where GPI detects no strong power differences. The analysis of l_i is not applicable in strong power structures, but rather GPI is used to predict the very robust profit differences that occur there. In summary, we detect power differences in two steps. First, GPI is applied to find strong power differences. Second, where no strong power differences are found, likelihoods of being included are calculated to assess any weak power differences that may exist.

As an example, consider the four-actor line of Figure 1A. GPI = 1 for all positions. Because positions have equal GPI, no strong power differences exist. Therefore, we turn to calculation of l_i to check for any weak power differences. In this network, A_1 can negotiate and exchange with B_1; B_1 may do so with A_1 or B_2; and so on down the line. Assuming that each actor can exchange only once per round and is indifferent to with whom, either B has a .5 probability of seeking exchange with an A and a .5 probability of seeking exchange with the other B. The probability that an A will seek exchange with a B is 1.0 because the A's have no alternatives.

Figure 1b shows a probability tree used to calculate l for each position. Each branch of the tree shows an exchange-seek and its associated probability. The Exchanges column shows mutual exchange-seeks and the l column shows the product of branch probabilities leading to each possible exchange. The likelihood of exchange between two actors is the sum of the probabilities associated with their mutual exchange-seeks in the Exchanges column. An actor's likelihood of being included in any exchange is the sum of the probabilities associated with all exchanges that include that actor. From the tree we derive that $l_{AB} = .75$ for both A-B pairs; $l_{B_1B_2} = .25$; $l_A = .75$; and $l_B = 1$.

The foregoing procedure generalizes to more complex networks and to networks where actors can exchange more than once in a round of bargaining (Markovsky 1992; Markovsky et al. 1993). The distinction between single and multiple exchange is theoretically important because it determines the pattern of exclusions. This was first shown by Markovsky, Willer & Patton (1988), who demonstrated that changing the number of exchanges allocated to positions altered the power exercised in every relation in the network. More recently, Skvoretz and Willer (1993) showed similar consequences for a new array of

FIGURE 1: Four-Actor Line and Its Likelihood



networks. A real-world example will show why altering the number of exchanges has such a great impact on power. Auctions are a network exchange process. The seller has only a finite amount of time to sell any and all items at the best possible price. The finite period for the auction corresponds to a round of negotiation, that is, the period in which exchanges involving existing pools of resources must be completed. A resource pool might consist of a single item or several identical items, or there might be several resource pools containing a wide variety of items as in a real auction. Different items may appeal to some or all of a wide variety of bidders, which determines the pattern of relations in the exchange network.

Consider two simple auctions. In both we have one seller and two buyers. In the first auction, there is only one item, an antique lamp, of interest to both buyers. In the second auction, there are two such lamps. In the first auction, because there is only one lamp, the seller and each of the buyers can make only one exchange during the auction but one of the buyers will be excluded from exchange. As the bidding opens, each buyer must try to provide the seller with the more lucrative offer. Because each buyer wants to make the higher bid, however, the offers "ratchet" higher and higher and become increasingly favorable to the seller. Eventually, one buyer backs down and the seller accepts a tidy profit.

In the second auction, each buyer (who wants only one lamp) still seeks exchange with the seller. But because there are two lamps, the seller now may exchange twice during the auction period — once with each buyer. The buyers do not need to outbid each other in order to obtain the lamp they desire, and so there is no structurally induced exclusion from exchange and no price ratcheting. Ironically, the combined prices for the two lamps may end up being less than what the seller could have obtained by placing only one up for auction. Varying the number of permitted exchanges emphasizes the importance of exclusion as the generator of structural power in networks, as well as the generality of the theory (Skvoretz & Willer 1991).

Despite the theory's generality, the structurally induced exchange likelihoods that it generates have been used to predict only the ordering of exchange outcomes across positions in weak power networks. We now turn to the problem of predicting exact exchange rates in weak power networks.

Profit Expectations

Network exchange theory depicts the generation of profit differentials in networks as an almost purely structural phenomenon. Profit differentials arise from differences in avoiding exclusion and from the sheer pattern of ties. The cognitions of actors play very little role in explanation. The strategy has been fruitful for two reasons. First, structural factors are often sufficient to predict accurately simple ordinal differences in earnings. Second, strong power networks have played an important developmental role in network exchange theory. In strong power networks, structural determinants are so powerful — as indicated by consistently extreme profit differentials — that actor cognitions can introduce only minor variation at best. But the study of weak power networks demands that more sources of variation be taken explicitly into account. In particular, we hold that more precise prediction requires that we extend network exchange theory to incorporate actors' profit expectations. We concentrate on possible sources of actors' expectations that might develop from initial network conditions and ongoing feedback that might result from them because our goal is to predict actor behaviors and exchange outcomes on the basis of initial conditions.

In exchange networks, initial conditions and ongoing feedback provide actors with information that they can use to estimate their potential profits, e.g., the maximum amounts they could hope for, the minimum outcomes they fear, and the profits that might reasonably be expected to obtain. To the extent that such profit expectations are affected by situational factors, negotiations will be modified and, in turn, exchange profits will be affected. The sensitivity of the negotiation process to contextual information should be especially evident in experimental settings. There, the simplicity of exchange conditions focuses attention on whatever minimal information is provided.

Our strategy is thus to employ a formal model that (1) accounts for the effects of profit expectations, (2) can be readily extended to accommodate situational factors that modify such expectations, and (3) may be integrated seamlessly into existing network exchange theory. In line with the existing theory's emphasis on the importance of exclusion and excludability, we assume that a situational factor also modifies actors' profit expectations. It would be surprising if it did not. We have all been excluded from social exchange at some time in our lives whether it was not being invited to a party or having our application to a university rejected. These events certainly affect our cognitions. The following section incorporates the actors' experience of patterns of exclusion into our model. The second factor we will highlight in the section entitled Expectations and the Number of Direct Ties. Previous research (Marsden 1983) suggests the significance of the number of direct relations an actor has in the network. But more important, the number of direct relations is a highly salient and immediately apprehensible feature of the actor's environment even under conditions of highly restricted information.

EXPECTATIONS AND RESISTANCE

The resistance model (Heckathorn 1983; Willer 1981) predicts rates of exchange based on each actor's beliefs or expectations about his or her own best and worst possible outcomes. Specifically, it assumes that the point at which actors agree to exchange is determined by balancing two interests: (1) Actors aspire to obtain the greatest possible profit from exchange. This is their "best hope." (2) Actors seek to avoid the worst possible outcome. This is their "worst fear." To decide whether to agree to exchange, actors balance their desire for maximum profit against their fear of receiving no profit or the profit that results if no exchange occurs.

In dyadic exchange, the scope of the resistance model overlaps the Nash equilibrium (1950, 1953), and under certain conditions the predictions of the two are the same. However, the scope of the resistance model is broader, extending beyond the dyad. It has been successfully applied to a wide range of exchange networks (Brennan 1981; Willer 1987; Willer, Markovsky & Patton 1989). Its predictions have also been shown to hold in cross-national experimental research (Willer & Szmatka 1993).

We use the resistance model to formalize our claims about the effect of profit expectations on negotiations. It specifies how negotiators arrive at agreements through each actor's beliefs or expectations about his or her own best and worst possible outcomes. Implicitly, the model may be interpreted as generating profit expectations for negotiating actors at a particular point in time, and these expectations then determine whether actors accept or reject offers.

