# Connections

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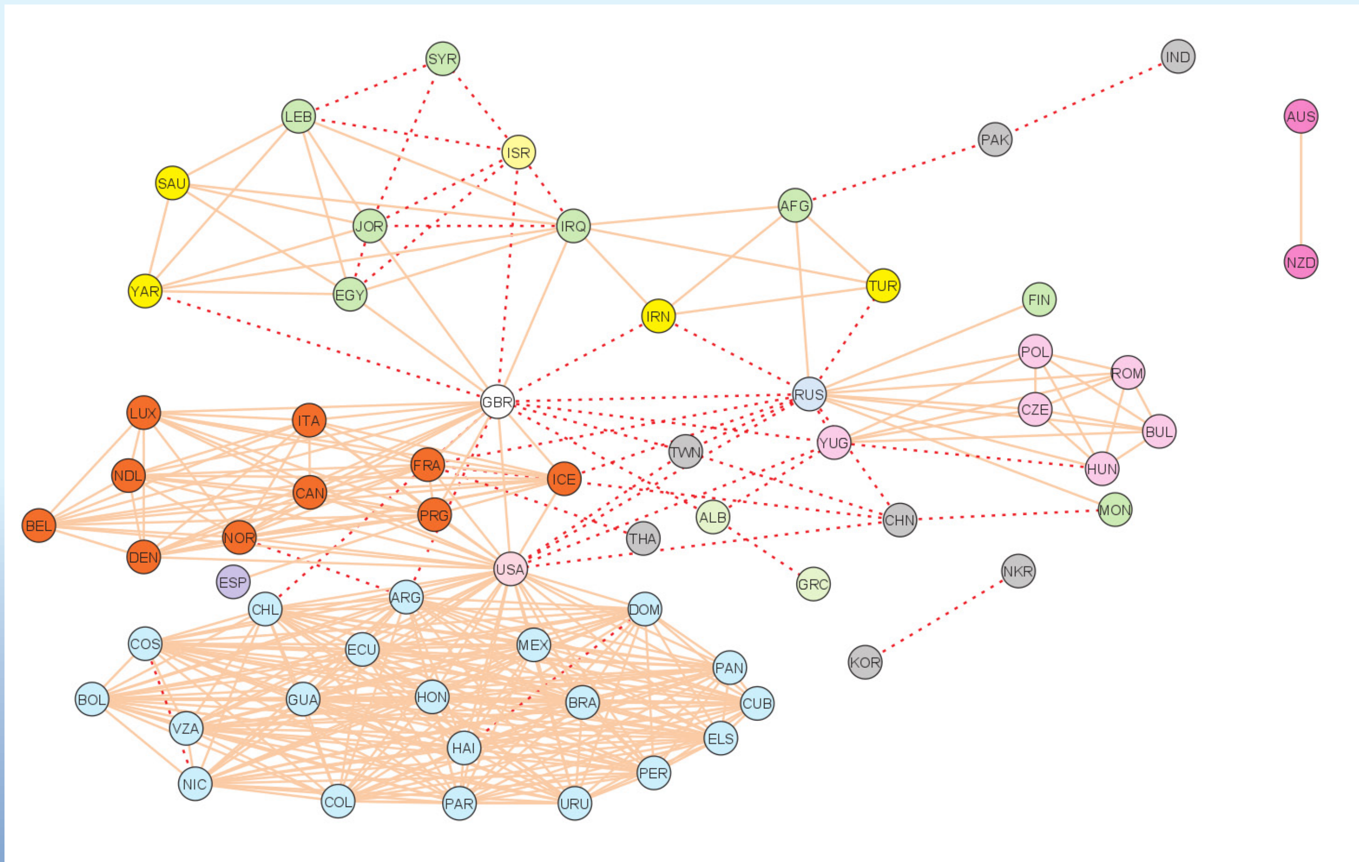


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*Cover image: Doreian, this issue pg. 14*

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# From the Editor

I am proud to introduce a new issue of Connections. In this issue you can find articles on: structural balance in signed networks (Doreian and Mrvar); operationalising oligarchic networks as rich clubs (Ansell, Bichir, Zhou); the use of experiments in social exchange networks (Neuhofer, Reindl and Kittel); Tom Valente's keynote on network influences on behaviour (Dyal); description of a dataset from a network exchange experiment (Skvoretz); and the description of a dataset from a health promotion study (Gesell and Tesdahl).

In the last few years we have introduced a section on datasets, codebooks and data collection methods (DEN); state of the art reviews; and the professionalization of the production process with the assignment of DOI numbers and copyright agreements with authors. Beyond our regular call for original research articles, I would like to invite submissions on network research design as a new section to the journal. Of particular interest are studies where the use of novel research designs reflect on the choice between alternative models.

