The Journal of Mathematical Sociology
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713618269

Testing Ten Theories

DAVID WILLER [a]; PAMELA EMANUELSON [a]
[a] Department of Sociology, University of South Carolina, Columbia, South Carolina, USA

Online Publication Date: 01 July 2008

To cite this Article WILLER, DAVID and EMANUELSON, PAMELA(2008)'Testing Ten Theories',The Journal of Mathematical Sociology,32:3,165 — 203

To link to this Article: DOI: 10.1080/00222500802148743

URL: http://dx.doi.org/10.1080/00222500802148743

Journal of Mathematical Sociology, 32:165–203, 2008

ISSN: 0022-250X print/1545-5874 online
DOI: 10.1080/00222500802148743

Routledge
Taylor & Francis Group

Testing Ten Theories

David Willer
Pamela Emanuelson
Department of Sociology, University of South Carolina, Columbia, South Carolina, USA

Using the most comprehensive data set now available, this investigation tests the precision of all exchange theories that now contend. Beyond precision, the investigation focuses on broad issues of effectiveness including consistency, parsimony, and whether the theories can be applied to structures larger than normally studied in the lab. Seeking greater parsimony, this investigation introduces a new model by combining parts of two contending theories. We find that all ten theories have scientific merit for all can predict with some effectiveness for the exchange structures experimentally investigated. Nevertheless, the ten vary in precision. Elementary Theory is the most precise. The new Expected-value Resistance model ranks second in precision and is the simplest. Both apply to large networks as well as the best of the other theories.

Keywords: experiment, explanation, network exchange, power, precision, prediction, science, scope, social structure, theory testing

As theories of exchange have proliferated, it has become increasingly difficult to determine which theory to use. To facilitate use, this paper brings together all nine existing theories of network exchange, explaining how each infers from initial conditions to predict subsequent exchange outcome. A new theory, more parsimonious than any previous outcomes, is introduced. Thus, we test fully ten theories. The test begins by considering the consistency and parsimony of each. Then the precision of the ten is tested using the most comprehensive data set now available. Of necessity, that test is bounded by the scope over which all ten contend.

Research reported here was supported by grants SBR-9423231, IIS-9817518 and SBR-9811323 to the first author from the National Science Foundation.

Address correspondence to David Willer or Pamela Emanuelson, Department of Sociology, University of South Carolina, Columbia, SC 29208. E-mail: dwiller@sc.edu or pamelaemanuelson@juno.com

These are theories that predict outcomes from social structure, long a central problematic in sociology. That problematic has been investigated by theorists as diverse as Marx ([1867] 1967), Weber ([1918] 1968), Blau (1964), and Merton (1968). More specifically, these are theories of exchange networks that seek to predict exchange ratios in structures of any configuration. To predict an exchange ratio is to predict an agreement achieved by those who occupy connected positions. In turn, the exchange ratios that actually occur indicate which positions are advantaged and which are disadvantaged by the structure. By convention, those who gain favorable exchange ratios are said to exercise power (Lovaglia et al., 1995; Lucas et al., 2001).

This investigation points to a perplexity not anticipated by sociologists who have focused on theoretic methods such as Wagner (1984), Cohen (1989), and Berger and Zelditch (1993, 2002), or by philosophers of science such as Popper (1959, 1994), Hempel (1952, 1965), Toulmin (1953), Kuhn (1970), and Lakatos (1970). Sociologists and philosophers alike recognize that two or even three theories might compete with each other, but in network exchange today, fully ten theories contend. Nor are those ten theories simply orienting perspectives which, like functionalism and conflict theory, disagree but fail to offer predictions that could be tested against each other. To the contrary, all ten theories compete over some or all of their scope and offer point predictions that are eminently testable.

Having as many as ten theories in network exchange points to both a strength and a weakness of sociology as a science. The strength lies in the very existence of ten viable theories and the creativity of formulation each can claim. That as many as ten can claim, and indeed have claimed, experimental support suggests that "the experimental model" is not irrelevant to sociology as some have asserted (e.g., Lieberson, 1985, p. 234). That the experimental method is relevant is good news because it is a particularly effective method for testing theory.[1]

That ten theories are current, however, means that the theory selection process basic to all science is not working. [2] The failure of

[1]As Lucas (2003) points out, the "external validity" problem, so often attributed to the experimental method, is resolved when experiments test theory that applies outside the lab, as do the theories tested here.

[2]Nevertheless, falsifications have occurred in network exchange. Friedkin demonstrated that Markovsky et al.'s (1988) graph theoretic power index gave multiple contradictory predictions for some networks (personal communication). That demonstration and the struggle to fix the index are recounted in Lovaglia et al. (1996). Earlier, Willer (1986) showed that Power-Dependence's vulnerability procedure offered logically and mathematically impossible predictions. It might be thought that if a theory is logically consistent, it cannot produce inconsistent predictions, but graph theoretic and vulnerability procedures show that the suggestion is wrong. Both are internally consistent, but both produce contradictory predictions.

the selection process holds back the explanatory use of any of these theories. Researchers who seek to apply theory to exchange networks, including historical and contemporary social structures, are confronted with too many theories, the relative capabilities of which are by no means transparent. Far better, as emphasized by Einstein (1933) and others, is to offer researchers the one most precise, parsimonious, and broadest theory.[3]

Previous tests of exchange theories (Skvoretz and Willer, 1993; Lovaglia et al., 1995) considered, at most, half of the theories tested here. Furthermore, those tests considered only one quality, precision. We test ten theories and consider four qualities furthering their effectiveness in prediction and explanation. We take it as axiomatic that to be effective, a theory should

1. be internally consistent and consistent in predictions,
2. be as parsimonious in application as possible,
3. offer precise predictions and explanations
4. over as broad a range of applications as possible.[4]

We add one further criterion: To be useful, a theory must be easily and publicly accessible. While a "private theory" may seem an oxymoron, not all of these theories are readily accessible.

What counts as parsimony in theory deserves comment. At first glance, it would seem that a count of each theory's basic assumptions would give its degree of simplicity, but that is not the case. As Popper pointed out, judgments of simplicity based on the internal structure of two or more theories require they be logically equivalent (1959, p. 139). But as far as we can determine, no two of the ten theories have logically equivalent structures. Because they do not, there is no criterion by which "basic assumptions" can be differentiated from assumptions of other kinds. Thus, in determining parsimony, we follow Popper who

[3]Also see Lakatos (1970), Popper (1994), and Kuhn (1970). For Kuhn, the evolutionary image employed in his 1969 Postscript (found in Kuhn, 1970) is particularly to the point.

[4]The four listed criteria are prominent in the works of philosophers of science and sociologists already referenced and in Fararo and Kosaka (2003). We adopt the following meaning for precision: "Theories are precise to the degree that they generate accurate and detailed statements about phenomena." (Markovsky, 1996, p. 34). Effectively the same meaning is also found in Wagner and Berger (1985) and Wagner (1984, 1994). By range of application we mean the variety of phenomena to which a theory can be successfully applied. That meaning is drawn from Walker and Cohen (1985) and agrees with meanings given in the previously cited papers.

equated simplicity with falsifiability, which is to say with parsimony, in application (1959, p. 140ff).[5]

As defined here, the parsimony of a theory in application varies with the numbers of steps needed to calculate its predictions. For all but one of these theories, that number is very large. Why is it large? Many of the theories are applied iteratively. That is to say, they are applied once and the results of that application are fed back to a second application, the second to a third, the third to a fourth and similarly until successive applications give the same results. Those results are the theory's predictions at equilibrium. As seen below, the only theories found to be parsimonious are not applied iteratively.

We begin by discussing the ten theories in the order in which they first occur in the literature, a discussion that centers on their consistency and parsimony. With ten theories to cover, the discussion of each is necessarily brief. The aim is to show how each theory works–how it calculates from structure to activity. For some readers, more detail will be wanted and they are referred to original sources that are liberally referenced. While reporting experiments that test the precision of the ten theories, we offer a test of the range over which each applies. The test is limited in that it focuses on size, on whether the theories can be applied to any network substantially larger than the ones experimentally investigated. Beyond size other issues of scope are not taken up in this paper for they would require its size to be at least doubled.[6]

[5]To our knowledge no one has suggested that a lack of simplicity is sufficient to reject a theory; nevertheless, parsimony is a desirable quality. For a theory to become rapidly more complex is a clue to the theorist that a new start would be fruitful. For example, shortcomings in the graph theoretic power index found by Friedkin (see footnote 2) were solved only by making that index massively more complex (Lovaglia et al., 1999) such that it has been displaced by the much simpler Girard and Borch method given later in this paper. As will be seen, some of the ten theories have become more complex as they were developed.

[6]Some of the theories tested here have no scope of application but that investigated in the experiments; however, others are broader. Comparing the broader theories, beyond the scope tested here, there is little or no scope overlap. This lack of overlap introduces incommensurability blocking judgments of relative breadth of scope. For example, Expected Value Theory also applies to influence structures, but Elementary Theory does not. By contrast, Elementary Theory recognizes seven power conditions, but Expected Value Theory recognizes only exclusion, the one investigated here. Which scope is broader? Incommensurability blocks any answer to that question.

SOCIAL STRUCTURES IN THE CONTENDED SCOPE

The experiments of this study test the whole of the scope common to the ten theories. The scope common to the ten theories is marked by two conditions that can be traced to the first network exchange experiments (Stolte and Emerson, 1977). The two are: 1) for each round of negotiation, each position is limited to, at most, a single exchange, and 2) exchange is simulated by a pool of resources that is divided upon agreement by subjects in connected positions.[7] A pool of 24 resources has become conventional (Cook and Emerson, 1978). As a result, only the shape of the network determines which positions are advantaged or disadvantaged, and that advantage/disadvantage is determined by whether positions are excludable or not (Skvoretz and Willer, 1993).

The L4 network of Figure 1 is used to show how exclusion works. The B positions are nonexcludable because each always has its A as partner for exchange. Each initially has the other B as well. Since all positions are limited to a single exchange, if the Bs exchange with each other, the As will have no partner, will be excluded from exchange, and will receive no payoff. To avoid exclusion, it is reasonable to infer that the As will make better offers to the Bs than the Bs will make to each other. Inferring further, the Bs will then exchange with the As. More generally, the problem for the ten theories is to predict from the possibility of exclusion to offers and from offers to exchange ratios.

The justification for studying networks like those of Figure 1, if such is needed, rests to an important degree on whether exclusion, as a power condition, is found outside the laboratory. Fortunately it is. As Corra (2005) points out, exclusion and "separation" refer to the same phenomenon. The concept of separation was first formulated by Marx, then used by Weber, and has subsequently entered into much mainstream thinking. For Marx, the ability of the capitalist to exploit the worker is based on the worker's separation from the means of production ([1867] 1967, p. 37ff). For Weber, the separation of the official from the means of administration, the warrior from the means of warfare and the researcher from the means of research are central to domination ([1918] 1968, p. 980ff). Separation indicates whether exclusion is possible, a condition ubiquitous in the field.

[7]Van Assen (2001) has shown that payoffs from resource pool divisions are similar to some but not all exchanges.