Let P_i represent i's profit from exchange, M_i is i's maximum expectation or best hope for profit from exchange, and C_i is i's worst fear or "conflict outcome."[4] Actor i's interest in gaining his or her maximum expectation is $M_i - P_i$ and in avoiding his or her worst fear is $P_i - C_i$. His or her resistance to a given exchange profit, R_i, is the ratio

$$R_i = \frac{M_i - P_i}{P_i - C_i}$$

Resistance is the ratio of $M_i - P_i$, the actor's interest in gaining a better outcome, to $P_i - C_i$, the actor's interest in avoiding disagreement. Because the ratio is small for favorable settlements and large for unfavorable settlements, resistances of two actors in an exchange relation vary inversely for a given settlement. Network exchange theory asserts that agreements to exchange occur when actors' resistances are equal. Thus, compromise occurs when:

$$\frac{M_i - P_i}{P_i - C_i} = \frac{M_j - P_j}{P_j - C_j}$$

This is the *equiresistance* solution.[5] Knowing the number of resource units in the pool (P) such that $P = P_i + P_j$, we may algebraically solve for the values of P_i and P_j. More than a decision strategy, resistance is conceived as a potential limit of power use when actors use the best available strategies. Consequently, it holds promise of more general applicability than any particular decision strategy.[6]

To predict negotiation outcomes, M_i and C_i must be determined for each actor. In strong power structures such as A-B-A, we assume that each A's maximum expectation (M_A) is initially at or near P. However, given that B seeks only one exchange per round, M_A declines as A's are consistently excluded. M_A may begin at or near P, but this best hope will approach zero as exchanges continue to yield ever-declining profits. In contrast, because B has no rivals, M_B remains close to P. Over a series of rounds all profit gravitates to the central, B, actor (Willer & Markovsky 1993).

C_i is determined by a position's best alternative (Willer 1987). Strong power structures such as A-B-A are characterized by bidding wars between rival A's. Thus, when B negotiates with one A, C_B is the last offer from the other A. As the two A's bid, however, C_B increases toward P. Because A has no alternative, C_A stays at zero. The result over a series of exchange rounds (derivable from the equiresistance model) is that P_A approaches zero and P_B approaches P (Willer & Markovsky 1993).

In weak power structures, an equilibrium exchange rate is reached such that neither actor gains the maximum available profit or is forced to accept almost none. To use resistance to predict exchange rates in these structures, it is necessary to determine the value of actors' maximum expectations and conflict outcomes, M_i and C_i, at equilibrium.

In weak power structures, actors do not initially have a realistic basis for estimating their maximum expectations and conflict outcomes, M_i and C_i. As a result, their initial expectations may be either optimistic or pessimistic. However, all equiresistance solutions assume that actors have expectations and that over a series of exchanges they come to be more or less realistic. Thus, we assume that during the interaction process actors learn more realistic expectations. For example, when initial expectations are too optimistic, actors are excluded by others and eventually adjust their expectations downward. If expectations are initially too pessimistic, then actors always gain agreements and eventually adjust their expectations upward. As a result, expectations become increasingly realistic. This model of actors' responses to inclusion and exclusion conforms to the scope specifications for offer adjustments first described by Markovsky, Willer & Patton (1988). Here, however, we make the more specific suggestion that actors adjust their offers in response to changes in their profit expectations.

Below, we offer a two-part solution for the problem of predicting exchange rates in weak power networks. First we predict the equilibrium exchange rate. If actors adjust expectations as we assume they do, then expectations will come to correspond more closely to actors' likelihoods of being included in exchange. The result will be a fairly stable equilibrium exchange rate.

Second, we note that initial rates may not be like equilibrium rates. Because actors do not initially know their likelihood of being included in exchange, their expectations for maximum profit and their worst fears must have other bases. Initial expectations may or may not be realistic. We also offer a simple model for initial expectations from which actors move, as a consequence of interaction, toward equilibrium. These initial expectations likely have an enduring impact on exchange rates. In a final step, we complete our theory by combining the model of initial expectations with equilibrium exchange rate predictions. In effect, our predictions assume that actors' beliefs remain biased to some degree by initial expectations.

RESISTANCE AND THE LIKELIHOOD OF BEING INCLUDED

We approach the problem of specifying the value of conflict outcomes and maximum expectations in weak power networks by first identifying theoretical restrictions for C_i and M_i. Within these theoretical limits, we then assume that C_i and M_i are proportional to an actor's likelihood of being included in exchange. That is, an actor's expectations for profit, her or his worst fears and best hopes, depend on how often she or he expects to be included in profitable exchange. The assumption of simple proportionality between inclusion expectations and likelihood of being included results in a modified resistance equation that can be used to make exact predictions of exchange rates between actors in weak power networks.

The conflict expectation, C_i, depends on the actor's expectations regarding available exchange alternatives, as noted above. For example in the four-actor line network, A_1-B_1-B_2-A_2, if B_1 knows that A_1 will agree to an equal division of profit at 12:12, then B_1 will not accept 11 from B_2. However, as Yamagishi and Cook (1990) noted, actors are not always certain of their alternatives. Nonetheless, weak power limits the range of conflict outcomes: the lower limit is zero — the amount an excluded actor receives — and the upper limit is half the total resource pool, as we will next explain.

In all weak power networks, actors cannot consistently exclude others from exchange without themselves suffering losses.[7] Still assuming 24-unit resource pools, this can be illustrated using the four-actor line. Suppose that C_{B1} is greater than 12, an equal division of the profit pool. This means that B_1 would refuse offers of less than 13. That is, B_1 will refuse an equal division of profit and hold out for more. Because B_1 cannot consistently exclude B_2, however, B_2 will not be penalized for refusing to exchange with B_1 at this rate. As long as B_1 demands 13 from B_2, B_2 effects a temporary break in the network by exchanging with A_2 at no worse than 12:12. For B_1 to ever reestablish the possibility of exchanging with B_2 (and thus reestablish weak power over A_1), C_{B1} must be reduced to 12, an equal division of the profit pool, or lower. Therefore, it is generally true that the "conflict" or worst-fear outcome in weak power structures is limited to the range from zero to half the size of the resource pool. Similarly, M_i is restricted to the range 12-24. M_i may be close to the total resource pool when exchange begins, but it cannot go below half the pool. Half the pool is always a competitive offer because no actor is ever consistently excluded.

At issue now is how to determine C_i and M_i from initial conditions within these theoretically determined ranges. We do so using l, the likelihood of being included, as derived from weak power calculations (Markovsky et al. 1993). Two assumptions integrate resistance with Network Exchange Theory. First,

Equiresistance Assumption: In weak power relations, actors' profits approach equiresistance solutions over a series of exchanges.

To the extent that actors use effective strategies to seek maximum profits, their profits should conform to the resistance predictions. For example, the behavior of more experienced actors or those with better training should conform more closely to resistance predictions than the behavior of less experienced or less well trained subjects.[8] The idea that resistance predicts a profit limit reached at equilibrium after a series of exchanges allows application of the theory to exchange situations in which actors have different amounts of information and training.

Second, we theoretically link inclusion probabilities to actors' conflict outcomes and best-hope outcomes in the resistance equation. We assume that an actor's perceived best-hope and conflict outcomes are proportional to that actor's likelihood of being included in exchange. For example, an actor who is consistently included and who makes a profit would resist offers that are lower than she or he is accustomed to receive. The fact that she or he is very likely to be included in exchange has increased her or his point of conflict. Conversely, a frequently excluded actor, accustomed to receiving no profit much of the time, would accept a low offer. The actor's low likelihood of exchange has reduced her or his point of conflict. The same argument can be made for actors' best hopes. Actors consistently included in exchange should have higher aspirations for profit than should actors consistently excluded from exchange.

Markovsky et al. (1993) demonstrated that likelihood of being included (l_i) ranks the power of positions in weak power networks. On this evidence, we assume that l_i will successfully rank power positions even where power differences are very small. Further, we assume that larger differences in l_i identify larger differences in power between positions. That is, we assume that weak power is proportional to a position's l_i. If as we suggest, this occurs because likelihood of being included acts on points of conflict (C_i) and best hopes (M_i), then setting C_i and M_i proportional to l_i should provide a good indicator of an actor's power.