The journal is moving towards distributed editorship, emulating the model adopted by Network Science as most pertinent for an interdisciplinary audience. We will shortly circulate the list of area specific editors.

We are looking forward to your suggestions and feedback at Sunbelt and via email. We are organising a short reception on Wednesday the 6th of April at 8pm at the Presidential Suite of the Marriot Hotel (i.e. the Hospitality Suite) and we would like to invite all authors, potential authors and friends of the journal to come and meet the Editorial Board.

Dimitris Christopoulos
Editor, Connections
www.dimitriscc.wordpress.com

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# Identifying Fragments in Networks for Structural Balance and Tracking the Levels of Balance Over Time

**Patrick Doreian**
*University of Ljubljana, Ljubljana, Slovenia &*
*University of Pittsburgh, PA USA*

**Andrej Mrvar**
*University of Ljubljana, Ljubljana, Slovenia*

**Abstract**
This paper presents three items. The first is a brief outline of structural balance oriented towards tracking the amount of balance (or imbalance) over time in signed networks. Often, the distribution of specific substructures within broader networks has great interest value. The second item is a brief outline of a procedure in Pajek for identifying fragments in networks. Identifying fragments (or patterns or motifs) in networks has general utility for social network analysis. The third item is the application of the notion of fragments to counting signed triples and signed 3-cycles in signed networks. Commands in Pajek are provided together with the use of Pajek project files for identifying fragments in general and signed fragments in particular. Our hope is that this will make an already available technique more widely recognized and used. Determining fragments need not be confined to signed networks although this was the primary application considered here.

*Keywords*: *Signed networks, structural balance, network fragments, temporal balance, and international relations*

**Authors**
***Patrick Doreian***, *Research Professor, Faculty of Social Sciences, University of Ljubljana, Ljubljana, Slovenia and Professor Emeritus, Department of Sociology, University of Pittsburgh, Pittsburgh, PA USA.*

***Andrej Mrvar,*** *Professor, Faculty of Social Sciences, University of Ljubljana, Ljubljana, Slovenia.*

**Notes**
Patrick Doreian and Andrej Mrvar have enjoyed a long collaboration focused on signed social networks. Patrick Doreian formerly edited the Journal of Mathematical Sociology and currently co-edits Social Networks with Martin Everett. Andrej Mrvar is a former editor of Metodološki Zvezki and co-author with Vladimir Batagelj of the award winning program suite Pajek.

*Correspondence concerning this work should be addressed to Patrick Doreian, Department of Sociology, University of Pittsburgh, 230 S Bouquet St, Pittsburgh, PA 15213. Email: pitpat@pitt.edu*



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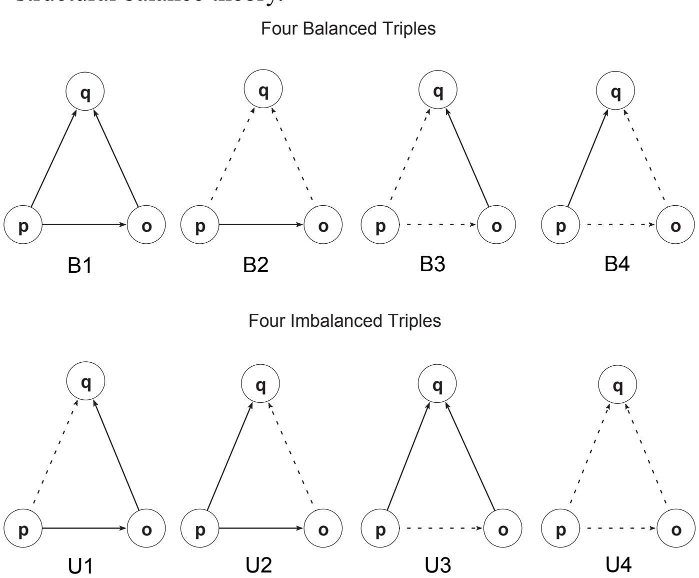
## 1. Introduction

As noted by Taylor (1970), Heider (1946) provided the initial statement of structural balance theory. There have been alternative formulations of 'consistency theories' of signed social relations, including Newcomb (1961), Nordlie (1958), Festinger (1957), Osgood and Tannenbaum (1955) and others (see Abelson *et al*., 1968). However, we use Heider's approach because Cartwright and Harary (1956) provided a formal generalization of his theory, one laying the foundations for analyzing signed social networks in balance theoretic terms. Given temporal data for signed relations, a natural question is how signed network structures change over time regarding balance and how this can be tracked. We demonstrate doing this by using Pajek (Batagelj and Mrvar, 1998). Section 2 provides a brief introduction to the relevant parts of structural balance for our purposes here. The ideas of defining and detecting network fragments are presented in Section 3. The application of fragments by creating specific signed fragments appropriate for measuring balance in signed networks follows in Section 4 where two empirical examples are considered. One is a directed network while the second is undirected. Section 5 extends these ideas so that balance can be tracked in signed networks over time. A summary and suggestions for future work are in Section 6.