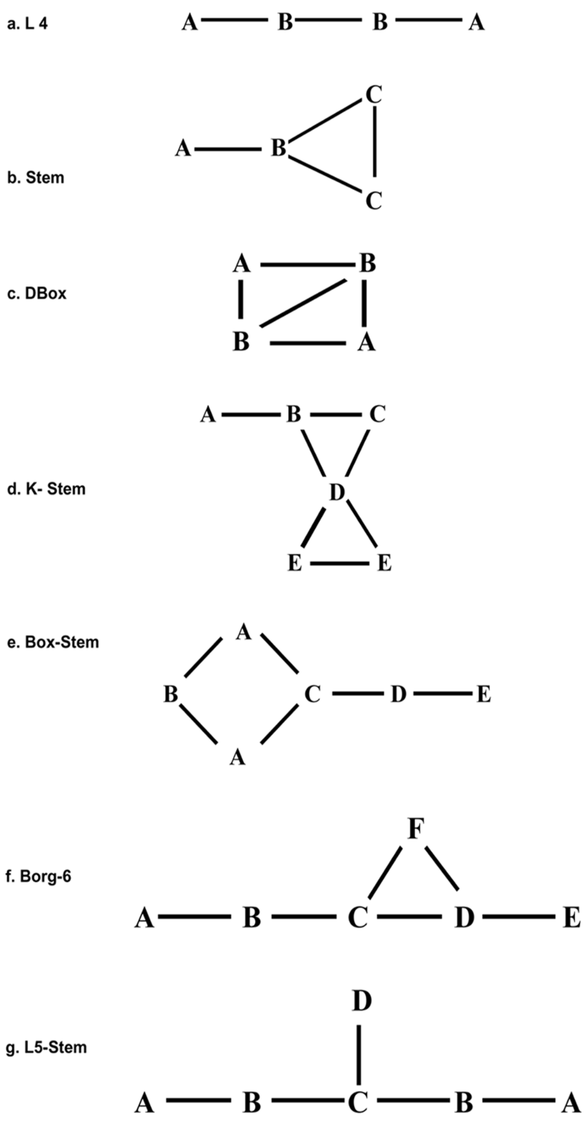

FIGURE 1 Seven weak power networks.

Why the Seven Networks Were Selected

Since there is an uncountable number of networks that could be employed to test the ten theories, it is quite impossible for any study to be exhaustive. We certainly do not make that claim. To the contrary, we first developed criteria for the kind of networks that would provide the best test and then strategically selected by those criteria. While the resulting data set is discussed later, it should be noted that, for the criteria 1) this is the *only* extant data set, and 2) it is larger by a factor of ten than the largest data set previously employed in testing exchange theories. Here are the criteria.

First, to evaluate relative precision, network structures must be selected such that different theories make predictions distinct enough to be differentiated by experimental results. Within the scope common to the theories, three types of exchange networks have been identified: strong, equal, and weak power (Skvoretz and Willer, 1993; Lovaglia et al., 1995). Applying the four oldest of the ten theories, we now show that weak power structures offer the best test.

In a previous investigation of a strong power network where 24 point pools were divided, the Core, Power-Dependence Theory, and Expected Value Theory predicted that the high power position would receive 24, 24, and 22 points, respectively (Skvoretz and Willer, 1993) while Elementary Theory predicts 23 (Walker et al., 2000). Far from being distinct, these predictions are very nearly identical. Moreover, the four theories make these predictions for all strong power networks. In equal power structures, the four theories make identical predictions. Since all positions are homomorphically equivalent, all receive equal payoffs.[8]

Unlike strong and equal power, weak power networks offer many opportunities to test theories. For the weak power Stem of Figure 1b, the four predict that the higher power position receives 20.1, 18, 17.8, and 14.4, respectively. But for the second to third, the predictions are distinct enough to be differentiated by experimental results. More generally, as can be seen in Table 1, the predictions of all ten theories for weak power networks vary substantially and it is for that reason that the test for precision will focus on that type.[9]

The second criterion asserts that the conditions of the test should fit conditions assumed by the theories. With one exception (Burke, 1997), all of the theories explicitly assume a rational actor model. It follows that experiments should allow subjects to decide rationally. Since rational actors consider all "relevant information" in making their

[8]Homomorphically equivalent positions cannot be distinguished once arbitrary labels are removed. Since positions are indistinguishable, it is logically and empirically impossible to assign different payoffs across positions.

[9]Beyond strong, equal and weak, there are also compound networks that contain breaks resolving them into strong, weak and/or equal power component parts. See discussion of Figure 2.

decisions, the best experimental setting is one that provides subjects with that information. By convention, the relevant information is all offers, counteroffers and agreements, not just of exchange partners, but of others distal in the network. Distal information is significant because distal events can affect local agreements (Markovsky et al., 1988; Girard and Borch, 2003). For example, in A–B–B–A network, all theories agree the As are disadvantaged, but after the A–B exchange at one end occurs, the pair at the other end are a dyad and the A's disadvantage disappears. As explained later, the procedures we employed provide the aforementioned information to all subjects. In fact, the data set of this paper is exhaustive of all research so conducted on weak power networks (see below).

The third criterion concerns the selection of the seven weak power networks of Figure 1 from the universe of weak power networks. There is precedent for the selection of these particular networks. Five of the seven were proposed as common networks for which predictions should be generated by three of the oldest theories: Power-Dependence, Expected Value, and Core. Those five networks, the three theories, and their predictions subsequently appeared in a special edition of *Social Networks* (1992).[10] The authors of all of the ten theories could have been aware of these networks–and we believe that all were aware–as they were developing their theories. As a further check, two more networks will be studied: DBox and Box-Stem. By including DBox, the investigation is exhaustive of all four-node weak power networks while the Box-Stem differs by only one connection from the two other six-node networks.

The fourth criterion concerns the selection of relations within the networks. Just as structures are selected such that different theories made distinct predictions, relations within those structures are similarly selected. Table 1 lists those relations. Other relations, like B–B in L4 and E–E in K-Stem are not reported because, like relations in equal power networks, these are relations between identical positions that offer no opportunity to compare differences in predictive precision. Relations between very similar positions like C and D of K-Stem and Borg-6 will also not be reported because, due to that similarity, predicted power differences are too small to be experimentally differentiated.

[10] One further network, the Kite also was listed in that special edition, but power differences predicted for it by all theories are too small. Thus, by criterion 1, it is not included here.

TEN THEORIES

Here we explain how each of the theories predicts for the Figure 1 networks and consider their parsimony and consistency. Later sections explain experimental procedures, report experimental results, evaluate precision of predictions, and compare range of application within the contended scope. The ten theories are taken up in order of initial publication date. When the predictive procedure is a part of a larger theory, it is referred to in the text as a "model." When the predictive procedure is the whole of the theory, it is called a "theory." Two of the ten theories, X-Net and Identity, are simulations: programs for them are available from their authors.

Of the ten theories, only two, Network Nash and the Expected Value - Resistance Model, are simple enough that they can be applied through hand calculations. Applying the other eight theories calls for calculations so extensive that hand calculations are not practical if only because of the risk of error. Those eight theories are applied through computer programs; unavoidably, many programs were not written by the author(s) of the theory. Nevertheless, we are confident that it is the theory in question and not merely the program that is being tested. When a program not written by the author of the theory is called into use, we have proved its accuracy by comparing it to all predictions published by the theory's author(s).

Power-Dependence Theory

The roots of Power-Dependence Theory are found in Emerson (1972a,b) where "*social structure* is taken as the dependent variable" (58 [italics original]). In that early work, the aim was to predict social structure from satiation effects on operant actors. In subsequent work the foundations of the theory were reversed such that social structure became the independent variable and a rational actor model was deployed to link structure to subsequent activity (Cook and Emerson, 1978; Cook et al., 1983). More recently, Cook and Yamagishi (1992) predict activity using an equidependence algorithm–a model that gives point predictions for exchange ratios in networks like those of Figure 1. In Power-Dependence Theory, a "connection is negative if exchange in one relation is contingent on nonexchange in the other" (Cook et al., 1983). Because positions in the Figure 1 networks are limited to maximally one exchange, the relations are negatively connected.

Equidependence sees actors as comparing payoffs in their relation to payoffs they could receive in their best alternative relation. Negotiations are seen as ongoing to equidependence that occurs when differences between payoffs for the two in their relation and payoffs from their best alternatives are equal (Cook and Yamagishi, 1992, p. 247). For example, when *i*'s payoff when exchanging with *j* is R*ij* and *i*'s payoff in the best alternative relation is A*ij*, then dependence for *i* and *j* are equal when:

$$Rij - Aij = Rji - Aji \tag{1}$$

Consider an $i - j$ relation in which i has an exclusive alternative to exchanging and j does not. When the *i-j* relation's pool has 24 points, i has a best alternative of 12 points and j has no alternative, R$ij - 12 =$ R$ji - 0$. Since, for any agreement, R$ij +$ R$ji = 24$, by substitution, at equidependence, R$ij = 18$ and R$ji = 6$.

In larger networks, negotiations are seen as ongoing until equidependence is reached throughout the network. Corresponding to that process is an algorithm that begins with the default of equal R*ij* values from which to calculate initial A*ij* values. Then R*ij* values are recalculated as are A*ij* values and similarly converging to the solution. Since this is an iterative solution, it is not practical to hand calculate R*ij* values. Instead, the values given for equidependence in Table 1 were produced by a program written by John Skvoretz.[11] His program is limited to 10 or fewer nodes and may be unsuccessful for highly dense networks. Values for five of our seven networks were also offered by Cook and Yamagishi (1992) and their values agree with those given by the program.

There is a consistency problem.[12] Some Power-Dependence predictions are not consistent with equidependence. For example, for L5-Stem of Figure 1g, the algorithm predicts $R_{AB} = 8$, $R_{BA} = 16$, $R_{DC} = 8$, and $P_{CD} = 16$. Since A and D have no alternative, plugging these values into equation 1 we find that B and C each earn 8 in their best alternative. That best alternative is when B and C exchange with each other. Since they each gain 8, they are dividing only 16 of 24 points, a division impossible for the rational actor of Power-Dependence Theory. That division is impossible because its rational actors in the B and C positions will not settle for the Pareto suboptimal division of 16 when fully 24 are available to divide.[13]

[11]This program and, with noted exceptions, others mentioned below are available from the authors of this paper.

[12]The consistency problem is not due to a glitch in Skvoretz's program: the inconsistent predictions are given by Cook and Yamagishi (1992).

[13]As can be seen by examination of equation 1, Power-Dependence predictions for agreed upon exchange ratios will shift as subject utilities differ. Predictions for experiments just referenced by Power-Dependence theorists are not qualified by those utility differences nor are ours. Power-Dependence theorists have not tested this part of their theory nor do we, a scope limit of this study. Still, even if differing utilities do shift agreements, random assignment and systematically changing subject pairings in exchange as in the reported experiments should wash out the effects.