The following resistance-likelihood assumption expresses the idea that C_i and M_i are proportional to l_i within their respective ranges. Our analysis demonstrated that C_i is limited to a range between zero and half the resource pool. Similarly, M_i is limited to a range from half the resource pool to the entire pool. This assumption predicts that the difference in profits for high-power and low-power actors in a weak power relation depends upon their likelihoods of being included in exchange.

Resistance-Likelihood Assumption: The higher an actor's likelihood of being included in exchange, (1) the higher the actor's perceived conflict outcome, C_i; and (2) the higher the actor's maximum profit expectation, M_i. Formally,

$$C_i = \frac{P}{2} l_i \tag{1}$$

$$M_i = \frac{P}{2}(l_i + 1) \tag{2}$$

In words, the perceived worst-case exchange outcome (C_i) is a fraction of half the pool, and that fraction is larger for higher likelihoods of being included (l_i), and smaller for lower l_i. As explained above, C_i is limited to at most half the resource pool in weak power situations. Equation (1) expresses the assumption that C_i is proportional to l_i and ranges between zero and half the resource pool.[9] Similarly, an actor's maximum expectation for profit (M_i) is half the pool plus a fraction of half the pool. We also showed that M_i is restricted to be at least half the resource pool but not more than the total pool, P, in weak power situations. Equation (2) expresses the assumption that M_i is proportional to l_i on that range. In weak power situations at equilibrium, it follows from equations 1 and 2 that M_i is a direct function of C_i, i.e., $M_i = C_i + P/2$. This feature pays considerable dividends in simplifying calculations and serves as a plausible assumption about perceived best- and worst-case outcomes.

The resistance model, resistance-likelihood assumption, and a little algebra yield the following prediction:[10]

$$P_i = \frac{(P + C_i - C_j)}{2}$$

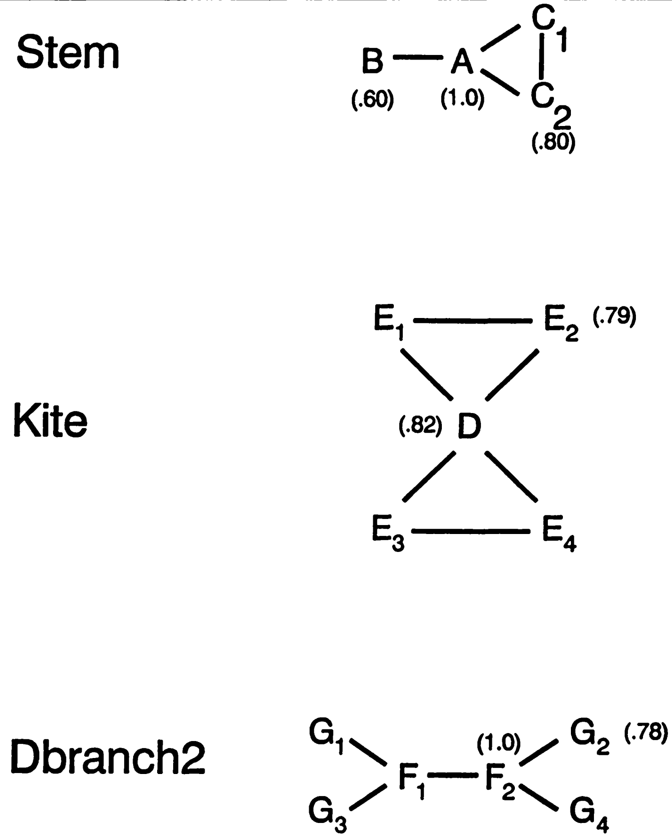
$$P_j = P - P_i.$$

In the Stem network (Figure 2), for example, likelihoods of being included for positions A and B are $l_A = 1$, $l_B = .6$. Assuming a typical 24-point resource pool, P, we can calculate profit distributions for the A-B relation. First, by the resistance-likelihood assumption, $C_A = (24/2) \bullet 1 = 12$, and $C_B = (24/2) \bullet .6 = 7.2$. Next, profits are calculated to be $P_A = (P + C_A - C_B)/2 = 14.4$, and $P_B = P - P_A = 9.6$. Profits for any position in any weak power network can be predicted by this method if the network structure and total value of each profit pool are known. Likelihood of being included indicates the structural power advantage of a network position. By balancing two competing motives — the desire to increase profit and the need to reach agreement and avoid exclusion — actors reach an equilibrium level of profit that is proportional to their relative likelihood of being included.

EXPECTATIONS AND THE NUMBER OF DIRECT TIES

In addition to the factors that we have previously related to profit expectations, there is good reason to assume that the number of an actor's direct relations in the network may also play an important role. In the parlance of network analysis, this refers to the actor's degree. Marsden (1983) employed a similar idea in his theory of power in exchange networks. Where t_i is the number of actor i's direct network ties, he defined $\log(t_i/t_j)$ as one of several factors affecting i's "price-making" behavior in exchanges with j. Although some of his

FIGURE 2: Three Weak Power Networks and Likelihoods of Inclusion



model's predictions diverge from experimental test results, the notion that degree biases actors' price negotiations in weak power situations has not been tested directly and may still be sound. Further justification is found in the judgment heuristics literature (e.g., Kahneman, Slovic & Tversky 1982). In a wide variety of judgment contexts, informational anchors have been shown to bias judgments of such properties as magnitude, numerosity, value, weight, color, loudness, pitch, etc. For example, a contrast anchor effect occurs when yesterday's 95 degree temperature (the anchor) makes today's 78 degrees seem cool. Today's judged temperature is biased away from yesterday's. The assimilation anchor effect is often found in negotiation settings where an initial offer (the anchor) may be blatantly unrealistic, but subsequent offers and counteroffers are still pulled toward that initial offer. (For more detailed examples and applications see Helson & Kozaki 1968 and Kahneman, Slovic & Tversky 1982.)

Assuming that human actors cannot fully evaluate the ramifications of their location in a network structure — especially when lacking systemwide information — it is reasonable to presume that information of a more localized nature becomes especially salient. The number of one's direct ties is just such a piece of information. An actor with more direct network relations will probably expect to have more successful negotiations than an actor with fewer direct relations. It seems plausible that an actor with many potential exchange partners would expect a better chance of being included in exchange than would an actor with only one or very few exchange partners. Of course, network exchange theory shows that this expectation is not necessarily justified. The extent to which having alternative partners can benefit an actor depends on broader network patterns, e.g., the alternative relations of each of one's alternative relations. Nevertheless, an actor's degree is a highly salient piece of information in network exchange contexts and should thus bias profit expectations via an assimilation effect.[11] This idea is captured in the following:

Degree Assumption: The higher an actor's degree, the higher the actor's expected profit.

An actor with higher profit expectations is assumed to adopt a tougher bargaining stance, e.g., to make lower offers to others, and to have higher thresholds of acceptability for incoming offers. If negotiating actors have equally high degrees, however, degree would not provide special advantages to either. Therefore, our index of relative degree (d_{ij}) for actor i in the i-j relation must actually be based on the relative number of ties (t) for each actor. This is accomplished in the formula

$$d_{ij} = \frac{t_i}{(t_i + t_j)}.$$

This specification standardizes the index to a 0-1 scale, a useful property when we combine d with other components of the theory. As a structural measure, d_{ij} does not depend on actors' knowing one another's degree. It captures what might be called the expectation advantage of one actor relative to another — a condition that will then manifest itself in the dynamics and outcomes of the negotiation process.

RESISTANCE AND DEGREE

Degree is assumed to bias profit expectations. Therefore, in the model, we incorporate the relative degree index as a biasing factor for best-hope and worst-fear outcomes. Given that we have already defined M (the maximum hoped-for profit) to be a function of C (the conflict or worst-fear outcome) in weak power networks, we need to show only how relative degree affects the latter. We assume that, in the same manner as the likelihood of being included, the higher the degree, the greater the inflation of the actor's worst-fear outcome:

Resistance-Degree Assumption: The higher an actor's relative degree, the higher the actor's perceived conflict outcome.