## 2. Structural balance

We consider the initial formulation of balance theory before outlining briefly the blockmodeling and triple counting approaches for measuring imbalance in a signed network.

*Figure 1:* The Eight signed triples in Heider's formulation of structural balance theory.




### *2.1 The initial formulation*

Heider's (1946) approach rests on considering the eight types of triples shown in Figure 1. Positive ties are marked with solid lines while negative ties are marked with dashed lines. One typical signed relation has, as positive ties, 'likes' while negative ties are 'dislikes' for personal relations. The vertices are labeled by $p$, $q$ and $o$. The ties are directed as shown by the arrows of the lines. In the top left triple, the ties $p \rightarrow o$, $p \rightarrow q$ and $o \rightarrow q$ are all positive. This was seen as 'balanced' in the sense of there being no discomfort for the three actors. In the second triple, $p \rightarrow o$ is positive with both $p \rightarrow q$ and $o \rightarrow$ q being negative. Both p and o agree by each having a negative tie to q with a positive tie, $p \rightarrow o$. The remaining triples in the top row can be read in the same fashion. When the signs on the three arcs in a triple are multiplied the resulting sign is taken as a measure of the balance of a triple. Triples with a sign of 1 are balanced while triples whose sign is -1 are imbalanced. These triples are shown as Pajek networks in Table 1.

All of the triples in the top row are balanced. We have labeled them B1, B2, B3 and B4 and use these labels in Table 1. They have been expressed in folk aphorisms: The top left triple is captured by "a friend of a friend is a friend" with all ties being positive; the second triple can be viewed as "an enemy of a friend is an enemy" with $p$ seeing $o$ as a friend with both $o$ and $p$ seeing $q$ as an enemy; the third triple can be viewed as "a friend of an enemy is an enemy" with $p$ seeing $o$ as a friend of $q$ when $p$ sees both $o$ and $q$ as enemies; the top right triple is "an enemy of an enemy is a friend" with $p$ viewing $o$ an enemy, seeing $o$ views $q$ as an enemy and $p$ sees $q$ as a friend. All of the triples in the bottom row have a negative sign and are imbalanced. These are labeled U1, U2, U3 and U4 with the labels used also in Table 1. According to Heider (1946), the bottom left triple in the bottom row would be problematic with $p$ seeing $q$ as an enemy while seeing $o$ as a friend but recognizes that $o$ views $q$ as a friend. The other triples can be viewed in a similar fashion. Heider emphasized that balance in a triple induced comfort while imbalance created stress for the actors in such triples.

In a complete network, if all triples are positive, the network is balanced. Empirically, most empirical signed networks are not exactly balanced. This is the case for the empirical networks considered here. The natural methodological issue arising is how to measure the extent to which a signed network is balanced or not balanced. One proposed measure of balance is the proportion of the balanced triples it contains. Its value for a balanced network is 1, the maximum possible value. When some imbalanced triples are present this measure departs from 1. If all triples in a network are imbalanced, the measure takes its lowest value, 0. The question arises: how do we measure the imbalance of signed networks in general? There are two broad approaches: using signed blockmodeling and counting triples.

*2.2 Using the line index of balance from a blockmodel*

Cartwright and Harary (1956) proved that if a signed network is balanced then the vertices can be partitioned into two subsets such that all of the positive ties are within subsets and all of the negative ties being between subsets. Davis (1967) extended this to *any* number of clusters with the same property of positive ties being located within clusters and negative ties between them. The crucial step for this extension was to define the all-negative triple as balanced. Doreian and Mrvar (1996) observed that the 'structure theorems' of Cartwright and Harary and of Davis implied a blockmodel structure. A positive block is one having no negative ties. In contrast, a negative block has no positive ties. The implied blockmodel of an exactly balanced signed network has positive blocks on the main diagonal and negative blocks elsewhere. As noted above, empirical networks are seldom balanced exactly. When a signed blockmodel is fitted to signed data it provides also a measure of imbalance in the form of the number of ties inconsistent with the relevant structure theorem. In essence, this is the line index of imbalance proposed by Harary, Cartwright and Norman (1965). While the intuitive foundations for blockmodeling are straightforward (Doreian, Batagelj and Ferligoj, 2005), fitting them can be time consuming, especially as the network size increases. Doreian and Mrvar (1996) provided a rapid method for fitting signed blockmodels in Pajek. This line index is one measure of imbalance.