Elementary Theory

Elementary Theory can be traced to Willer and Anderson (1981) and Willer (1984). The theory consists of a modeling procedure for representing social relations and structures, two principles–the first of which asserts that theoretic actors are rational–and two laws. The goal of the theory is to predict from initial conditions of relations in structures to actions such as rates of coercion and exchange ratios. For networks like those of Figure 1, three different models for predicting exchange ratios have been offered (Lovaglia et al., 1995; Lovaglia and Willer, 1999). The simplest of the three, "GPI-R," has also proved to be the most precise (Emanuelson, 2005; Burke, 1997). As explicated in the paragraph to follow, the GPI-R model has two components: A "seek-likelihood" method for calculating the chance that each position will be included in exchanges (the 'GPI'), and resistance equations for predicting exchange ratios from the likelihoods of each pair of positions (the 'R').

GPI-R is a 2-level procedure. At the actor level the 'R' refers to resistance, the values of which are affected by those seek-likelihoods. At the level of structure, "GPI" originally referred to the graph-theoretic power index, but that index was first supplemented and then supplanted by seek-likelihoods. While "Seek-R" would be a better term today, following usage elsewhere we use GPI-R.

Resistance uses each actor's mixed motives in exchange to predict exchange ratios and thus power exercise. P_A is A's payoff, $P_A$max is A's best payoff and $P_A$con is A's payoff at confrontation, when A–B agreement does not occur, and similarly for B. Then for an A–B equal power dyad,

$$R_A = \frac{P_A \max - P_A}{P_A - P_A \text{con}} = \frac{P_B \max - P_B}{P_B - P_B \text{con}} = R_B \tag{2}$$

and, when Pmax = 24 and Pcon = 0 for both, by symmetry, $P_A = 12$ and $P_B = 12$.

GPI-R sees actors as exchanging at equiresistance as affected by the likelihood that their positions are not excluded from exchange. The l_i seek-likelihood values are calculated for L4 in the following way. Each position is seen as seeking exchange equally with all partners. Thus each B seeks exchange with it's A .5 of the time and with the other B .5 of the time while each A seeks exchange with its B 1.0 of the time. The joint probability that the Bs exchange is $.5 \times .5 = .25$ and when they exchange the As are excluded. Thus, $l_A = .75$ and $l_B = 1.0$. When resource pools = 24, the weak power model assumes that Pmax varies between 24 and $24/2 = 12$ and Pcon between $24/2 = 12$ and 0; and that both vary proportionally with the likelihood (l) that the position is included. That is, $P_A max = 12\,(1 + l_A)$ and $P_A con = 12\, l_A$. Therefore, $P_B max = 24$, $P_B con = 12$, $P_A max = 21$ and $P_A con = 9$ and

$$\frac{21 - P_A}{P_A - 9} = \frac{24 - P_B}{P_B - 12}$$

Since the sum of A's and B's payoffs is 24, solving $P_A = 10.5$ and $P_B = 13.5$.

Calculation of l values has proven to be problematic. As numbers of relations and nodes increase, the procedure for calculating l values rapidly becomes complex. Furthermore, the procedure given in Markovsky (1992) and later in Willer (1999) is underdetermined and produces contradictory l values.[14] A new solution by Girard solves the underdeterminacy problem, but computation is substantially more complex making hand calculation infeasible. Fortunately, the solution is available as an applet on the Website of the first author where it is limited to maximally 13 positions and 33 relations. Girard's applet values are used for GPI-R predictions.

X-Net

The third oldest theory of network exchange is X-Net, a simulation program developed by Markovsky: the program is available by request.[15] Though first described in the 1992 special edition of *Social Networks* (Markovsky, 1992) and reviewed in detail three years later (Markovsky, 1995), the theory was being distributed to interested scholars by 1990 as a working program. It may be older still:

> The core idea for X-Net was the idea of simulating negotiations by having actors reduce their offers one unit when included and raising one unit when excluded. This came directly from simulations by Yamagishi described in Cook et al. (1983). So it could hardly be said that X-Net was a new theory. (Markovsky, p.c.)

In fact, X-Net is an agent-based modeling procedure in which simulated agents using simple rules are interdependently connected into exchange networks (Macy and R. Willer, 2002). The actors are backward-looking and the patterns they produce emerge from the conditions of the network in question.

[14]The simplest network for which contradictions are produced is A–B–C–B–A. Beginning l calculations at either B gives distinct and different values to the two Bs and also to the two As. Giving different values to the Bs is contradictory because the two are identical and similarly for the two As.

[15]In some of the exchange literature, simulation results have been presented as data supporting theory. Simulations like X-Net are theories and its results are predictions.

In testing X-Net, something more than a simulation is implicated. The idea of actors adjusting offers in light of exclusion is a part of the theory offered by Markovsky, Willer and Patton (1988) where it occurs as a scope limit. Alternatively, treated as a predictive mechanism, X-Net is a realization, in simulation form, of that part of their theory.

To generate X-Net's predictions, we used the program to construct and run each of the Figure 1 networks. The initial conditions have already been discussed–one exchange per round and 24 resources in each relation–but other values could have been chosen. All simulated actors initially divide resource pools equally and then revise offers in subsequent rounds by keeping one more unit when included and offering one more unit when excluded as described above. Agreements occur between actors with complementary offers and, when any agent receives more than one complementary offer, one is selected randomly. All of X-net's conditions were left at their default settings but for the number of rounds that the simulation was run. The default is 25 rounds but 99 were run–the maximum possible for the program–with predictions drawn by averaging resource divisions in the last 10 rounds.

Problems of inconsistency generally show up first in predictions. (See footnotes 2 and 12.) For the default settings used, X-Net predictions as given in Table 1 do not appear to include inconsistencies. Barring the possibility of bugs and glitches for other settings, X-Net can be applied to any network with 24 nodes or less and any number of relations–including the 276 relations of a fully connected 24 position network.

Quantified Core

Bienenstock and Bonacich (1992, 1993) adapt the Core from Game Theory where it was developed by Shubik (1982) to find the payoffs that could be gained by coalitions. The Core applies to exchange networks by analogy: Exchanges are identified with the Core's coalitions. The Core employs Rapoport's (1970) three kinds of rationality. Individual rationality asserts that no individual in a coalition will accept less than she could gain individually; coalition rationality asserts that no set of actors will accept less than they can earn in a coalition together; and group rationality asserts that the coalition of all will maximize total reward. Since actors in exchange networks can gain nothing individually, individual rationality asserts only that any actor prefers to exchange than not. Applying group rationality to exchange networks infers that no exchanges will occur in "suboptimal" relations. A relation is suboptimal if, when exchange occurs in it, there are fewer exchanges in the network than would occur maximally. Examples in Figure 1 include B–B in L4 and DBox and either B–C in L5-Stem.

Coalition rationality provides most of the predictive power and does so by drawing "characteristic functions" and their contingencies in the following way. For the A–B–C strong power network under the 1-exchange rule, two possibilities exist: B can exchange with A or with C. Therefore,

$$P_A + P_B = 24 \quad or \quad P_B + P_C = 24$$

and only $P_B = 24$ satisfies both. That is to say, $P_B = 24$ is the core. Therefore, the Core predicts here and for any strong power network that the high power position(s), like B, gains all the pool (or all minus Δ, the smallest unit). By extension, for the weak power L4,

$$P_A + P_B = 24 \quad and \quad P_B + P_B \geq 24$$

Referring to either A–B exchange, "While an equal division within each pair is in the core, inequality is also possible if it favors the Bs" (Bienenstock and Bonacich, 1992, p. 237). When a weak power network has a core (and some do not), the core offers, not a point prediction, but, following Bienenstock and Bonacich, a range within which resource divisions should occur. Whereas point predictions are preferred, both for their precision and falsifiability, the strength of the core lies in its parsimony.[16]

Skvoretz and Fararo (1992) offer a quantification for the Core that averages across a systematic enumeration of all possible outcomes in the Core. For example, enumerating outcomes for L4, when one A–B pair divides 0–24, there are 25 divisions possible for the second pair: 24–0, 23–1, 22–2 . . . to 0–24—and similarly for all possible pairs of divisions. In slightly larger networks, like K-Stem and others with six nodes, there are triples to enumerate. It is not practical to carry out this complex enumeration by hand. Having written the program in Mathematica, Bonacich provided the authors with predictions for DBox and Box-Stem while the remaining predictions were sourced from Skvoretz and Fararo (1992). The Quantified Core reverses the strengths of the Core. The Core is simple but predicts a range of payoffs for positions in weak power networks, while the Quantified Core gives point predictions, but at the cost of substantial complexity.

[16]But in L4 it is not clear to us that both Bs must gain 12 or more. For example, if one B gained $P_B = 18$, by the expressions above the other could gain as little as $P_B = 6$. Thus it seems to us that both Bs need not be favored. Nevertheless, for testing this and other networks we follow Bienenstock and Bonacich.

Expected Value Theory

Friedkin's Expected Value model (1992, 1993, 1995) sees network structures as defining opportunities to exchange. Each configuration in which those opportunities are realized is a subnetwork: the set of all subnetworks that can occur is the sample space. Only maximal subnetworks, where all exchanges that can occur do occur, are considered. For example, in the 1993 formulation, the sample space of A–B–B–A consists of three subnetworks: one where the A–B exchange to the right occurs before the B–A exchange to the left, one where that sequence is reversed, and one where the B–B exchange occurs. Assume that each subnetwork is equally likely. Since the Bs are included in all subnetworks, the probability that either B is included is 1.0. By contrast, since each A is included in only two of three subnetworks, the probability that A is included is $2/3 = .667$. Here, as in Elementary Theory, likelihoods of being included indicate the relative structural power of each position in the network. A position with a likelihood of 1.0 is more powerful than its partner with a likelihood of .667 and will be able to demand and receive better resource divisions.

Resource divisions are predicted in the following way. "The dependency of actor i on actor j is the probability that actor i is excluded from an exchange and that the two actors do not exchange with each other." (Friedkin 1992: 222). For example, the dependency (d) of A on B in L4 is .333 and of B on A is zero. Friedkin calculates "f," the initial offer for each using

$$f = 24 - 23(1/23)^{\mathrm{d}} \tag{3}$$

Initial offers do not necessarily match so three compromise rules infer from them to predicted divisions. If the sum of two initial offers is more than the resource pool (24), they split the difference back to the pool. If both ask less than half the pool, they divide the difference equally. If one asks for half or more of the pool and the other less and the sum is less than the pool, the difference goes to the actor with the lower claim.