Combining this assumption with the resistance-likelihood assumption yields

$$C_{ij} = \frac{P}{2} l_i d_{ij}$$

We now subscript C by both i and j, because the inclusion of the biasing factor, d_{ij}, in the equation implies that i's expected conflict outcome may be different for each actor with whom i negotiates.[12] Again using the Stem network as an example, and using the earlier formulas for P_i and P_j with a 24-point resource pool, $d_{AB} = 3 / (3 + 1) = 3/4$. Substituting the values for variables in the equation, $C_{AB} = 24/2 \bullet 1 \bullet 3/4 = 9$; $C_{BA} = 24/2 \bullet .6 \bullet 1/4 = 1.8$. Then we can solve for the prediction that incorporates both resistance and relative degree into the GPI model, $P_A = (24 + 9 - 1.8)/2 = 15.6$, and $P_B = 8.4$. We label this elaborated model GPI-RD.

Higher relative degree is thus assumed to bias the effects of the likelihood of being included. However, because advantages in relative degree are based only on actors' expectations and not on actual structural advantages, there is a potential cost to actors who try to exploit degree advantages. Though an actor with more potential exchange partners may be a tougher negotiator and receive more resources from completed exchanges, such exchanges may be less frequent than for actors of lower degree. This is because higher-degree actors are prone to tougher negotiation than is warranted by their actual structural positions. The result would be higher profit when exchange occurs, but a higher likelihood of being excluded from exchanges. In addition, actors with fewer potential exchange partners still seek more favorable alternative agreements whenever possible. In networks where all actors can be excluded — l_i less than 1.0 for all actors — a situation could arise in which an advantaged actor is excluded from exchange so frequently that she or he can actually acquire fewer resources than the disadvantaged actor over a series of exchanges. Markovsky et al. (1993) report this phenomenon in the "Kite" network (Figure 2). Subjects in the D position have an advantage over those in E positions both in likelihood of being included, .82 to .79, and relative degree, 4/6 to 2/6. For experienced subjects, despite the very small advantage in likelihood of being included, D position subjects averaged a 14:10 profit point advantage in exchanges with E partners. However for D these victories were Pyrrhic. Ds were excluded — and earned no profit — on 41% of rounds, while Es were excluded on only 15% of rounds.[13] Es preferred to exchange with each other rather than the more aggressive D. It seems strange that a high-power actor can actually earn less overall than a low-power partner. Incorporating degree into the theory explains this result — a result that previously had been considered anomalous. Though frequency of exchange can also be predicted using likelihood of being included and degree (Skvoretz & Lovaglia n.d.), here we focus on testing the model's predictions for exchange profits.

Method

We tested the model's predictions using experimental data from four networks. Subjects in the test setting had full information on the network structure and on all other actors' exchange outcomes. We also replicated the test on one of these networks using a restricted information setting where each subject knew only his or her own dealings with potential exchange partners and his or her own profits from exchanges.

EXPERIMENT 1: "FULL INFORMATION" NETWORKS

Skvoretz and Willer (1991) described in detail the experimental setting used for these tests. Custom software ("ExNet") was used to configure networked PCs into "virtual" exchange networks. ExNet can establish networks of any shape and size, limited only by the number of PCs. Subjects in experiments know the network structures and their positions within them. In an initial session, assistants explain how to make offers and counteroffers, what it means to divide the 24-point resource pool, the dollar value of profit units, and that exclusion from exchange yields no points for that round. A practice session familiarizes subjects with the operation of the system. Subjects then return at a later date to participate in the actual research. In the experiments, each subject rotates through all network positions, negotiating for a total of four rounds at each position. The computer records the timing and content of all communications.

We investigated four experimental structures of theoretical import (Figure 1a and Figure 2). The Double Branch 2 is a simple weak power network that allows two positions multiple exchanges. It was converted from a strong to a weak power structure via a two-exchange rule: The central Fs could exchange up to twice per round. Actors are only allowed one exchange per round in the other structures. These networks also have interesting theoretical properties that warranted our attention: The four-line is the simplest weak power network; the Stem and Kite sparked a debate between competing research programs over the validity of the GPI (Markovsky, Willer & Patton 1990; Yamagishi & Cook 1990); and in the Kite, no position is guaranteed inclusion.

Five alternative theories are capable of generating ratio-scale profit predictions for positions in weak power networks. Most of these were presented in a special issue of *Social Networks* (Bienenstock & Bonacich 1992; Cook & Yamagishi 1992; Friedkin 1992; Skvoretz & Fararo 1992). Bienenstock and Bonacich's core theory takes a game-theoretic approach. Cook and Yamagishi's equidependence theory extends the power-dependence program originated by Emerson (1962). Friedkin's expected value theory developed out of his work on network analysis in general. Skvoretz and Fararo (1992) apply Coleman's (1973, 1990) rational exchange theory to these exchange structures. In addition, Skvoretz and Willer (1993) present exchange resistance theory, a model that incorporates resistance into the GPI but does not include degree. These five theories are briefly described below. Except for Coleman's rational exchange model, Skvoretz and Willer (1993) provide details for using each to calculate predicted exchange outcomes.

CORE THEORY

Core theory (Bienenstock & Bonacich 1992, 1993) models network exchange in terms of cooperative game theory.[14] Three rationality criteria establish the "core" of an exchange network. First, agreements are individually rational when each actor's profit is equal to or greater than the profit that could be earned by not exchanging. That is, actors are assumed to exchange only when they receive at least as much profit from agreement as they do from being excluded from exchange. Second, agreements are rational for the coalition of exchange partners when the sum of the profit of both actors is at least as much as could be obtained if they exchanged with other partners. Third, group (or network) rationality obtains when the total profit of all positions of the network is at least as large as the total profit available from some other pattern of exchange agreements.

The core of an exchange network usually narrows the range of preferable exchange rates but does not necessarily predict a single ratio-scale exchange outcome. To make predictions when this occurs, we follow Skvoretz and Fararo (1992) in assuming that each core outcome is equally likely and then average the payoffs to various positions. In some cases, networks contain no core at all, which precludes a prediction.

RATIONAL EXCHANGE THEORY

Coleman's (1973, 1990) rational exchange model is not easily applied to our exchange networks because it operates under scope conditions that differ from those of other network exchange theories. It assumes, for instance, that every actor may exchange with any other actor in a network. Marsden's (1983) model solves the problem by adding network restrictions and a variety of additional assumptions. However, he noted that some predictions ran contrary to data previously published. Coleman partially solved the problem by assuming that there are transaction costs between actors. When transaction costs are high, they effectively prohibit exchange from occurring, thus setting the stage for structural power to emerge. As it stands, however, Coleman's conception of power is not relational. Power manifests in an actor's resource holdings rather than in her or his relative ability to extract resources through exchanges. Also, it does not address the situation where one actor's exchange is contingent on whether another actor exchanges. Skvoretz and Fararo (1992) have modified and added assumptions to Coleman's theory to make it applicable in the kind of exchange networks discussed here. Predictions for the Coleman model are based on their analysis. A technical description of the method and a computer program that calculates predictions are available from the second-named author on request.

EQUIDEPENDENCE THEORY

Equidependence theory (Cook & Yamagishi 1992) assumes that actors compare how much they will receive in exchange with a potential partner against how much they could get in exchange with some other partner. The difference between what an actor can obtain from this exchange relation and that of an alternative relation is deemed to be the dependence of the actor on the potential partner. This comparison process goes on simultaneously with all an actor's direct ties. Actors are assumed to exchange at a point where their dependence on the relation is equal to the dependence of their potential partner. In other words, exchange occurs when actors are equidependent, and each actor can get no more profit by some alternative exchange. An actor's reward from exchange is given by the equation $R_{ij} = (P_{ij} + A_{ij} - A_{ji})/2$, where R_{ij} is the profit that actor i obtains in exchange with partner j; P_{ij} is the pool size, and A_{ij} is the best alternative available to i.