*2.3 Using counts of triples to measure imbalance*

Another approach is very simple: count the number of signed triples in a signed network. When the triples shown in Figure 1 are counted there are two possible measures of imbalance. The traditional one is the *proportion* of imbalanced triples with the other being the *number* of them (Doreian and Mrvar, 2015). Counting triples is obviously useful when the signed network is complete. However, when signed networks are not complete, this necessitates counting all closed walks and semi-walks (which include triples). Doing this is a non-trivial computational problem. When done, the proportion of imbalanced semi-walks, most likely, would depart from the corresponding measure using only triples. The obvious question is whether this matters. We think it does not. The core substantive ideas of Heider are formulated in terms of triples. This suggests counting triples is more appropriate for socio-psychological processes than counting the longer semi-walks. How can this be done simply? An effective way of counting triples can be achieved by using the concept of fragments. The general approach is to define fragments of specific forms, identify them and count them. Doing this is achieved straightforwardly in Pajek (see Batagelj and Mrvar (1998)). Our focus here is on signed triples as fragments, an idea described in Section 3.

We note that, hitherto, the line index and proportion of imbalanced cycles as measures of imbalance have been closely related: they ought to tell the same story. As the size of the networks we can study has increased dramatically in recent decades, the blockmodeling approach is likely to be less useful due to the computational complexities involved. For these larger networks, counting triples will be a practical alternative.

## 3. Fragments

Characterizing networks when they are large has posed problems. One strategy is to consider carefully constituent parts of networks. As a result, researchers have been interested in identifying such smaller parts of larger networks having special properties (characteristic shapes) across multiple fields. Such smaller parts are called fragments, patterns, or motifs. Fragment searching was first implemented in Pajek in 1997. (See also Milo, Shen-Orr, Itzkovitz S., Kashtan N, Chklovskii D., and Alon, U (2002) for a discussion of motifs from the perspective of physicists approaching network analysis.) Fragment (pattern) searching is a general approach for investigating the structure of large complex systems. Frequencies and locations of such interesting fragments often provide short descriptions of network structures in terms of the distributions of well-defined fragments contained in them. This could include cycles, k-stars and cliques of any size. Given an interest in structural balance, defining the eight triples in Figure 1 as fragments is a natural step. Doing this sets up the use of fragment searching for all signed triples.

We provide a simple example of fragment searching in Section 3.1 following some remarks on this topic. See also de Nooy, Mrvar and Batagelj (2011). A general backtracking algorithm is applied for fragment searching. Several applications have shown that if the selected fragments do not occur too frequently in a large sparse network, the algorithm is extremely fast. It can be applied to very large sparse networks.

Fragment searching in networks was first applied to large molecules in chemistry (e.g. DNA), for searching for carbon rings and other structures. Later, fragment searching was successfully applied to searching for relinking families through marriages in genealogies. Every semi-cycle found in a p-graph representation of a genealogy represents some relinking (via blood or non-blood ties) through marriages. See White, Batagelj and Mrvar (1999), Batagelj and Mrvar (2008).

### 3.1 A simple motivating example

Consider the small unsigned network in Figure 2. Suppose the task is to identify all 3-cycles and 4-cycles as fragments. Some clear 3-cycles - {*a, b, c*} and {*o, p, q*} - are marked with green edges. Some clear 4-cycles – {*e, f, g, h*}, {*k, l, m, n*} and {*q, r, s, t*} – are marked with blue edges. The subgraph involving the vertices i, j, k and t is a little more complicated. There is a 4-cycle involving all four of them. The relevant edges are marked in maroon. Note there are also two 3-cycles in this subgraph – {*i, j, k*} and {*j, k, t*}. The (*j, k*) edge is unambiguously part of the two 3-cycles and is marked in green. The edges marked in maroon are each in a 4-cycle and a 3-cycle. By a visual inspection, there are four 3-cycles and four 4-cycles. However, such visual examinations have no practical value when searching larger networks having hundreds or thousands of vertices. A systematic and practical procedure is required.

*Figure 2:* An undirected graph with 3-cycles and 4-cycles to be identified and counted.