By 1995, the assumption of equal likelihoods for subnetworks is withdrawn in favor of formulations calculating weights, w_{ij} of each exchange relation and thus each subnetwork. According to Friedkin, "exchange between actors i and j is likely only when the exchange is relatively attractive to both parties" (1995, p. 215). Following that logic, w_{ij} is set equal to the ratio of the payoff to i in the $i-j$ relation over the sum of all i's possible payoffs times the ratio of j's payoff in $i-j$ over the sum of all of j's possible payoffs. This formulation requires an iterative solution. Beginning with 1993 likelihoods, application of Eq. 3 and the compromise rules, w_{ij} values are calculated that are used to weight subnetworks giving new predicted rates of exclusion. Then those rates feed back through Eq. 3 and compromise rules to new payoffs, to new weights, and similarly to equilibrium when successive calculations give similar payoffs.[17]

In application to weak power networks, the 1993 version of Expected Value is more parsimonious than Elementary Theory, Power-Dependence, or the Quantified Core. Unlike Elementary Theory, Expected Value's 1993 procedure for assigning likelihoods to the networks of Figure 1 can be easily hand calculated. By contrast, the 1995 version is far more complex. It is at least as complex in application as Power-Dependence and Quantified Core. Nevertheless, that complexity buys greater precision, and it is the 1995 predictions that will be used. Expected Value appears free of contradiction, but its complexity in application makes hand calculation impractical. We are indebted to Marcel van Assen whose program gave the predictions of Table 1.

Rational Exchange

Coleman's Rational Choice Theory (1973, 1990) initially assumes that every actor can exchange with every other actor, but barriers between actors that produce network structures are also considered (1990, p. 892). Skvoretz and Fararo (1992) have offered a modified version for 1-exchange networks. In that version, network structure is produced by the distribution of *i*'s "consent rights" that designate the positions in the network with which *i* may exchange. There is an exchange relation linking *i* and *j* if the consent rights of each includes the other. Following their discussion, in the B–A–C network, assume that B and C are interested in their own and A's consent rights, but A is interested only in B's and his own consent rights. It follows that only A and B can exchange and the network collapses into a dyad. More generally, beginning with an all-to-all network of at least six nodes, varying the distribution of consent rights produces all possible connected networks of six or fewer nodes including the experimental networks of this investigation.

While Skvoretz and Fararo's description of the theory is sketchy, the prominence of Coleman's work and the existence of a modified version adapted to exchange networks argue strongly for its inclusion–as does its prior inclusion by Lovaglia et al. (1995).[18] The program for it by

[17]The calculation of w_{ij} values allows the 1995 formulation to be applied to networks in which resource pools are not equal in size. See Bonacich and Friedkin (1998).

[18]We date the Skvoretz-Fararo version of Coleman's theory to 1995 for it was then that predictions from it were first tested (Lovaglia et al., 1995).

Skvoretz is used here to generate the predictions given in Table 1. The program is limited to ten or fewer nodes. Beyond the fact that the program produces plausible predictions, we can say little about the parsimony or consistency of this theory.

Substitutable Exchange

Borrowing the terms substitutable and complementary from neoclassical microeconomics, Yamaguchi (1996) offers a theory for exchange networks grounded in Coleman but developed from those roots in a way quite different from that offered by Skvoretz and Fararo (1992) above. Yamaguchi identifies substitutability with Power-Dependence Theory's negative connection, but Yamaguchi's substitutability is a variable quantity whereas negative connection is dichotomous–it is either present or absent. The exclusively connected networks of Figure 1 are negatively connected in the sense that exchange in one relation is contingent on nonexchange in another (Cook et al., 1983). But according to Yamaguchi, "negative connection exists in the relations B–A–C when, for actor A, resources available from actors B and C are substitutes for one another." (1996, p. 310)[19]

For economists, two commodities are substitutable if an increase in the price of one increases demand for the other (Clower and Due, 1972, p. 81; Case and Fair, 1994, p. 129). Since exchange networks are not markets and resource divisions are not commodity purchases, it is necessary to interpret the term for the network exchange application. For Yamaguchi, exchange relations "are *closely substitutable* (or negatively connected) to the extent that actor A's exchange of resources with one actor (say, B) *decreases* actor A's demand for exchange of resources with the other actor C" (1996, p. 310 [italics original]). In fact, the restriction of each position to maximally one exchange, together with the identity of resources across relations, assures perfect substitutability by his definition for all Figure 1 networks.[20]

[19]Yamaguchi (2000) identifies complementarity with Power-Dependence Theory's positive connection. Since that condition is not within the contended scope it is not discussed here.

[20]Details of the experimental design used here had been published prior to Yamaguchi's 1996 paper. In that paper he suggests that, in these experiments, relations are not perfectly substitutable because time constraints introduce transaction costs when switching partners, but that suggestion is not correct. In these experiments, negotiations do not go on first in one relation and then switch to become ongoing in another. To the contrary, subjects negotiate in all of their relations simultaneously and normally have standing offers in all prior to selecting their best deal. Pretests allow time constraints to be set so that subjects can optimize across their alternatives.

Predictions for resource divisions are calculated iteratively using two equations found in the Appendix of his 1996 paper. These iterative calculations are too complex to be carried out accurately by hand. A program written by Simpson and Markovsky allows calculation of the predictions. As a check, predictions from that program were found to agree with ones given in Yamaguchi. For Table 1, since these networks have perfect substitutability, we set s = 200, the highest substitutability value that could be run for all of the networks.

It is difficult to evaluate the internal consistency of this theory because it is incomplete (Markovsky et al., 1997). No procedure is offered by Yamaguchi–and none is available from microeconomics–to set values for "s," the 'closeness' of substitutability. Yet as s varies so do predictions offered by the theory. Resource divisions should be most unequal when substitutability is perfect–when s is large–because then positions are free to switch partners to select their best offers. Differences should decline as s declines because switching across relations is inhibited. As seen in predictions offered in Yamaguchi's 1996 paper, however, the inequality of divisions increases as s declines and decreases as substitutability becomes perfect.

Identity Theory

Burke's Identity Theory for exchange networks (1997) is a simulation. The simulation is agent-based and, like X-Net, 1) each actor in each of the Figure 1 networks is an agent, 2) the actors are backward-looking adjusting their behavior relative to their goals, and 3) the patterns produced emerge from the social structural conditions of the network under consideration. Unlike X-Net, Burke's simulated actors are engaged in an identity process in which behavior controls the match of the actor's perceptions to assigned goals with the whole process being mediated by the social structural environment. The assigned goal is to maximize participation which is to say to avoid exclusion and, to the extent that that goal is reached, to avoid gaining zero points.

We did not run this simulation. Resource divisions were supplied by Burke. As in the first resource divisions reported in Burke (1997), the Figure 1 values are from a run of 40 rounds of the simulation. Burke calls 40 "an arbitrary limit" (p. 145). Equilibrium values are found by running the simulation longer. We say more about equilibrium predictions below. Contrary to Identity Theory, (p. 140) the subjects in our experiments are *not* instructed to participate in as many exchanges as they can. Instead they are instructed to earn as many points as they can. Because the agent's and subject's goals are not identical, the experiments are formally outside the scope of Identity Theory. That

Identity Theory's scope is distinct should not, in itself, exclude it from contending with the other nine theories. Identity Theory may be able to predict effectively even in experiments that are outside its scope. Whether it does or not, below we suggest a new line of research investigating action in structures with subjects motivated like Burke's agents.[21]

Network Nash

Braun and Gautschi (2005) offer a theory that generalizes the Nash bargaining model to predict resource divisions in exchange networks. When x_{ij} is i's share of a resource division with j, the Nash solution is the maximum of the product of the payoff to i and the payoff to j (max $x_{ij} \times x_{ji}$). In exchange networks the sum of x_{ij} and x_{ji} is v, the size of the pool.

Braun and Gautschi generalize Nash by adding the term, b_i that is i's bargaining power:

$$\max b_i x_{ij} \times b_j x_{ji} \tag{4}$$

or $x_{ij} = v\ b_i/(b_i + b_j)$. In "negatively connected" networks like those of Figure 1, when w is a constant of proportionality and c_i is i's control, the bargaining power of i, $b_i = -1/\ln\ (wc_i)$.

Here is how c_i and w are calculated. The term c_i is i's control and it is the sum of the reciprocals of the number of ties of each of i's exchange partners divided by the number of i's partners. For example, in the Stem, B has three exchange partners, A, $C_{1,}$ and $C_{2,}$ while A has one partner and each C has two. For B the sum of the reciprocals is $1 + 1/2 + 1/2 = 2$. Since B has three partners, $c_B = 2/3 = .667$. Since A has one partner who has in turn three partners $c_A = 1/3/1 = .333$. Specific to any given network, w is a constant of proportionality that is the sum of the number of positions in a network and the number of relations divided by that sum plus 1. For the Stem, $w = (4 + 4)/(1 + 4 + 4) = 8/9 = .889$. Plugging w together with c_A and c_B values into the equation for b_i above: $b_B = 1.911$ and $b_A = .8224$. Finally, plugging into the equation for x_{ij}, B's payoff when exchanging with A is 16.78.

Here are the strengths and a possible shortcoming of Network Nash. The strengths of Nash when adapted to networks are 1) its parsimony and 2) freedom from internal contradictions. It is easy to apply

[21]It is *not* unusual for theories to be applied outside their scope. The classical gas laws are for an "ideal gas" that, because its atoms are dimensionless, cannot exist. Thus all applications of gas laws are formally outside their scope, yet useful predictions result.

Network Nash: the values of the previous paragraph were found using a hand calculator. A possible shortcoming is that Network Nash is simple because it considers only local networks–only two steps from *i*–when calculating *i*'s bargaining power. By contrast, in formulating predictions, all other theories take into account the whole network structure. Whether this proves to be a problem is beyond the scope of this investigation.

Expected Value-Resistance Model: An Exercise in Theoretical Unification

The Expected Value-Resistance (EV-R) Model, constructed by the authors of this paper, is presented here for the first time. Looking over the theories above, we were struck by their complexity yet saw an opportunity to build a particularly simple model. The opportunity arose because a central idea is shared by Elementary Theory and Expected Value Theory. Both measure the structural power of network positions by their likelihood of avoiding exclusion. Each has its own procedure for calculating likelihoods, and each has its own procedure for inferring from likelihoods to exchange ratios. From Expected Value we borrow the 1993 procedure for finding likelihoods of being included. From Elementary Theory we borrow resistance in order to calculate exchanges from those likelihoods.

Predictions are generated in just three steps: 1) find likelihoods, 2) use likelihoods to find Pmax and Pcon values, and 3) plug those values into the resistance equation and solve. Take as an example the L5-Stem network. To find likelihoods first list all exchange events that can happen together in all possible orders as in: 1) A–B, C–D, B–A; 2) A–B, B–A, C–D; 3) C–D, A–B, B–A . . . and similarly through the ten event possibilities. Looking through the event possibilities, both Bs occur in all ten events and both As in eight. Assuming all events are equally likely, $l_{\mathrm{B}} = 1$ and $l_{\mathrm{A}} = .8$. From the discussion of Elementary Theory above, $\mathrm{P_A max} = 12\,(1 + l_{\mathrm{A}})$ and $\mathrm{P_A con} = 12\, l_{\mathrm{A}}$. Therefore, $\mathrm{P_A max} = 12\quad(1 + .8) = 21.6$ and $\mathrm{P_A con} = 12 \times .8 = 9.6$ while $\mathrm{P_B max} = 12\,(1 + 1) = 24$, $\mathrm{P_B con} = 12 \times 1 = 12$. Plugging into Eq. 2,

$$\frac{21.6 - P_A}{P_A - 9.6} = \frac{24 - P_B}{P_B - 12}$$

$\mathrm{P_A} = 10.8$ and $\mathrm{P_B} = 13.2$. The ten event possibilities above also give $l_{\mathrm{C}} = 1$ and $l_{\mathrm{D}} = .6$ that, plugged into the equations just used, give the B payoff displayed in Table 1.