Cook and Yamagishi use the example of two actors, *i* and *j*, negotiating over a 24 point resource pool. Actor *i* has another partner who offers *i* 10 points, while *j* has no other partner. If *i* and *j* were to divide the pool at 13 for *i* and 11 for *j*, actor *i* gets 3 points more than his or her best alternative (10), but *j* gets 11 points more than his or her alternative (zero). Thus equidependence between *i* and *j* has not been reached. Negotiation is assumed to continue until *i* gets 17 points and *j* gets 7 points. Here, equidependence has been attained because both *i* and *j* get 7 more points from exchange with each other than they would outside the *i*-*j* relation. Actor *i*'s power is defined as the maximum profit she or he can obtain from any partner.

EXPECTED VALUE THEORY

Friedkin's (1992) expected value theory first identifies all subnetworks that can result from various patterns of exchanges. Expected values are predictions about a structure's outcomes determined by weighting the value of a predicted outcome by the probability of its occurrence. For example, in the four-actor line network, A_1-B_1-B_2-A_2, there are two possible exchange patterns. Either each B exchanges with its related A, or the two Bs exchange with each other. To make predictions from initial conditions, Friedkin assumes that either pattern is equally likely to occur. Actor *i* is dependent on actor *j* if failure to exchange with actor *j* results in *i*'s exclusion from exchange. Dependency is an actor's likelihood of being excluded, calculated over all possible exchange outcomes. An offer-making function translates a particular degree of dependency into an offer to a potential exchange partner. Predicted earnings from exchange are a function of reciprocal offers modified by compromises when offers are inconsistent.

EXCHANGE RESISTANCE THEORY

Skvoretz and Willer (1993) use the likelihood of being included and the resistance model to make "baseline" predictions for exchange in both strong and weak power structures. Their goal is a simple formula that can be used in a single step to yield predictions in all exchange networks. We give their formula for predicting the profit of actor *i* using the notation for our own resistance-likelihood assumption:

$$\frac{\ln(M_i - P_i)}{\ln(P_i)} = \frac{l_j}{l_i}$$

They assume that conflict points and maximum expectations for profit for all actors remain constant. The conflict point for all actors is assumed to be zero, and their maximum expectation for profit is assumed to be the entire profit pool. A power function is then applied in which the difference between the maximum expectation for profit and what an actor would receive from an offer is raised to the power of that actor's likelihood of being included in exchange. The equiresistance equation can then be reduced to the above equation using natural logarithms.

All five theories make ratio-scale predictions for at least some of the network relations we examined. Below we compare our predictions to those of the five alternative theories and to experimental results.

Results

Four groups of subjects participated in Stem and Kite experiments, and five groups in the four-line and Double Branch 2. All were university students who signed up to participate in paid experiments. In Table 1, the column headed GPI-RD shows the predictions for our new model that integrates GPI, resistance, and degree. The column headed GPI-R shows the predictions for our resistance model without the biasing effects of degree. Also shown are the predictions from five alternative models and the observed means by network relation. Because we assume that profits approach predicted equilibria over a series of negotiations, we use data from the final experimental periods.[15]

Observed profits conform well to GPI-RD predictions. The largest discrepancy between a predicted and an observed value is less than one profit unit. One-sample t tests determined the probability that the differences between predictions and observed means were due to chance. No GPI-RD prediction differed significantly from its corresponding observed mean at or below the .40 probability level. The smallest probability that a prediction did not differ from the observed value was .47 for the Kite network. Two predictions from Coleman's (1973, 1990) rational exchange model, while not as close, were better than those of other alternatives. The probability that rational exchange predictions did not differ from observed values was .13 for the four-line and .11 for the Stem. In contrast, significant differences were found between observed means and the predictions of other alternative theories. For the Kite network, Skvoretz and Willer's (1993) exchange resistance model, GPI-RD, Cook and Yamagishi's (1992) equidependence model, and Friedkin's (1992) expected value model all make acceptably close predictions. However, both the equidependence and expected value models predict no difference in power between D and E actors in the Kite — a difference that did occur in an empirical test and was statistically significant (Markovsky et al. 1993).

Establishing a GPI-RD prediction for the Double Branch 2 network requires some interpretation. Calculating degree as for a one-exchange network, Fs have three direct ties and Gs have one. The GPI-RD model then yields predicted profits for F of 15.33, about 1 profit point away from the observed value. A one-sample t test also finds this difference significant: $t(63) = 2.29, p = .03$. However, degree can be calculated differently when two exchanges are allowed. Fs exchange twice per round while Gs exchange only once. At the beginning of a round, F has three potential exchange partners. If F's first exchange in a round is with a G, then there are two actors left with whom to attempt a second exchange. If Fs first exchange with each other, then they have three actors left with whom to attempt a second exchange. Fs then have either five or six direct ties while Gs have only one. If F's first exchange is with a G on two-thirds of the rounds (i.e., F is indifferent between the other F and its two Gs), then Fs effectively have 5.33 direct ties. This produces a GPI-RD prediction for F in

TABLE 1: Goodness of Fit[a] for Predicted and Observed Profits in Exchange Networks

	Models and Predictions							Observed Means
Structure, Relation	Core	Rational Exchange	Equi-depend.	Expected Value	Exchange Resistance	GPI-R	GPI-RD	
4-Line								
B-A[b]	16.0	15.0**	16.0	21.0	16.0	13.5	14.5****	14.4
t (29)	4.27	1.54	4.27	13.01	4.27	-2.54	0.18	
Stem[c]								
A-B	20.1	17.2**	18.0	22.0	18.3	14.4*	15.6****	15.9
t(13)	5.46	1.72	2.76	7.91	3.15	-1.88	-0.33	
Kite								
D-E	unstable	15.2*	12.0****	12.0****	12.5****	12.2****	13.7****	12.8
t(7)		1.95	-0.61	-0.61	-0.20	-0.46	0.77	
Double Branch 2								
F-G	16.8***	13.8	16.0****	20.2	14.6	13.3	16.3****	16.4
t(63)	0.93	-5.68	-0.82	8.38	-3.89	-6.69	-0.14	

[a] One-sample *t* tests were used to estimate the probability of no difference between prediction and observation. Larger *p* values suggest an increased likelihood that prediction and observation are identical. Degrees of freedom are in parentheses.

[b] Predictions are for profits of the first position listed in a relation; here, for example, actor B in B-A.

[c] The A-C relation is also of interest in this network. However, during the last period of the experiment, A exchanged with C only twice, both times at 14-10. This precludes meaningful comparison. With that caveat, we report only for completeness that the GPI-RD prediction of 13.7 for this relation was closest among the models, though the equidependence and rational exchange models were also close.

* $p > .05$ ** $p > .10$ *** $p > .20$ **** $p > .40$

exchange with G of 16.31. A *t* test finds no difference between this value and the observed mean, 16.36, $t(63) = -.14$, $p = .89$. While this is the closest prediction of any model, Table 1 shows that the Bienenstock and Bonacich (1992, 1993) core and Cook and Yamagishi (1992) equidependence models also make acceptable predictions for the Double Branch 2.

In sum, the GPI model incorporating resistance and degree formulations produced very accurate predictions for exchange outcomes. These predictions were superior to alternative models in their goodness of fit to experimental data: Only GPI-RD makes acceptably close predictions ($p > .40$ of no difference between predicted and observed values) for all four experimental networks.