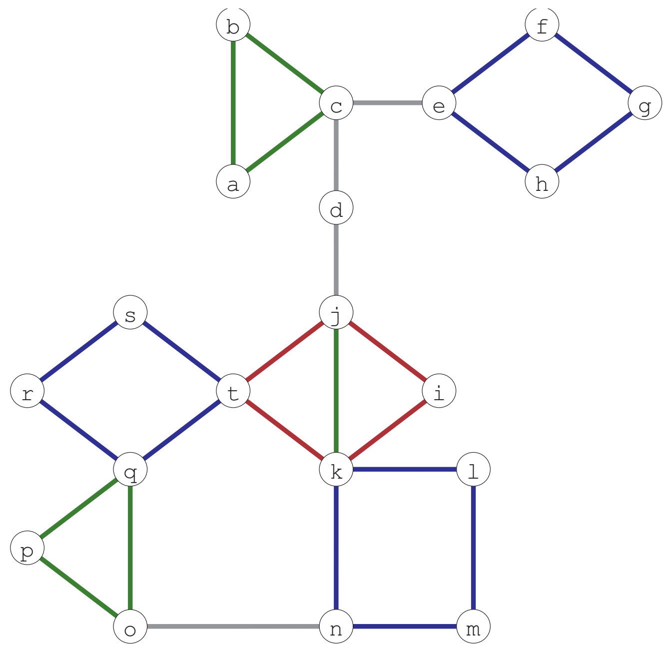
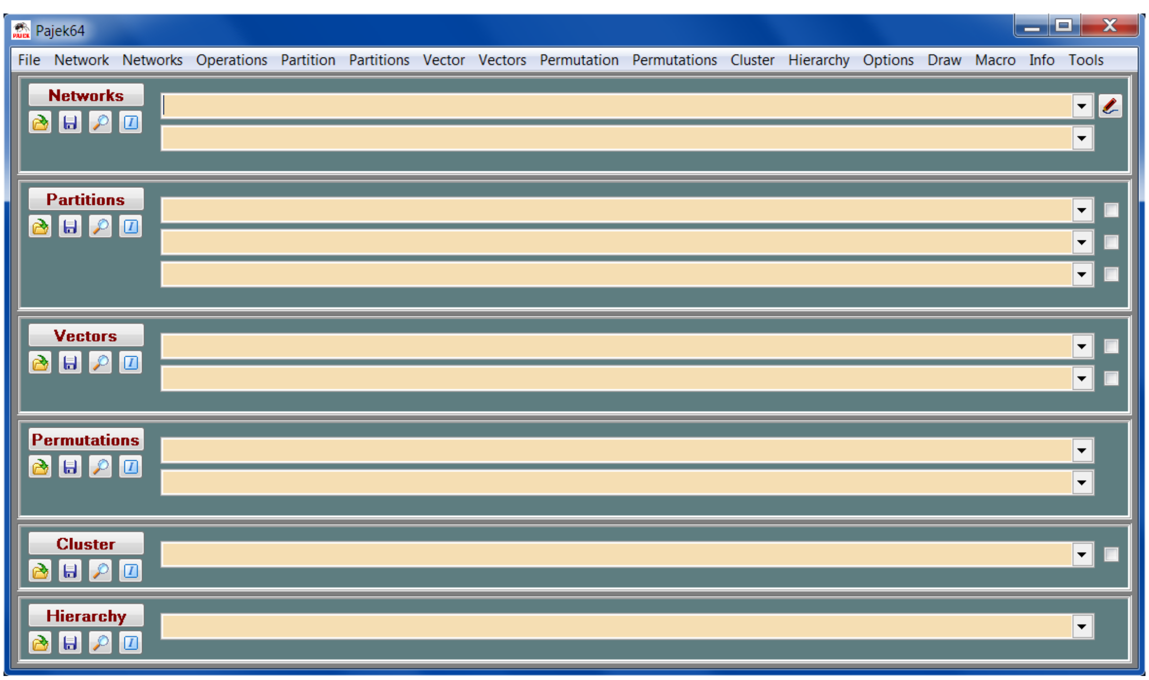



*Figure 3.* The main window for using Pajek



Pajek provides such a practical method. Figure 3 shows the main window for Pajek when it is run. Across the top of this window is main menu containing items: File, Network, Networks, Operations, Partition, Partitions, Vector, Vectors, Permutation, Permutations, Cluster, Hierarchy, Options, Draw, Macro, Info and Tools. Checking on any of these opens a dialogue box. Each dialogue box has its own set of relevant objects and operations. The primary one we use in the following is Networks (which as the name implies leads to working with multiple networks) because fragments are defined as networks. We search for such fragments in a larger network. This requires two networks. In the simple example of Figure 2, the network within which the search is done is the one in the figure and a 3-cycle would be a fragment for which a search is done. When there are searches for multiple fragments, each fragment has its own search. (We note that the Draw option was used to draw all of the network diagrams we show.) Much fuller descriptions can be found in the Pajek manual and in de Nooy, Mrvar and Batagelj (2011).

There are six horizontal panels in the main body of the window for Networks, Partitions, Vectors, Permutations, Cluster and Hierarchy. Under each of these names are some icons. Reading from the left the icons are used to read Pajek files, save Pajek files, view or edit a file that has been read (or created in Pajek) and obtain information about that file. We use the Networks horizontal panel for identifying and counting fragment types. There are horizontal lines in this panel and two are used for fragment searching as described below. The first line will contain the fragment with the second containing the network within which the search is done.