This conjunction of procedures is more parsimonious than the models of either theory from which it borrows. It is simpler than

Elementary Theory's model because Expected Value's 1993 method of calculating likelihoods is substantially less complex. It is simpler than any Expected Value model because resistance is a simpler way to calculate from likelihoods to resource divisions. In fact, the EV-R Model is substantially simpler than any of the other theories with the possible exception of Network Nash.[22] Given its simplicity, the lack of internal contradictions is easily seen. One desirable result is that the model is fully public and, being parsimonious, its predictions in Table 1 can be easily calculated with paper and pencil or with hand calculator. The model is compatible with and could be incorporated into Elementary Theory. It could also be used in Expected Value Theory.

EXPERIMENTAL DESIGN

Experiments were conducted at a large public university with undergraduate subjects who participated for pay. Subjects were not misdirected. Instead they were told, truthfully, that 1) the aim was to study the effects of network structure on negotiation and exchange and 2) they would be paid by points earned in exchange. All were asked to seek the best deals they could negotiate. Subjects interacted using PCs. Each subject's PC displayed full information on offers and exchanges throughout the structure in which they interacted. To learn how to read the PC screen, make offers, and complete exchanges, subjects paged through a tutorial and were allowed to negotiate and exchange prior to the experiment in a practice network distinct from the one being studied.

Experiments on the Figure 1 networks were conducted at various times from the 1990 s to now using the best instrumentation available. Some data were collected using ExNet 2.0, a Windows-based system. Using mouse control, subjects seated at PCs in individual rooms viewed the network being investigated as an active display, and clicked icons to make offers and complete exchanges. The research was recently completed using ExNet 3.0, a JAVA-based system that looked much like ExNet 2.0 to subjects. For ExNet 2.0 and 3.0, because experimental conditions were actively displayed, interactions were intuitive and subjects' training time was substantially reduced.[23]

[22]Whereas the Core is the simplest of the theories, it does not make point predictions for weak power networks.

[23]Interested scholars can replicate this research on ExNet 3.0 that is located at weblab.ship.edu. An earlier system, ExNet 1.0 was used to collect some of the data for L4, Stem and Box-Stem. Though the screen was not active, the network was displayed at each subject station as were all ongoing offers and exchanges.

Experiments were organized in sessions, periods and negotiation rounds. For each session, there was a new group of subjects and in each there were as many periods as subjects. Within each period there were a number of rounds of negotiation (see Table 1). At the conclusion of each period, subjects were rotated to new positions, altering subject pairings.[24]

For example, the DBox experiments had four periods each while the K-Stem experiments had six. Each period had several rounds in which subjects negotiated and exchanged. Each round was completed when all exchanges possible for the network were completed or after four minutes. The experiment concluded when each subject had occupied each position for one period.

All networks were investigated under the contended conditions. Each position was limited to, at most, a single exchange per round and all resource pools were identically sized at 24.

THE DATA SET

The purpose of this section is to explain the relation of the current data set to ones previously reported. It will be helpful to begin by clarifying the 'n' values reported in network exchange research. That 'n' is not the number of exchanges completed by subjects. Instead, to avoid repeated measures, exchange ratios were averaged within each period to give one datum point. Thus a session with four periods has four data points for each reported relation. As discussed previously, results from some, not all relations are reported. For example, the A–B–B–A L4 network has three relations, but only data for the two A–B relations are reported and, being identical, the two are grouped. That is to say, data for one relation are reported for L4. More generally, 'n' is the number of periods times number of sessions.

Data previously reported in multiple publications were from a single data set and that set forms a *small* part of the data set used here. For the networks satisfying the conditions of this research reported by Skvoretz and Willer (1993) and Lovaglia et al. (1995), n = 36 for each. Both report on the same two weak power networks, L4 and Stem, each

[24]Rotating subjects through positions, a procedure that has been used for more than 20 years to control for individual differences, allows stronger inferences from structure to exchange ratios. By generating new subject pairings, each session gives more than one datum point. Subject rotation may also reduce equity concerns and reactions to injustice that might affect power and exchange dynamics (Cook and Emerson, 1978; Molm and Cook, 1995; Hegtvedt and Killian, 1999). Lovaglia et al. (1995) find that mean payoffs by position are not significantly different when, under more limited information conditions, subjects are held in a single position.

with four periods; one had four sessions and one had five. Thus $(4 \times 4 = 16) + (4 \times 5 = 20) = 36$. As suggested by these n's, Skvoretz and Willer (1993) and Lovaglia et al. (1995) employed exactly the same data.[25] Burke (1997) reports those as two data sources. He also reports a third data source, Skvoretz and Fararo (1992), but they performed no experiments. Instead, they reported results from Markovsky et al. (1991, published as 1993) and Skvoretz and Willer (1991). As might be inferred from overlapping authorship, these data are also a part of the Skvoretz and Willer (1993) and Lovaglia et al. (1995) data set.

The data set of this research is more than ten times larger than the one just discussed. Here $n = 380$ (see Table 1). Nevertheless, for two networks, previously reported data form a part of the set employed here. More precisely, of the $n = 44$ we report for the network called 'Stem,' $n = 16$ were reported previously, and of the $n = 32$ we report for the network called 'L4,' $n = 20$ were reported previously. Data for the remaining five networks are new and were not previously reported.

PRECISION AND RANGE OF APPLICATION OF THE TEN THEORIES

Sociology is a science in which few theories have had predictive power of any kind and, of those, fewer still could offer point (metric) predictions. By contrast, the ten theories considered here all offer point predictions. This section tests those predictions for eleven relations in seven networks. Table 1 displays those predictions and the results of the experiments.[26] As can be seen by looking through the table, all ten theories are meritorious for all have predictive power.

Nevertheless, the ten theories vary in precision and two measures are given in Table 2 to gauge it. The first is "Deviation Score," a procedure borrowed from Burke (1997). It is the weighted average deviation of the theory's predictions from the eleven observed means. Each deviation is weighted by the likelihood that the exchange will occur in the relation, a likelihood calculated by the 1993 procedures

[25]That those data are the same is masked by the different exchange ratios reported in the two papers. Exchange ratios differ, at least in part, because the two papers use two different modes of calculation. Skvoretz and Willer (1993) estimate exchange ratios by a constrained regression whereas Lovaglia et al. (1995) take the mean.

[26]Previous analyses suggest that means reported in Table 1 represent equilibrium values. Using the data set of this research, Emanuelson (2005:158) found no significant differences between the lowest observed mean of the first two experiment periods and the highest observed mean of the last two experiment periods for all networks studied here. By Emanuelson's analysis, exchange ratios of weak power networks, unlike those of strong power networks, do not increase over time. Following that analysis, means reported here are taken as equilibrium values.

of Expected Value Theory explained above. The second measure for precision is a rank order from most to fewest predictions not significantly different from observed means.[27] The theories are discussed in order by the first measure, from least to most precise.[28]

Beyond precision, the range of application of each of the theories within the contended scope is also tested. As explained earlier, that test is concerned with the size of network to which the theory can be applied. Figure 2 is the test network. While having only 13 nodes, that network is more than twice the size of any of the experimental networks. Like the test of precision, the test of range of application is a test of the current capabilities of each theory. Importantly, in some cases, current capabilities are determined by the limits of the program used to apply the theory. Can new programs with broader scope capabilities be developed? Undoubtedly. Will they be developed? We do not know. What is known is which of the ten theories now offer predictions for the Figure 2 network.

The Quantified Core

Having the highest Deviation Score, 3.49, the Quantified Core is the least accurate of the ten theories. It also ranks last (tenth) in number of supported predictions. Though not an accurate predictor, the

[27]Here the use of t-tests is unconventional for it is a test of H_1 not H_0. The predicted values are tested against the observed. When the two are close, the test is not significant. More importantly, the purpose is not evaluate a single theory, a use where their liability for type one error might be considered to be a shortcoming. Instead they are used only to rank order the relative precision of the ten theories. Standing in the rank order is determined by the number of predictions not significantly different from observed values. In principle, that standing can be affected by the cut off point chosen. Fortunately, as the reader can determine, this rank ordering is relatively immune to the chosen cut off point. There are no reversals when $< .1$ or $< .01$ are counted as supported predictions.

[28]Bonacich objects to the testing of point predictions asserting that it has been shown that the results of all social science experiments are culture bound. Therefore, all point prediction tests are meaningless (Personal Communication). We offer two comments on this objection. First, dispensing with point predictions is undesirable for it dispenses with precision, a crucial and well established criterion by which scientific theories have long been compared. Second, it has not been shown that all social science experiments are culture bound. Some certainly are. Cross cultural studies of ultimatum, public goods and dictator games have shown very substantial variation (Henrich et al., forthcoming). Others have not. Experiments on an array of coercive and exchange structures conducted in the United States and in Communist Bloc Poland failed to show different outcomes (Willer and Szmatka, 1993). Since those experimental structures are included in the scope of the theories studied here, they are the ones from which possible cross-cultural variations should be inferred.

Quantified Core is complex enough in application to inhibit calculation of predictions by hand. Turning to the Figure 2 network, the Core offers a meritoriously simple method for breaking it into simpler parts. It asserts that networks break at suboptimal relations. As explained above, a relation is suboptimal when exchange in it reduces the total number of exchanges below the maximum possible for the network. A maximum of six exchanges can occur in the Figure 2 network, but if B exchanges with either C or D, at most five exchanges can occur. Both B–C and B–D are suboptimal. In fact, B–E, E–H, and H–J are also suboptimal. Removing those five relations substantially alters the distribution of power in the network. Now B and A are in a dyad and exchange at equipower as do H and I. J, K, L and M also exchange at equipower because they are in an equipower box.[29] But the A, B, C, D network is a Stem and the H, I, J, K, L, M network is a Box-Stem and the predictions of the Quantified Core for those networks do not agree with an analysis that breaks them into equipower components–nor do the means observed for those networks. In fact, it has already been shown that suboptimality is necessary but not a sufficient condition for breaks (Simpson and Willer, 1999).

Power-Dependence Theory

By Deviation Score, Power-Dependence ranks ninth in precision with a score of 2.66. By number of supported predictions, it is tied with Network Nash at rank 7.5. Like the Quantified Core, Power-Dependence Theory is not an accurate predictor and yet it is complex enough to inhibit calculation of predictions by hand. Power-Dependence cannot currently offer predictions for the Figure 2 network because the program through which it is applied is limited to networks with ten or fewer nodes.[30] There would still be hope for application were the theory able to cut the network into smaller parts by finding "network breaks" prior to application. Power-Dependence recognizes that networks break, but finds breaks only *after* application of the program that cannot be applied here because the Figure 2 network is too large.