EXPERIMENT 2: RESTRICTED-INFORMATION NETWORKS

There is a theoretical distinction between full- and restricted-information settings used for network exchange experiments. Full-information settings more closely model rational, forward-looking actors who use whatever information is available. Restricted-information settings conform better to backward-looking actors who adjust their response only on the basis of their experience in the situation. Our model requires that, minimally, three information conditions must be satisfied for negotiated social exchanges to occur:[16] (1) An actor in the network must be informed of, and have access to, other actors with whom it is possible to exchange. We assume that actors negotiate separately with each potential partner and are thus aware of each partner as a distinct person or organizational unit. Implicitly, then, actors also know the number of others with whom it is possible to exchange. (2) The actor must be informed of whether an exchange has been completed with each potential partner. (3) The actor must be informed of the magnitude of her or his profits from exchanges. In order to evaluate an offer, it must be at least ordinally scalable. This requires information on the offer's relative magnitude. In a typical experiment, this takes the form of an agreement between two partners to allocate a pool of resources at the conclusion of a given negotiation round. Implicitly, if actors know the magnitude of the offer upon which agreement was reached, then they also know the magnitude of their own shares of subsequent resource allocations stemming from the agreement. Knowledge of others' profits is not essential. Therefore, to examine the empirical scope of our model, we examine data from experiments in a new, restricted-information setting that differs in several ways from the full-information setting described above. The new setting restricts information to the minimum necessary for the operation of factors deemed important in the model.

As our theory evolves, refinements in its predictions demand that we study increasingly subtle network exchange phenomena. Consequently, our experimental setting must be made increasingly sensitive to predicted phenomena, and it must exert more stringent controls over potentially extraneous factors such as equity concerns. We have attempted to accomplish this by creating a new experimental setting that spreads the negotiation process across a larger number of rounds and limits information to the minimum necessary for negotiation and exchange. Each subject has information only on his or her own (1) negotiations and exchanges, (2) potential profit vis-à-vis particular offers received from others, and (3) realized profit when an exchange occurs. In addition, subjects negotiate for many more rounds because a subject's intraround negotiations with a partner are simplified to a choice of three options: increase or decrease the previous offer by one "profit point" or do not change the previous offer. Cook et al. (1983) limit information in a similar fashion but allow subjects to select their offers from a wide range of possibilities on each round. The new setting then makes possible tests of our theory under information conditions similar to those of earlier restricted-information exchange experiments.

Custom software was used to configure networked PCs.[17] Subjects were isolated in separate rooms and knew only the coded designations for their own potential exchange partners. They were informed that the shape of the full network would not be revealed and that their potential partners might have other potential partners of their own. An interactive tutorial guided subjects through the mechanics of conducting negotiations via the computerized system. On each round, subjects sent messages to a central computer telling it the lowest amount of profit they were willing to accept from each potential partner. If an agreement was reached, the subject was informed of this fact but did not know the amount of profit received by the partner; only her or his own profit was reported. Subjects completed a total of 60 rounds at the same network position. Each relation contained 30 profit points at the outset of each round, although subjects did not know the pool size. At the outset of negotiations, each partner could receive 15 points from an agreement, which was awarded as a 15-cent "bonus" for reaching an agreement. Subjects could raise or lower the amount they were willing to accept from each partner by 1 point, or leave the amount unchanged. Each 1-point change resulted in a 1-cent change in the amount of bonus for agreement. The computer declared an agreement when the sum of the profits for which two potential exchange partners were willing to settle did not exceed 30 points. If the sum was less than 30 points, the computer split the excess and awarded half to each subject in addition to the amount on which she or he had settled.

Because subjects made offers to all potential partners on each round, some could reach provisional agreements with more than one partner. Due to the fact that subjects were allowed only one agreement on each round, the central computer used the following algorithm to prioritize agreements: (1) Assign zero profit to subjects who do not reach any provisional agreement. (2) For those who remain, declare agreements for pairs of subjects whose best deals are with each other. (3) Select a subject randomly from those remaining and award her or his best deal. (4) Repeat the random selection until no more deals are possible.

This restricted-information setting differs from the full-information setting in several important ways.[18] Nevertheless, the settings are identical in several respects crucial to our model. First, in both settings the number of direct relations a subject has to others is immediately apparent and obvious. Therefore, degree can influence profit expectations. Second, in both settings, actors can over time get a sense of the range of acceptable terms through experiencing rounds in which they are excluded from exchange and rounds in which they are included. (This is true in the restricted-information setting even if some inclusions have a chance element because of computer intervention when multiple provisional exchanges could be made.) Therefore, excludability can influence expectations. On the basis of these essential similarities, we make the same predictions for profit differentials by position at equilibrium in the new restricted-information setting. That is, exchange rates in the last rounds of an experiment should be comparable across settings.[19]

RESULTS

Eleven groups participated in the Stem network. We treated the last ten agreements in a session for each relation as an indicator of its equilibrium exchange rate. This provides sufficient cases for a stringent statistical test and roughly corresponds to our use of last-period results in the full-information experiments. For the A-B relation, the last ten agreements varied by no more than a few points in all groups, allowing us to conclude that equilibrium had been reached. The maximum range over which agreements varied was 4 ($M = 2.0$; Std. dev. = 1.05).[20] In exchanges with B, the subject in the A position achieved mean profit of 20.13 (std. dev. = 4.29) out of a pool of 30 points, compared to the GPI-RD predicted level of 19.5. A one-sample t test found no difference between prediction and observation, $t(10) = -.49$, $p = .64$. Profit of 20.13 on a 30-point scale is equivalent to 16.10 on a 24-point scale, and thus very close to the 15.86 observed in the full-information experiment.

In previously reported experiments using the Stem network (Cook, Donnelly & Yamagishi 1992; Markovsky et al. 1993), A-C exchanges were infrequent. We had hoped that with 60 rounds in the new setting, we could establish an equilibrium value for this relation. This was not the case. A-C exchanges were still infrequent, especially during the final 30 rounds of a session. Two groups had no A-C exchanges during the last 30 rounds, and only four groups had ten or more. With such limited data, we lack confidence that equilibrium was reached. However, we attempted to test our prediction for A in the A-C relation by taking the overall mean for all A-C exchanges that occurred in the last half of a session ($M = 17.46$, Std. dev. = 3.77). GPI-RD predicts A will receive 17.10 profit units at equilibrium, a difference of less than half a profit unit from the observed mean. A t test found no difference between predicted and observed values, $t(82) = -.88$, $p = .38$. While this result does support the GPI-RD model, the variability in frequency of exchange argues against giving it much weight.

A significant difference was found in the C_1-C_2 relation. As with the A-B relation, we were able to use C_1's mean profit for the last ten exchanges for each group as an indicator of the equilibrium exchange rate in C_1-C_2 ($M = 18.18$, Std. dev. = 4.31). This difference in profit between isomorphic network positions is puzzling; all models predict an equal, 15:15, division of profit. Comparing this predicted value to the observed mean, we find that $t(10) = -2.45$, $p = .03$. The anomalous finding may be a chance occurrence, or an artifact of the experimental setting: The program treats C_1 and C_2 identically, with the one exception being that C_1 appears above C_2 as a potential partner on *A*'s video screen. Possibly because of simple ordering, A may pay more attention to C_1 than to C_2, thereby affecting C_1's negotiations with C_2 in C_1's favor. While this might not affect the A-C or A-B equilibrium values (and thus show how robust GPI-RD predictions are for these relations), it could affect the C_1 - C_2 value. For the present, we regard this finding as a spur to additional research rather than as a disconfirmation of GPI-RD, since the finding is completely unanticipated by any alternative model.

To summarize, we replicated our test of the GPI-RD model using the Stem network in an information-restricted exchange situation. The key hypotheses were again supported.

Discussion and Conclusions

We developed a theory to explain how actors in social exchange networks reach agreements on divisions of resources. The model incorporates previous ideas about the effects that network structure has on the power of individual positions, specifically the graph-theoretical power index of network exchange theory and its weak power extension (Markovsky, Willer & Patton 1998; Markovsky et al. 1993). To this model we added theoretical ideas borrowed from several areas of sociology.