## 4. Two Empirical Signed Networks

### *4.1 Analyses for a directed signed network*

Section 4.1.1 focuses on the global-level analysis of counting all of the signed triples in an empirical network and presenting the results. In addition, given such distributions, it is natural to ask about the involvement of specific or all egos in them. This is considered briefly in Section 4.1.2 before returning to the measurement of imbalance in signed networks.

#### *4.1.1 Counting all triple types*

We demonstrate doing this for larger and/or more complex networks by identifying and counting the triples of Figure 1 as the fragments to be identified in the network shown in Figure 4. The data come from Lemann, and Solomon (1952). Women in a college were asked about signed preferences about whom the women would like or not like to do activities. Each woman was asked to name others but did not know the preferences of anyone else in their group. The data for all four relations were reanalyzed from a blockmodeling perspective (Doreian, 2008).

The data used here feature one relation (going on a double date) as shown in Figure 4. Blue lines represent positive ties and red lines show negative ties. Some positive and some negative ties are reciprocated. For visual simplicity, pairs of positive reciprocated arcs are represented by solid blue edges rather than by two arcs. Pairs of negative reciprocated arcs are represented by dashed red edges rather than by two arcs. Remarkably, some reciprocated pairs have opposite signs (e.g. *m-r* and *j-s*). There are 21 vertices with 63 positive arcs and 63 negative arcs.[1] We provide these data in the zipped file available at: http://mrvar.fdv.uni-lj.si/pajek/SVG/CoW/cow.zip.

Table 1 shows each of the eight triples in Figure 1 written out as Pajek network files. These define a set of fragments that were contained in a Pajek project file (see below) to facilitate fragment searching. This project file is provided in the zipped file as well.

The first listed network (as a fragment) has three lines at the top started by *: a signal to Pajek as to how the line in the file is to be read. Having the * start these lines is mandatory. The first line gives its name 'Network Only Positive', the second gives the number of vertices (there are three) and the third gives the type of lines in the network (arcs). The next three lines contain the data with positive ties. The first network in the second column is the first imbalanced triple (bottom left in Figure 1). There are three imbalanced triples with a single negative tie. We keep them distinct by giving them different names as they are searched for separately.

[1] Given the data were collected a long time ago it is not surprising the data collection design was fixed choice for all actors. While there are drawbacks with this design, they are irrelevant for demonstrating the signed fragments analysis.

*Table 1*: The eight network fragments defined by the triples in Figure 1.

| Balanced Triples | Imbalanced Triples |
|---|---|
| *Network Only Positive (B1)<br>*Vertices 3<br>*Arcs<br>1 2 1<br>1 3 1<br>2 3 1 | *Network One Negative /1 (U1)<br>*Vertices 3<br>*Arcs<br>1 2 1<br>1 3 -1<br>2 3 1 |
| *Network Two Negative /1 (B2)<br>*Vertices 3<br>*Arcs<br>1 2 1<br>1 3 -1<br>2 3 -1 | *Network One Negative /2 (U2)<br>*Vertices 3<br>*Arcs<br>1 2 1<br>1 3 1<br>2 3 -1 |
| *Network Two Negative /2 (B3)<br>*Vertices 3<br>*Arcs<br>1 2 -1<br>1 3 -1<br>2 3 1 | *Network One Negative /3 (U3)<br>*Vertices 3<br>*Arcs<br>1 2 -1<br>1 3 1<br>2 3 1 |
| *Network Two Negative /3 (B4)<br>*Vertices 3<br>*Arcs<br>1 2 -1<br>1 3 1<br>2 3 -1 | *Network Only Negative (U4)<br>*Vertices 3<br>*Arcs<br>1 2 -1<br>1 3 -1<br>2 3 -1 |
| The labels B1, B2, B3 and B4 are the same as in Figure 1. (The secondary labels /1, /2 and /3 are for the three types of triples having two ties that are negative.) | The labels U1, U2, U3 and U4 are the same as in Figure 1. (The labels /1, /2 and /3 are for the three types of triples having one tie that is negative.) |

*Note: The eight fragments are stored after each other in one column in Pajek, not in two panels.*

*Figure 4.* A Directed Signed Relational Network
Notes: Blue solid lines - positive relation; red dashed lines - negative relation