[29]Above it was noted that, in equal power networks, all positions are identically connected such that, but for their labels, they cannot be distinguished. The same rule applies when subnetworks, like the J, K, L, M box, when broken from a larger network.

[30]As already mentioned, the program used here for Power-Dependence was not developed by the authors of the theory but by Skvoretz who was interested in experimental tests on relatively small networks. (See Skvoretz and Willer, 1993.) Until more capable programs are developed, the Skvoretz program defines the range over which the theory can be applied.

TABLE 1 Payoffs to the High Power Positions in Tested Relations: {sd} and [t]

			Predictions									
Network	Position/ relation	Observed mean	Power-Dependence	Elementary Theory	X-NET	Quan. Core	Expected Value	Rational Ex.	Substitute Ex.	Identity	Network Nash	EV-R Model
L4	P_B *in A/B*	13.58	16***	13.5	14	16***	15.48***	13.71	12.08***	13.8	15.9***	14.04
n = 32a		{1.787}	[7.54]	[0.249]	[1.31]	[7.54]	[5.93]	[0.405]	[4.68]	[0.686]	[7.23]	[1.43]
Stem	P_B *in A/B*	14.41	18***	14.4	16***	20.1***	17.76***	15.6**	12.17***	15.6**	16.78***	15
n = 44b		{2.740}	[8.59]	[0.0239]	[3.80]	[13.40]	[8.02]	[2.85]	[5.36]	[2.85]	[5.67]	[1.41]
DBox	P_B *in A/B*	12.8	12*	12.9	14***	16***	14.81***	13.61*	12.07*	12.87	13.63*	13.2
n = 26c		{1.60}	[2.50]	[0.313]	[3.75]	[10.0]	[6.28]	[2.53]	[2.28]	[0.219]	[2.59]	[1.25]
K-Stem	P_B *in A/B*	13.69	20***	14.5*	18***	21.1***	18.35***	15.03***	12.25***	16.4***	16.26***	14.58*
n = 40d		{2.165}	[18.20]	[2.34]	[12.43]	[21.37]	[13.44]	[3.87]	[4.15]	[7.82]	[7.41]	[2.56]
Borg-6	P_B *in A/B*	14.02	18***	13.5	15*	16.9***	16.13***	13.33	12.12***	13.9	16.21***	13.72
n = 42e		{2.953}	[8.59]	[1.13]	[2.12]	[6.24]	[4.60]	[1.50]	[4.12]	[0.260]	[4.75]	[0.650]
	P_D *in D/E*	14.52	18***	14.4	14	20.2***	17.93***	15.28*	12.18	15.70*	16.21***	14.58
		{2.877}	[7.75]	[0.267]	[1.16]	[12.24]	[7.58]	[2.36]	[0.757]	[2.63]	[3.76]	[0.134]
L5-Stem	P_B *in A/B*	12.91	16***	13.2	13	14.9***	14.91***	13.4*	12.06***	13.2	14.71***	13.2
n = 47f		{1.459}	[14.37]	[1.35]	[0.418]	[9.25]	[9.32]	[2.28]	[3.95]	[1.35]	[8.36]	[1.35]
	P_C *in C/D*	13.72	16***	14.3	14	18.1***	16.41***	14.93***	12.12***	14.4*	16.96***	14.4*
		{2.162}	[7.15]	[1.82]	[0.878]	[13.74]	[8.43]	[3.80]	[5.12]	[2.13]	[10.16]	[2.13]
Box-Stem	P_B *in A/B*	12.71	12	12.6	11.07***	16***	14.13**	12.37	12.05	12.5	13.27	12.75
		{1.824}	[1.70]	[0.265]	[3.92]	[7.86]	[3.38]	[1.05]	[1.58]	[0.502]	[1.34]	[0.096]
n = 20g	P_C *in A/C*	12.82	12	12.6	11.06**	16***	13.85	13.19	12.05	12.5	13.27	12.75
		{2.233}	[1.60]	[0.429]	[3.43]	[6.21]	[2.01]	[0.723]	[1.50]	[0.624]	[0.879]	[0.137]
	P_D *in D/E*	12.69	18***	13.3*	14***	16***	15.36***	13.35*	12.10*	12.99	14.74***	13.5**
		{1.099}	[21.06]	[2.42]	[5.20]	[13.13]	[12.66]	[2.62]	[2.34]	[1.19]	[8.13]	[3.21]

a. Eight sessions were run each consisting of four periods containing four rounds. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used.

b. Eleven sessions were run each consisting of four periods containing four rounds. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used.

c. Seven sessions were run each consisting of four periods containing four rounds. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used. In two periods of one of the sessions, no agreement was reached.

d. Seven sessions were run each containing six periods consisting of four rounds each. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used. In two periods agreements were not reached.

e. Seven sessions were run each containing six periods consisting of four rounds. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used.

f. Eight sessions were run each containing six periods consisting of four rounds. At the end of each period, subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last three rounds. Round one was never used. In one period agreement was not reached in two of the last four rounds and the datum point was not used.

g. Five sessions were run each containing four periods consisting of ten rounds each. At the end of each period subjects were rotated to a new position. Data points were calculated for each period by taking the average value obtained in the last six rounds. Rounds one through four were never used.

Note: All predictions without a star are not significantly different from the observed means.

*Significant at $<.1$.

**Significant at $<.01$.

***Significant at $<.001$.

TABLE 2 Experimental Support by Theory

Theory	Deviation Score[a]	Rank by number of supported predictions
Elementary	.275	1
Expected Value-Resistance	.423	2
Identity[b]	.498	3
Rational Exchange	.642	4.5
X-Net	1.12	4.5
Substitutable Exchange	1.18	6
Expected Value	1.46	9
Network Nash	1.69	7.5
Power-Dependence	2.66	7.5
Quantitative Core	3.49	10

[a]The Deviation Score is the average deviation between predictions and observed means weighted by the number of expected exchanges as calculated using Expected Value (1993) likelihoods.
[b]Deviation Score and rank by number of Supported Predictions not at equilibrium. See text.

Network Nash

Ranking eighth in precision by a Deviation Score of 1.69 is Network Nash and, as just mentioned, it is tied with Power-Dependence with a ranking of 7.5 by numbers of supported predictions. Still, Network Nash's basic formulations are parsimonious, free from internal contradiction and, being simple, should be easily applied in the field. Since it considers only a position's local network, its application to the Figure 2 network is straightforward. It finds E to be the highest power position followed by B and then H, an ordering that is undoubtedly correct. (See below.) Furthermore, Network Nash finds breaks. It asserts that

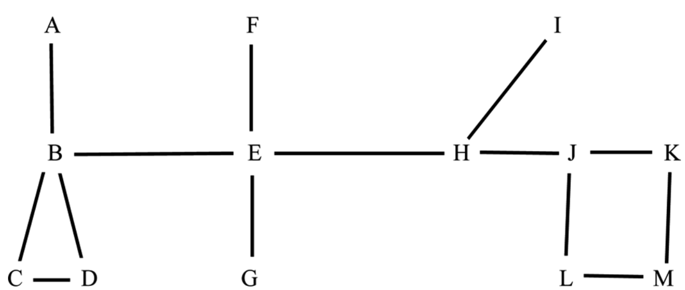

FIGURE 2 A thirteen position network.

a relation is a break if either of the two positions connected by the relation gains higher payoffs 1) in its other relations and 2) when the relation is removed. With no relation removed, E's payoff is predicted to be 18.00, with only B–E removed it increases to 18.39, with only E–H removed it increases to 18.98, and with both removed E's predicted payoff is 19.81.

While Network Nash is simple in basic formulation, in application there can be a serious loss of parsimony. Accurate predictions require that breaks be found, but breaks are found by applying the theory over and over again, first with relations removed one at a time, then with all combinations of two relations removed, then with all combinations of three removed, and similarly. For example, determining whether there are breaks in any five node tree network–that has only four relations–requires 14 applications of the theory. To find just two breaks in the Figure 2 network, required four applications: once to the original network, twice more with one relation removed and a fourth time with both relations removed. Having stopped at two breaks, we cannot say whether Network Nash finds more breaks. Later we will show that only B–E and E–H are breaks, but that there is a simpler way to find them.

Expected Value Theory

Expected Value ranks seventh in precision by Deviation Score, 1.46, but ninth by number of supported predictions. Nevertheless, the 1995 formulations of Expected Value Theory importantly advance its precision. By comparison, the Deviation Score using likelihoods from 1993 is 2.82, almost twice as large. We are informed that the program for Expected Value Theory developed by van Assen applies to the Figure 2 network. As will be seen below, theory and previous experimental evidence agree that there will be no B–E or E–H exchanges in that network. Thus no power can be exercised in those relations. Yet Expected Value predicts that there will be exchanges and thus power exercise in those relations.

Substitutable Exchange

Substitutable Exchange ranks sixth in precision both by Deviation Score and numbers of supported predictions. Substitutable Exchange is neither precise nor parsimonious. It is incomplete. Though predictions for resource divisions vary with s, it offers no procedure for determining s. Substitutability is necessary but not sufficient to produce the resource pool differences observed in the experiments.

For example, if all positions of all networks of both figures were allocated, not maximally one exchange as tested, but as many exchanges as they have partners, substitutability would be unaffected; but exclusion would be eliminated. With no exclusion, all resource divisions would be equal.[31] Since it mistakes the condition that produces differences in resource divisions, it is either immediately falsified or it does not apply to exchange networks within the contended scope and should be appropriately scope limited.

X-Net

X-Net ranks fifth in precision by Deviation Score and is tied at rank 4.5 by number of supported predictions. Since X-Net is a simulation program in which actors make better offers to others after being excluded and better offers to self after being included, it arrives at its predictions by iteration. Has iteration reached equilibrium for the listed predictions? As explained earlier, X-Net was run 99 rounds, the maximum now possible, and data are given for the last 10 rounds. For seven of the predictions there was no variation of predicted value over the last ten rounds. For example, for L4, all values were 14; thus the standard deviation was zero suggesting that these seven predictions are at equilibrium. Four of the predictions had standard deviations larger than zero, 1.05, .966, .802, and .561. Since the largest of the aforementioned values is smaller than the smallest standard deviation for data reported in Table 1, and since data are at equilibrium, these values suggest that X-Net predictions are at equilibrium.[32]

X-Net readily applies to the Figure 2 network and finds the B–E and E–H relations to be breaks. No exchanges occur in those relations. Removing those relations, we find three subnetworks, the Stem to the left, the F–E–G strong power branch and the Box-Stem to the right. It will be remembered that these are the same breaks found by Network Nash. X-Net's prediction for the strong power subnetwork, that E gains 22 of 24, is consistent with findings reported elsewhere for networks of that type (Willer and Skvoretz 1997). Its predictions for the Stem and Box-Stem subnetworks are very close to its predictions for those networks in Table 1, as they should be.

[31]See results for null connected networks in Willer and Skvoretz (1997).

[32]By contrast, at X-Net's default of 25 rounds, standard deviations are all nonzero and many are substantially larger indicating that equilibrium is not attained.