From elementary theory's concept of resistance, we borrowed the idea that actors balance two competing interests to reach agreement in exchange: (1) their "best hope" for maximum profit and (2) their "worst fear" of being excluded from exchange entirely. We combined this with an idea from network exchange theory: Likelihood of being included in exchange ranks the power of network actors. This resulted in a new assumption: Actors' best hopes and worst fears are proportional to their likelihood of being included in exchange. Actors who are frequently excluded from exchanges (and profit) are likely to lower both their maximum and minimum aspirations for profit. Conversely, actors frequently included in exchanges become accustomed to receiving profit and raise their expectations accordingly. Integrating these previous theoretical strands yielded a model that generates ratio-scale predictions for the outcomes of negotiating actors in exchange networks.

The fact that actors adjust their expectations through negotiation implies that structural power differences emerge over time. In strong power networks identified by network exchange theory, these differences never reach an equilibrium point short of the point of extreme differentiation. They continue until powerful actors receive all (or nearly all) available resources from exchange with less powerful actors. In weak power structures, an equilibrium point is reached well short of maximum differentiation. It is this equilibrium point that we attempt to predict theoretically and measure experimentally.

We felt that the equilibrium point eventually reached will likely be affected by actors' initial expectations formed on the basis of prominent features of their structural context. From network analysis we borrowed the idea that an actor's degree, the number of her or his direct ties to other actors, would influence her or his initial expectations for success in exchange. That is, actors with more direct ties would be biased toward resisting exchange offers that they would otherwise accept. We included degree as a biasing factor in predicting the equilibrium exchange point that experimental subjects would eventually reach. Results of an experimental test in a setting specifically designed to measure the equilibrium point suggest that our theoretical integration was successful. This brings up potential avenues for future research. The theory suggests that actors' expectations have significant effects on resource distribution only in weak power networks. What effects, if any, do expectations have in strong power networks? Also, certain expectations about the social structure were shown to have important effects in weak power networks. Do other kinds of cognition have important effects? And under what conditions are cognitions likely to be more or less important?

Our extension of network exchange theory provides a number of advantages over earlier versions and current alternatives. By highlighting the ways that actors' profit expectations interact with structural properties of their locations in the network, it generates predictions for all positions in weak power networks on a ratio rather than an ordinal level of measurement. Moreover, these predictions are more accurate than those of alternative theories, and the theory generalizes across experimental designs. Our predictions closely approximate experimental results from the full-information experiments of Skvoretz and Willer (1991, 1993), the restricted-information experiments of Cook, Donnelly & Yamagishi (1992), and the results reported here for equilibrium rates in both full and restricted settings. In addition, results reported by Bienenstock and Bonacich (1993) for two weak power networks, the four-actor line and Kite, are extremely close to our predictions. Their experimental setting has features quite different from either the Skvoretz and Willer or Cook, Donnelly & Yamagishi designs. This remarkable convergence of experimental results in different settings demonstrates both the increased precision of the theory and its enhanced generality.

The empirical results also clearly suggest that equity concerns are not inextricably woven into social exchange network settings. This is not to say that equity effects are unimportant, but rather that equity is a distinct process that may or may not be activated in a given social context and that depends upon whether certain conditions are satisfied (Markovsky 1985). In developing our restricted-information setting, we struggled with the powerful effects of subjects' equity concerns when they felt they were receiving less than a partner who in other ways was their status equal. In some cases, subjects would refuse to exchange in as many as 50 out of 60 rounds because another subject would receive more profit than they would. That is, subjects would refuse five or six dollars in pay to avoid receiving a few pennies less than their partner in exchange. This study demonstrates that once equity concerns are controlled, different experimental settings produce comparable structural effects on resource distributions resulting from exchange. Structural positions have an effect on power independent of equity concerns. An interesting area for further inquiry is exactly how equity effects combine with the effect of structural position under different conditions to produce power and profit differences in social exchange networks.

Let us note that the equation for actor profit, P_i, converges with part of Cook and Yamagishi's (1992) theory — their equation $R_{ij} = (P_{ij} + A_{ij} - A_{ji})/2$. In this model, R_{ij} is the profit that actor *i* obtains in exchange with partner *j* and corresponds to our P_i; P_{ij} is the pool size and corresponds to P; A_{ij} is the best alternative available to *i*, which corresponds to C_{ij}, *i*'s expected conflict outcome. That is, *i*'s best alternative is the least amount of profit *i* expects if exchange with *j* does not occur. A_{ji} is *j*'s best alternative, i.e., C_{ji}. Despite these similarities, however, our model diverges from Cook and Yamagishi's in significant ways. Unlike A_{ij}, which refers to the objective profit under "conflict," C_{ij} is assumed to be a subjective assessment or expectation of long-range profit from failure to reach agreement. We believe that one reason for our model's predictive success stems from this incorporation of the actor's point of view. This allows the new model to generate contrasting predictions that are here shown to be significantly more accurate than alternatives.

Although the predictions that we derived are accurate for the networks tested, these findings tell us only that the model is developing in potentially fruitful directions. Establishing its broader generality will require continued testing in a wider variety of networks. Further enhancements will be required to allow predictions with theoretical restrictions further relaxed. Of course, these have been our goals all along: to generate increasingly precise and accurate predictions for network exchange outcomes under increasingly robust conditions. With the theoretical and empirical developments reported above, we have worked toward achieving these goals.

APPENDIX: Network Exchange Theory

Key Terms

p = power	h = length of the longest nonintersecting path
d = domain	m_{idk} = number of i's nonintersecting paths of length k in domain d.
i, j = network positions	e = maximum exchanges per round

A network path is a series of connected positions, e.g., A-B-C-D. Two paths stemming from a given position i are nonintersecting only if i is the only position common to both. Thus, relative to the A position, A-B-C-D and A-B-E-F are intersecting paths (at B), but neither intersects with A-G-H.

Domains are network substructures. When $e > 1$, a position can have different power indices within different domains (see Markovsky, Willer & Patton 1988). The following criterion determines whether i and j are in the same domain. First, define an $e+$ position as one having more than e relations. Then, given the set V of all positions on a path (i.e., a series of linked positions) between i and j, i and j are in the same domain only if there exists a path such that either V = {∅}, or all positions in V are $e+$ positions.

SCOPE CONDITIONS

The theory is deemed applicable when the following conditions are met or approximated:

1. All actors use identical strategies in negotiating exchanges.
2. Actors consistently excluded from exchanges raise their offers.
3. Those consistently included in exchanges lower their offers.
4. Actors accept the best offer they receive and choose randomly in deciding among tied best offers.
5. Each position is related to, and seeks exchange with, one or more other positions.
6. At the start of an exchange round, equal pools of positively valued resource units are available in every relation.
7. Two positions receive resources from their common pool if and only if they exchange (Markovsky, Willer & Patton 1988:223).

AXIOMS

Four axioms determine the relative power of connected positions and whether they will exchange:

Axiom 1. $$P_{id}(e_d) = \left(\frac{1}{e_d}\right)\sum_{k=1}^{h}(-1)^{(k-1)}m_{idk}$$

Axiom 2. i seeks exchange with j only if $p_i > p_j$, or if $(p_i - p_j) \geq (p_i - p_k)$ for all k related to i.

Axiom 3. i and j can exchange only if each seeks exchange with the other.

Axiom 4. If i and j exchange, then i receives more resources than j if and only if $p_i > p_j$.

APPENDIX: Network Exchange Theory

WEAK AND STRONG POWER

Markovsky et al. (1993) provide an iterative method, GPI^2, used to derive more precise hypotheses.

Step 1. Apply Axiom 2 to determine exchange seeks.

Step 2. Apply Axiom 3 to remove nonmutual exchange seeks.