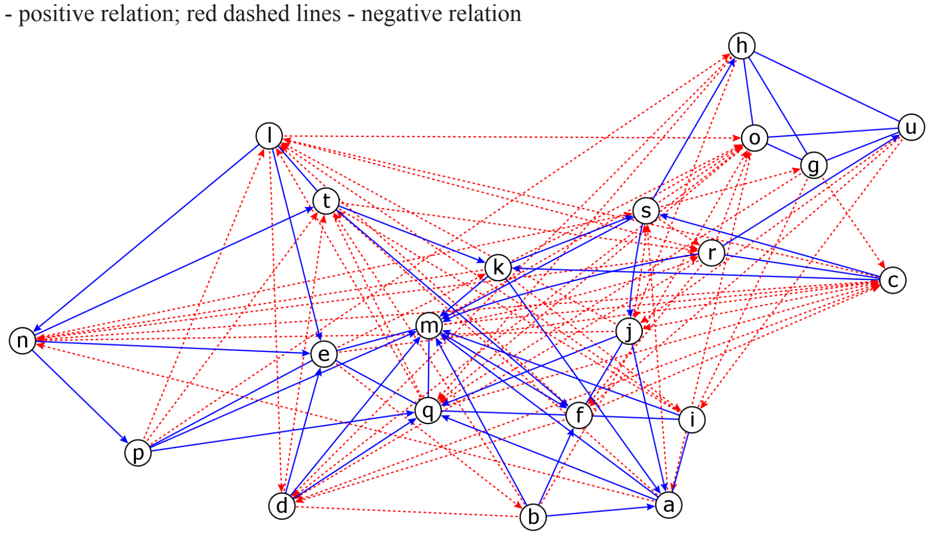
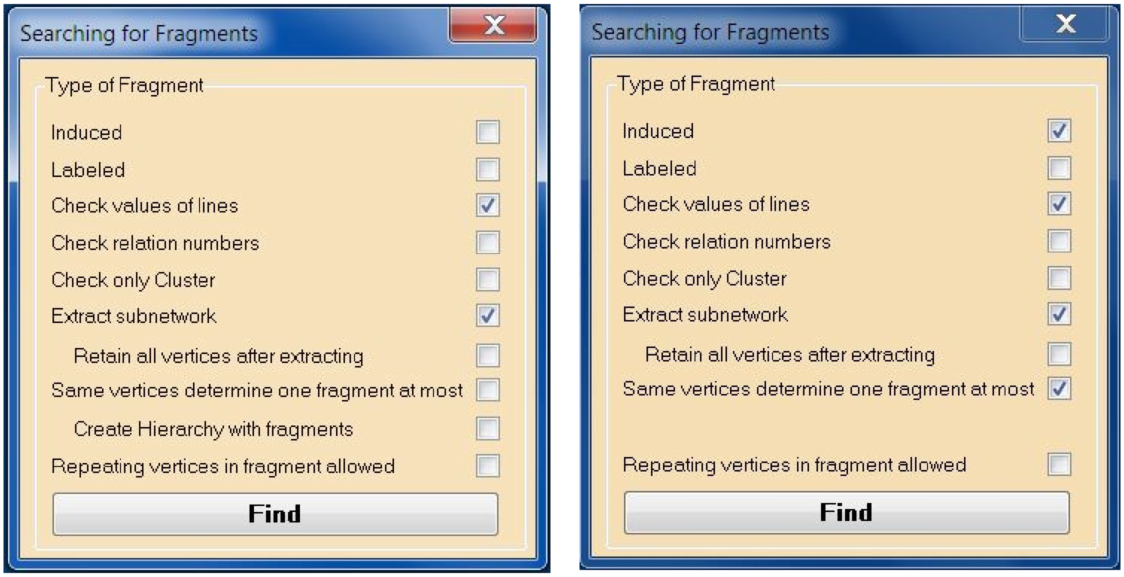


*Table 2.* Options for the searching for fragments procedure
Notes: The dialogue box on the left shows the options for obtaining the triples of Table 1 as fragments in the network shown in Figure 4.




A particularly useful feature of Pajek is the option for saving Pajek project files. At any stage of an analysis, most usefully at a provisional end, all of the objects that have been defined can be saved to a project file with a single command. This project file can then be read subsequently by Pajek. Clicking on File in the top row of Pajek's main window opens a dialogue box in which two of the options are for saving and reading Pajek project files which will have the extension paj. For fragment identification, the networks defined by the fragments can be stored in such a project file. This means the fragments can be defined once and then recalled for each new analysis. For structural balance with arcs, the eight networks defined by the triples of Figure 1 are stored in a project file as shown in Table 1. The project file for them has a single column rather than the two shown in the table. It is provided in the zipped file. The starting * for each fragment is read by Pajek as signaling a new fragment. When the file is read, all of the fragments are read but each fragment search is done separately.