Rational Exchange

By Deviation Score Coleman's Rational Exchange, is substantially more precise than the theories just discussed. Its score is just over half that of X-Net. Still, in number of supported predictions it is tied in rank with X-Net at 4.5. Though its precision is meritorious, Rational Exchange is applied through a program that is limited to maximally ten positions. Having no procedure for finding breaks prior to that application, this theory cannot be applied to the Figure 2 network. In spite of its precision, currently Rational Exchange is hardly more than a theory fragment that can only be applied narrowly. Nevertheless, its precision suggests that further work on this theory might well have high payoff.

Identity Theory

Ranking third in precision is Identity. Its Deviation Score is smaller than all but two other theories and it also ranks third by number of supported predictions. Nevertheless, that ranking occurs, not at equilibrium, but at what Identity Theory considers an "arbitrary limit" of 40 rounds. Equilibrium values are attained after 100 rounds; those values are given in Table 2 (Burke 1997, p. 146). Five networks and six relations reported there are common to his study. For them the Deviation Score is 2.74 moving Identity's rank to ninth. We looked closer at predicted values for L4 and Stem and found that the higher power Bs are predicted to gain 11, which is to say less than half the resource pool. By that prediction, the Bs are lower in power than their As. More generally, all equilibrium predictions but one (given as equipower) reverse predictions made at 40 rounds. These predictions are sharply at odds with the observed means and predictions of all other theories.

Earlier the disjuncture between Identity's agent and goals set for experimental subjects was noted. From that disjuncture, it was explained that the experiments are not formally within the scope of the Identity simulation. It follows that these data are *not* a test of Identity Theory. Instead, they indicate whether that theory can accurately predict outside its scope. It cannot. This result is not a failure, but an opportunity.

The distinct scope of the Identity simulation suggests that new experiments should be run in which subjects' goal is not to optimize points gained in exchange, but, as in the Identity simulation, to avoid exclusion and avoid scoring zero. For the new experiments, no new software or hardware would be needed: only a straightforward change of instructions. Unlike all previous network exchange experiments where experimental subjects were instructed to earn as much as they can, now they would be instructed to avoid exclusion and be paid by the numbers of exchanges completed. Will subjects so instructed produce resource divisions like those found by Burke at equilibrium? No one can now say, but experiments run to answer that question will importantly broaden the scope of network exchange research.

Expected Value-Resistance and Elementary Theory

The two most precise procedures, Expected Value-Resistance model and Elementary Theory's resistance model have Deviation Scores of .423 and .275, respectively. The Expected Value-Resistance model ranks second in numbers of supported predictions while Elementary Theory's model ranks first. Examination of the two models' predictions shows them to be very similar. The two are similar because both calculate power differences from likelihoods of being included and both plug those likelihoods into the same resistance equation in the same way (see above). Still there are small differences and Table 3 explains why. The two procedures identify exactly the same positions as "always included" assigning values of 1.0 to them. For positions that are "sometimes excluded," the two give similar but not identical likelihoods. For example, in L4, Elementary Theory's model predicts marginally less power than does the Expected Value-Resistance model because it sees the As included .75 not .67 of the time–and similarly for other likelihoods and predicted divisions.

TABLE 3 Seek-Likelihoods and Expected Values (1993) of Being Included for Positions in Tested Relations

Network	Connected positions	Seek likelihood	Expected value
L4	A/B	.75/1.0	.67/1.0
Stem	A/B	.60/1.0	.50/1.0
DBox	B/A	.85/1.0	.80/1.0
K-Stem	A/B	.59/1.0	.63/1.0
Borg6	A/B	.76/1.0	.71/1.0
	E/D	.60/1.0	.57/1.0
L5-Stem	A/B	.81/1.0	.80/1.0
	D/C	.61/1.0	.60/1.0
Box-Stem	A/B	.90/1.0	.88/1.0
	A/C	.90/1.0	.88/1.0
	E/D	.79/1.0	.75/1.0

To predict exchange ratios for the Figure 2 network, Elementary Theory first finds breaks using a parsimonious network-level procedure developed by Girard and Borch (2003). That procedure is a simplification of one proposed earlier by Simpson and Willer (1999). Both are based on tests run in the latter paper that indicate that all breaks occur between high power positions in strong power subnetworks and positions that are never excluded. Step one of the Girard and Borch procedure labels positions "E" if they are ever excluded and "I" if always included. Inspecting the Figure 2 network, five nodes, B, E, H, J, and M are always included I nodes: the rest are E nodes. Furthermore, F–E–G, by the definition offered earlier, is a strong power substructure with E high power. Testing for breaks, B–E and E–H are removed and it is found that B and H are still never excluded. Thus, B–E and E–H are breaks and the Figure 2 network has three parts, the Stem to the left, the strong power F–E–G and the Box-Stem to the right. Stem and Box-Stem predictions for both models are already displayed in Table 1. For the F–E–G strong power structure Elementary Theory predicts that E gains 23 of 24 resources at equilibrium.

Summing Up Precision and Breadth of Application

The purpose of this analysis was to find the most precise theory and determine which theories cover a broad range within the contended scope. The most precise predictor is Elementary Theory's resistance model followed by Expected Value-Resistance. Expected Value-Resistance is the most parsimonious in application of all ten theories. It is more parsimonious than Elementary Theory's model because it uses Expected Value Theory's 1993 likelihoods, not seek-likelihoods that are substantially more complex to calculate. As a consequence, it is the most accessible. Since both can predict for the Figure 2 network, the range of application of the two is identical and is as good as the best of the other theories.[33]

Because there is no common measure for precision and parsimony, no one can say how much parsimony balances how much precision.

[33]It has been suggested that a "theory" that predicts equal 12 - 12 divisions will score better than any of the theories evaluated here. That suggestion is easily checked. The 12 - 12 "theory," if it be such, has a deviation score of 1.28 and two supported predictions. Thus it qualifies just under mid-pack of the theories. By contrast, the best theory has a deviation score less than 1/4 as large and has more than four times the number of supported predictions. Nor does the 12 - 12 "theory" stack up well against even the least precise theories. Unlike the 12 - 12 "theory," both Power-Dependence and Expected Value correctly rank many power differences across networks. For example, Stem > L4 > DBox.

Therefore, there is no objective base to judge which is the better theory. Nevertheless, the following can be said. When predictive precision is most important, Elementary Theory's model should be used, but when simplicity and ease of accessibility are paramount, Expected Value-Resistance should be used.

CONCLUSIONS AND NEW DIRECTIONS

Unlike orienting perspectives such as functionalism and conflict, the ten theories investigated here all have scientific merit because all have predictive and thus explanatory power.[34] That they do is a remarkable achievement and should be recognized as such. Nevertheless, that merit is not equal across the ten. If a theory is internally consistent, its precision in prediction and the range over which it predicts are crucial. This investigation began by explaining how each theory calculates from initial conditions of structure to payoffs by position. First, logical consistency was checked and problems were found in the predictions of some theories. Parsimony was also evaluated. Then experiments compared the relative precision of the theories. Finally, as a test of the range over which the theories could be applied within the contended scope, the ten were checked against the larger Figure 2 network.

Of the ten theories, Elementary Theory's resistance model was found to be most precise. Like application of Expected Value to weak power structures, that model uses the likelihood that a position is included/excluded as the indicator of structural power. But Elementary Theory's method of calculating likelihoods is not parsimonious. The Expected Value-Resistance model borrows the simpler method of calculating likelihoods from a competing theory, Expected Value of 1993. Though somewhat less precise, it is substantially more parsimonious. Lacking a common measure by means of which to compare parsimony and precision, no selection between the two was suggested. Turning to range of application, since the experimental networks were relatively small, it was asked whether any of the theories could be applied to a network as large as Figure 2. Whereas Expected Value, Network Nash, the X-Net simulation, Elementary Theory and Expected Value-Resistance offer predictions for that network, their precision and parsimony in that application vary.

Two caveats qualify all conclusions. First, this investigation compares the precision of all ten theories. Therefore, *of necessity*, this

[34]Here we follow Hempel (1952, 1965) and Toulmin (1963). Prediction and explanation differ only by whether the derivation came before or after the fact, respectively.

investigation is limited to the scope over which they all apply–the contended scope. As discussed earlier, the contended scope is by no means trivial. Yet many–not all–of the ten theories have predictive and explanatory capability beyond that scope. As important as that scope may be, it must remain beyond the limits of this investigation. Second, the norms of science demand this: We are authors of substantial parts of Elementary Theory. We, together with our colleagues, ran the experiments that compared the precision of the theories. With those caveats, this investigation concludes that Elementary Theory combines the most useful qualities. It is free of contradictions; it is the most precise of the ten theories and is as broadly applicable within the contended scope as any.

Nevertheless, scientific objectivity calls for others to replicate this research. Fortunately, and almost uniquely for the methods of sociological research, theory-driven experiments like those reported here are eminently replicable. (cf. Willer and Walker, 2007, p. 58ff.) Furthermore, in this case, that replication will be straightforward because software for experiments is already on the Web (weblab.ship.edu).

Beyond replication, two directions for future research can be suggested. First, but for the issue of size, larger questions of scope of application of these theories were not taken up here. Of the ten, only two theories, X-Net and the Core, do not apply to exchange networks outside the contended scope. (But the Core has many applications in game theory.) The remaining theories apply to some conditions beyond the contended scope, but it is by no means clear that any two overlap. Nor have we investigated here whether applications outside the lab demand scope broader than the contended scope, though we suspect that they do. Certainly, much would be learned from investigating larger issues of theoretic scope.

The second direction is implied by the first. Though exchange theories have been intensively investigated in the lab, what is largely lacking are applications of these theories outside the laboratory. Can any of the ten theories be applied to historical and contemporary structures? If so, can any explain why exchange structures in the field work as they do? It is time that those questions are taken up.

REFERENCES

Berger, J. & Zelditch, M. Jr. (eds.). (1993). *Theoretical Research Programs: Studies in the Growth of Theory*, Stanford, CA: Stanford University Press.

Berger, J. & Zelditch, M. Jr. (2002). Theory programs, teaching theory and contemporary theories. In J. Berger & M. Zelditch, Jr., (eds.), *New Directions in Contemporary Sociological Theory* (pp. 3–14). Lanham, MD: Rowman & Littlefield Publishers, Inc.

Bienenstock, E. J. & Bonacich, P. (1992). The core as a solution to exclusionary networks. *Social Networks*, *14*, 231–244.

Bienenstock, E. J. & Bonacich, P. (1993). Game-theory models for exchange networks: Experimental results. *Sociological Perspectives*, *36*, 117–35.

Blau, P. (1964). *Exchange and Power in Social Life*, New York: John Wiley and Sons.

Bonacich, P. & Friedkin, N. (1998). Unequally valued exchange relations. *Social Psychology Quarterly*, *61*, 160–171.

Braun, N. & Gautschi, T. (2005). A Nash bargaining model for simple exchange networks. *Social Networks*, *28*, 1–23.

Burke, P. (1997). An Identity model for network exchange. *American Sociological Review*, *62*, 134–50.

Case, K. E. & Fair, R. C. (1994). *Principles of Microeconomics*, Englewood Cliffs, NJ: Prentice Hall.