Step 3. Apply Axiom 1 to each subnetwork that results from Step 2; $p = 1$ for isolates.

Step 4. Re-form the full network with new p values; repeat from Step 1 until values do not change.

If after the above analyses $p_i > p_j$ for actors in the i - j relation, then i has strong power over j, and it is predicted that profits from exchange in this relation will favor i and approach their maximum differentiation. If $p_i = p_j$, then there are exactly two possibilities: either the actors are equal in power, or else one has weak power over the other.

Weak power differences are detected using a probability analysis. The analysis assumes that actors seek exchanges randomly among their potential partners and counts relative proportions of mutual exchange seeks as exchange likelihoods. If i and j have unequal exchange likelihoods, then the actor with the higher likelihood is predicted to have a weak power advantage over the other. This is identified as GPI_3. Examples of its application are provided in Markovsky et al. (1993) and in the theoretical discussion of this article. A computer program for calculating likelihood of inclusion is available at no charge from the second author.

Notes

1. It should be noted, however, that network exchange theory predictions also generally agree with data from exchange situations with greater information restrictions, e.g., Cook, Donnelly, and Yamagishi (1992), Cook and Emerson (1978), and Cook et al. (1983), and also from the setting used by Bienenstock and Bonacich (1993).

2. These conditions are probably sufficient but not necessary to determine whether a network displays strong power. In general, casual inspection often fails to classify networks properly as strong power or weak power. Full application of the GPI method is required.

3. Theoretical integration requires integration of notation systems as well. Markovsky et al. (1993) use the notation $p\{i\}$ to denote the probability of inclusion of position i in an exchange network. But the letter p also occurs in resistance equations to denote profit. To avoid confusion and simplify our notation, we switch to l_i (actor i's likelihood of exchange).

4. C_i is similar to Thibaut and Kelley's (1959) "comparison level for alternatives" or CL_{ALT}, i.e., "the lowest level of outcomes a member will accept in the light of available alternative opportunities" (21). M_i and C_i define the range of possible offers. The model does not assume that actors have objective knowledge of their values. "Best hopes" and "worst fears" need not be reasonable, though actors are likely to refine their estimates as they interact. We have again simplified the notation of earlier presentations of the theory: e.g., Willer, Markovsky & Patton (1989) use $P_{MAX}(A)$ to represent M_i and $P_{CON}(A)$ to represent C_i.

5. Assumptions are evaluated on their effectiveness in producing testable hypotheses that conform well with observation. The assumption that actors exchange when their resistances are equal has been very fruitful in previous studies (Skvoretz & Willer 1993; Willer 1987), including cross-national comparisons (Willer & Szmatka 1993).

6. Cook and Yamagishi (1992) also suggest that the idea of a limit to power use in networks holds promise for a general formula to predict resource distribution. Willer (1987) demonstrat-

ed such generality when he applied the resistance model to a wide variety of network situations both inside and outside the laboratory.

7. Individuals participating in experiments or acting in natural exchange situations will exhibit a range of "best hopes" and "worst fears." This in no way interferes with the model's ability to predict exchange rates. Coalitions among actors are ruled out by the scope conditions of the theory though they may occur often in exchange situations. Erger (1993) has extended the theory to include the effects of coalitions.

8. Markovsky et al. (1993) provide support for this idea. They found that ordinal predictions for weak power networks based on likelihood of being included were more strongly corroborated for experienced than for inexperienced subjects.

9. While simple proportionality is a straightforward way to incorporate likelihood of being included into the resistance model, other specifications are possible. For example, Skvoretz and Willer (1993) take the difference between M_i and P_i, then raise it to the power of l_i. Our model is the simplest expression we could devise of the theoretical idea that actors' worst fears and best hopes in the exchange situation depend on — and are proportional to — the likelihood of their being included in exchanges.

10. The mathematical derivation is available on request from the first author.

11. Markovsky (1988) specifies the conditions under which anchoring will occur: judgments are indeterminate, an anchor is available, and anchors are salient. These conditions are satisfied in experimental tests of network exchange theory. Markovsky's "anchoring proposition" predicts when assimilation as opposed to contrast effects will be observed. According to this proposition, assimilation would be predicted in the present context because degree informs best-hope and worst-fear outcomes, each of which appears on the same scale as the "response" variable, i.e., expected profit. (An anchor on the stimulus scale — as in the temperature example — produces a contrast effect.)

12. An actor's maximum expectation for profit may differ among exchange partners in the same way.

13. In a replication using a different experimental exchange setting, Bienenstock and Bonacich (1993) obtained similar results.

14. Some readers of earlier versions of this article noted the similarity between network exchange and noncooperative game theory (e.g., Harsanyi 1980; Nash 1951; Osborne 1990; Rosenthal & Rubinstein 1984; Rubinstein 1982, 1991). Also, the few experimental tests of noncooperative game theory use experimental situations similar to that used in network exchange experiments but without the complication of network structure (see, e.g., Nydegger & Owen 1974). While intriguing, these similarities mask very real difficulties in applying noncooperative game theory to network exchange. Rubinstein (1982) states the bargaining problem in noncooperative game theory as "Two individuals have before them several possible contractual agreements. Both have interests in reaching agreement but their interests are not entirely identical. What 'will be' the agreed contract, assuming that both parties behave rationally?" (97). He goes on to distinguish this problem from two others: "(i) the positive question — what is the agreement reached in practice; (ii) the normative question — what is the just agreement." Perhaps because of these distinctions, noncooperative game theory places little emphasis on theory testing through experimental or field research and does not fare well in experimental tests. Network exchange theories place more emphasis on the "positive question," on how subjects behave in controlled settings. Experimental results are then used to inform theoretical development in cumulative research programs. Bienenstock and Bonacich have made the most successful use of game theory to analyze network exchange structures.

15. Markovsky et al. (1993) and Skvoretz and Willer (1993) analyze data from these full information experiments. Markovsky et al. (1993) use data from the Stem and Kite networks; Skvoretz and Willer use data from all four experiments. Their analyses are based on all rounds of the experiments. Here we use data from just the last period, which is four rounds long. Although suitable for testing ordinal predictions, using the mean of all rounds in an experiment as an indicator of power is problematic for testing exact predictions. For example, exchange may begin at an even split of the profit pool, 12:12, in early rounds then progress to a stable pattern of 20:4 exchanges. In this case, 20:4 is a good estimate of the power difference

in the relationship. The mean exchange rate for all rounds (about 16:8) would seriously underestimate the magnitude of the equilibrated power difference.

16. Our model requires these assumptions; we do not assume that all naturally occurring social exchanges satisfy these conditions.

17. This system was designed to be relatively "low-tech" and portable to other laboratories. The software is written in Microsoft QuickBASIC (4.5), and PCs are connected in a ring configuration via cables connected to standard serial ports. The ring consists of one master control PC and any number of subject PCs. The program is available from the authors upon request.

18. Equity concerns, for instance, are controlled in the two settings in different ways. If actors feel the exchange situation is unfair, they may refuse to accept the best offer available to them. The full-information setting described solves the potential equity problem by rotating subjects through all positions. Actors disadvantaged in one position know they will be compensated when they rotate through an advantaged position. Restricted-information settings in which subjects typically do not change positions solve the problem by not telling a subject the earnings of his or her partner in order to prevent comparison of subject's rewards with partner's rewards.

19. Because of the differences in intraround negotiation options and total number of rounds between the two settings, we would not expect averages from all rounds to be similar across settings. The restriction to equilibrium rates is essential to the "no setting difference" prediction.

20. In contrast, the first ten A-B agreements for each group varied more widely; the maximum range was 9 ($M = 4.23$, Std. dev. $= 2.35$). The mean range of the first ten agreements was significantly greater than the mean range of the last ten agreements, $t(10) = 3.09$, $p = .01$.

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