Clower, R. F. & Due, J. F. (1972). *Microeconomics*, Homewood, IL: Richard D. Irwin, Inc.

Cohen, B. P. (1989). *Developing Sociological Knowledge: Theory and Method*, Chicago, IL: Nelson-Hall, Inc.

Coleman, J. S. (1973). *The Mathematics of Collective Action*, Chicago, IL: Aldine.

Coleman, J. S. (1990). *Foundations of Social Theory*, Cambridge, MA: Belknap.

Cook, K. S. & Emerson, R. M. (1978). Power, equity and commitment in exchange networks. *American Sociological Review*, *43*, 721–739.

Cook, K. S., Molm, L. D., & Yamagishi, T. (1993). Exchange relations and exchange networks: Recent developments in social exchange theory. In J. Berger & M. Zelditch, Jr., (eds.), *Theoretical Research Programs: Studies in the Growth of Theory* (pp. 296–322). Stanford, CA: Stanford University Press.

Cook, K. S., Emerson, R. M., Gillmore, M. R., & Yamagishi, T. (1983). The distribution of power in exchange networks: Theory and experimental results. *American Journal of Sociology*, *89*, 275–305.

Cook, K. S. & Yamagishi, T. (1992). Power in exchange networks: A power-dependence formulation. *Social Networks*, *14*, 245–66.

Corra, M. (2005). Separation and exclusion: Distinctly modern conceptions of power? *Canadian Journal of Sociology*, *30*, 41–70.

Einstein, A. (1933). On the method of theoretical physics. In S. Bargmann (tr. and rev.), *Ideas and Opinions* (pp. 270–76). New York: Crown Publishers, Inc.

Emanuelson, P. (2005). Improving the precision and parsimony of network exchange theory: A comparison of three network exchange models. *Current Research in Social Psychology*, *10*, 149–66.

Emerson, R. M. (1972a). Exchange theory, part I: A psychological basis for social exchange. In J. Berger, M. Zelditch, Jr., & B. Anderson, (eds.), *Sociological Theories in Progress, vol. 2* (pp. 38–57). Boston, MA: Houghton Mifflin.

Emerson, R. M. (1972b). Exchange theory, part II: Exchange relations and networks. In J. Berger, M. Zelditch, Jr., & B. Anderson, (eds.), *Sociological Theories in Progress, vol. 2* (pp. 58–87). Boston, MA: Houghton Mifflin.

Fararo, T. J. & Kosaka, K. (2003). *Generating Images of Stratification*, Dordrecht, The Netherlands: Kluwer Academic Publishers.

Friedkin, N. (1992). An Expected Value model of social power: Predictions for selected exchange networks. *Social Networks*, *14*, 213–30.

Friedkin, N. (1993). An Expected Value model of social exchange outcomes. In E. J. Lawler, B. Markovsky, K. Heimer, & J. O'Brien, (eds.), *Advances in Group Processes, vol. 10* (pp. 163–93). Greenwich, CT: JAI Press.

Friedkin, N. (1995). The incidence of exchange networks. *Social Psychology Quarterly*, *58*, 213–22.

Girard, D. & Borch, C. (2003). Optimal seek simplified. *Current Research in Social Psychology*, *8*, 225–42.

Hegtvedt, K. A. & Killian, C. (1999). Fairness and emotions: Reactions to the process and outcomes of negotiations. *Social Forces*, *78*, 269–302.

Hempel, C. G. (1952). *Fundamentals of Concept Formation in Empirical Science, vol 2*, Chicago, IL: University of Chicago Press.

Hempel, C. G. (1965). *Aspects of Scientific Explanation and Other Essays in the Philosophy of Science*, New York: Collier-Macmillian Limited.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., Alvard, M., Barr, A., Ensminger, J., Hill, K., Gil-White, F., Gurven, M., Marlowe, F., Patton, J. Q., Smith, N., & Tracer, D. (Forthcoming). 'Economic man' in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. www.santafe.edu/research/publications/workingpapers/01-11-063.pdf

Kuhn, T. (1970). *The Structure of Scientific Revolutions*, Chicago, IL: University of Chicago Press.

Lakatos, I. (1970). Falsification and the methodology of scientific research program. In I. Lakatos & A. Musgrave, (eds.), *Criticism and the Growth of Knowledge* (pp. 91–195). Cambridge: Cambridge University Press.

Lieberson, S. (1985). *Making It Count*, Berkeley, CA: University of California Press.

Lovaglia, M., Skvoretz, J., Markovsky, B., & Willer, D. (1996). Automated theoretical analysis of exchange networks: Prerequisites and prospects. *Connections*, *19*, 38–52.

Lovaglia, M., Skvoretz, J., Willer, D., & Markovsky, B. (1995). Negotiated outcomes in social exchange networks. *Social Forces*, *74*, 123–55.

Lovaglia, M. & Willer, D. (1999). An alternative for predicting weak power. In D. Willer, (ed.), *Network Exchange Theory* (pp. 185–192). Westport, CT: Praeger.

Lucas, J. W. (2003). Theory-testing, generalization, and the problem of external validity. *Sociological Theory*, *21*, 236–253.

Lucas, J. W., Wesley Younts, C., Lovaglia, M., & Markovsky, B. (2001). Lines of power in exchange networks. *Social Forces*, *80*, 185–214.

Macy, M. & Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, *28*, 143–66.

Markovsky, B. (1992). Network exchange outcomes: Limits of predictability. *Social Networks*, *14*, 267–286.

Markovsky, B (1995). Developing an exchange network simulator. *Sociological Perspectives*, *38*, 519–45.

Markovsky, B (1996). Theory, science and 'micro-macro' bridges in structural social psychology. *Current Research in Social Psychology*, *1*, 30–42.

Markovsky, B., Willer, D., & Patton, T. (1988). Power relations in exchange networks. *American Sociological Review*, *53*, 220–36.

Markovsky, B., Skvoretz, J., Willer, D., Lovaglia, M., & Erger, J. (1993). Seeds of weak power: An extension of network exchange theory. *American Sociological Review*, *58*, 197–209.

Markovsky, B., Willer, D., Simpson, B., & Lovaglia, M. (1997). Power in exchange networks: Critique of a new theory. *American Sociological Review*, *62*, 833–37.

Marx, K. ([1867] 1967). *Capital*, New York: International Publishers.

Merton, R. K. (1968). *Social Theory and Social Structure*, New York: Collier-MacMillan Limited.

Molm, L. D. & Cook, K. S. (1995). Social exchange and exchange networks. In K. S. Cook, G. Alan Fine, & J. S. House, (eds.), *Sociological Perspectives on Social Psychology* (pp. 209–35). Stanford, CA: Stanford University Press.

Popper, K. R. (1959). *The Logic of Scientific Discovery*, New York: Harper & Row Publishers.

Popper, K. R. (1994). *The Myth of Framework: In the Defense of Science and Rationality*, London: Routledge.

Rapoport, A. (1970). *N-Person Game Theory*, Ann Arbor, MI: University of Michigan Press.

Shubik, M. (1982). *Game Theory in the Social Sciences: Concepts and Solutions*, Cambridge, MA: MIT Press.

Simpson, B. & Willer, D. (1999). A new method for finding power structures. In D. Willer, (ed.), *Network Exchange Theory* (pp. 270–284). Westport, CT: Praeger.

Skvoretz, J. & Fararo, T. J.(1992). Power networks and exchange: An essay toward theoretical unification. *Social Networks*, *14*, 325–44.

Skvoretz, J. & Willer, D. (1991). Power in exchange networks: Setting and structural variations. *Social Psychology Quarterly*, *54*, 224–38.

Skvoretz, J. & Willer, D. (1993). Exclusion and power: A test of four theories of power in exchange networks. *American Sociological Review*, *58*, 801–18.

Stolte, J. & Emerson, R. M. (1977). Structural inequality: Position and power in exchange structures. In R. Hamblin & J. Kunkel, (eds.), *Behavioral Theory in Sociology* (pp. 117–38). New Brunswick, CT: Transaction Books.

Toulmin, S. (1953). *The Philosophy of Science: An Introduction*, London: Cambridge University Press.

van Assen, M. A. L. M. (2001). Two representations of negotiated exchange: A review and comparison. In M. Van Assen, (ed.), *Essays on Actor Models in Exchange Networks and Social Dilemmas* (pp. 137–81). Groningen, The Netherlands: RUG.

Wagner, D. G. (1984). *The Growth of Sociological Theories*, Beverly Hills, CA: Sage Publications.

Wagner, D. G. (1994). The growth of theories. In M. Foschi & E. J. Lawler, (eds.), *Group Processes: Sociological Analysis* (pp. 25–41). Chicago: Nelson-Hall Publishers.

Wagner, D. G. & J. Berger. (1985). Do sociological theories grow? *American Journal of Sociology*, *90*, 697–728.

Walker, H. & Cohen, B. P. (1985). Scope statements: Imperatives for evaluating theory. *American Sociological Review*, *50*, 288–301.

Walker, H., Thye, S., Simpson, B., Lovaglia, M., Willer, D., & Markovsky, B. (2000). Network exchange: Theory, recent developments and new directions. *Social Psychology Quarterly (Millennial Edition)*, *63*, 324–37.

Weber, M. ([1918] 1968). *Economy and Society*, Berkeley, CA: University of California Press.

Walker, H. & Willer, D. (2007). Experiments and the science of sociology. In M. Webster & J. Sell, (eds.), *Laboratory Experiments in the Social Sciences*, San Diego, CA: Elsevier Inc.

Willer, D. (1984). Analysis and composition as theoretic procedures. *Journal of Mathematical Sociology*, *10*, 241–70.

Willer, D. (1986). Vulnerability and the location of power positions: Comment on Cook, Emerson, Gillmore and Yamagishi. *American Journal of Sociology*, *92*, 441–44.

Willer, D. (ed.), (1999). *Network Exchange Theory*, Westport, CT: Praeger.

Willer, D. & Anderson, B., (eds.). (1981). *Networks, Exchange and Coercion*, New York: Elsevier/Greenwood.

Willer, D. & Skvoretz, J. (1997). Network connection and exchange ratios: Theory, predictions and experimental tests. In B. Markovsky, M. Lovaglia, & L. Troyer, (eds.), *Advances in Group Process, vol. 14* (pp. 199–234). Greenwich, CT: JAI Press.

Willer, D. & Szmatka, J. (1993). Cross national experimental investigations of elementary theory: Implications for the generality of the theory and the autonomy of social structure. In E. J. Lawler, B. Markovsky, K. Heimer, & J. O'Brien, (eds.), *Advances in Group Processes, vol. 10* (pp. 37–81). Greenwich, CT: JAI Press.

Willer, D. & Walker, H. (2007). *Building Experiments: Testing Social Theory*, Stanford, CA: The Stanford University Press.

Yamaguchi, K. (1996). Power in networks of substitutable and complementary exchange. *American Sociological Review*, *61*, 308–32.

Yamaguchi, K (2000). Power in mixed exchange networks: A rational choice model. *Social Networks*, *22*. 93–121.