*Table 3:* Counts of signed triples for the directed signed network

| Balanced | | Imbalanced | |
|---|---|---|---|
| Triple type | Count of triples | Triple type | Count of triples |
| Only positive | 65 | One Negative/1 | 8 |
| Two Negative/1 | 57 | One Negative/2 | 6 |
| Two Negative/2 | 25 | One Negative/3 | 21 |
| Two Negative/3 | 22 | One Negative | 20 |

The network file in which the searching is done has a similar structure but will be much larger with 21 vertices, and each is listed on a separate line with the network ties also listed on separate lines. The steps in Pajek for extracting these types of triples and counting them are as follows:

*Getting the data into Pajek:*

- Read the data from a network file (*.net) with * replaced by the file's name.[2]
- Read the Pajek project file (with the form (*.paj). (We labeled this as balancefragarcs.paj as it contains the eight triple types for use with any signed directed network. The label name is arbitrary.)

*Mobilizing Pajek to determine and count the types of triples*

- Select the each fragment type (one at a time) from the Pajek project file as the first network.
- Select the network data as the second network.
- Check Networks from the top menu bar in Pajek (to open a dialogue box).

[2] There are two conventions for use a * that need to be kept distinct. The one described thus far for Pajek files in this paper is internal to Pajek. The second convention is for all files when it is used a token for any name of a file. Users are free to choose their own names for files. The network with the data of figure 4 was called haddate1.net. Again, the file name is arbitrary. The data are provided in the zipped file. We recommend strongly that Pajek users upgrade always to the most recent version. When this paper was finalized. The Pajek version was 4.04. Older versions required that there be no spaces in Pajek file names. This is no longer the case.

- Check ‘Fragments (First in Second)’ in this dialogue box. This opens another small dialogue box with the options shown in Table 2.
- Select the appropriate options.
- Check Find

Table 2 shows two alternatives for selecting options for finding fragments. In the left panel, the options we selected for completing the above analysis were: ‘Check values of lines’ and ‘Extract subnetwork’. These choices are the checked boxes in the left panel of Table 2. They are appropriate for the directed network in Figure 4. An alternative set of options is shown in the right panel. When these options are used for obtaining the signed fragments in Figure 4 the outcomes are incorrect. However, both sets of options led to the same outcomes for the undirected network in Figure 2. Care is needed in selecting options as they can produce different outcomes depending on the structure of the network and the goals of the analysis.

Directed signed networks present problems for using the right hand set of options when there are reciprocated ties present. This holds regardless of whether these ties have the same sign or different signs. The directed network in Figure 4 has such dyads. When checking ‘Induced’ in Fragment options, such triples are not counted as correct triads (since there are additional arcs not only the ones needed for fragment). For undirected networks, this issue does not arise.

The number of fragments when Find is checked in the fragment dialogue box will appear in the output appearing on the screen. The counts of the signed fragments are shown in Table 3. At face value, the proportion of balanced triples for Table 3 is 169/224 = 0.75 indicating more balance than imbalance. However, the blockmodel analysis of Doreian (2008) showed there were more than two positions (clusters) of the actors. This value for imbalance is not appropriate. Fortunately, the Davis (1967) formulation provides a solution.

As noted above, the Davis generalization of the initial structure theorem of Cartwright and Harary (1956) dealt with networks having more than two positions by defining it as balanced. Indeed, a strong general case can be made for not considering it as imbalanced when there are more than two positions. When this is done, the measure of balance is 189/224 = 0.84, more consistent with the small line index of balance obtained from the signed blockmodel. We note that the blockmodel fitted according to the method presented in Doreian and Mrvar (2009) contains a negative diagonal block.

*4.1.2 Ego-level properties for fragments*

Given the primary purpose of this paper, the above task completion is enough. But having identified fragments, a natural avenue of inquiry is to think about specific vertices being located within fragments. In addition to the global result of counted fragment types, Pajek also provides ego-level results. Table 3 shows, among other things, there are 21 triples of the type labeled ‘One Negative/3’. We can ask about the frequency with which the vertices are present in this type of triple. The results are shown in Table 4. In terms of frequencies, vertex m heads the list by belonging to eight of these triples. Vertex f comes next with six followed by d, e, and t each with five. At the other extreme, vertices c, j and n belong to none. The sum of fragment counts in the bottom row of Table 4 is 63 (there are altogether 21 triples, each contains 3 vertices).

The same type of analysis can be done for each of the types of triple. As one further example, consider membership in the all-negative triples, labeled ‘Only negative’. The results are shown in Table 5. This time, vertex d heads the list with nine such memberships followed by vertices l and r with seven of them. There are six vertices having no involvement in all-negative triples. Of some interest is vertex m which had the highest count for the triples in Table 4 but is very low regarding the memberships in all-negative triples.

It seems clear that the place of specific vertices can be assessed through the types of triples defined in terms of structural balance. This suggests ways of coupling global features of a signed network expressed in triple types and the involvement of egos in them.

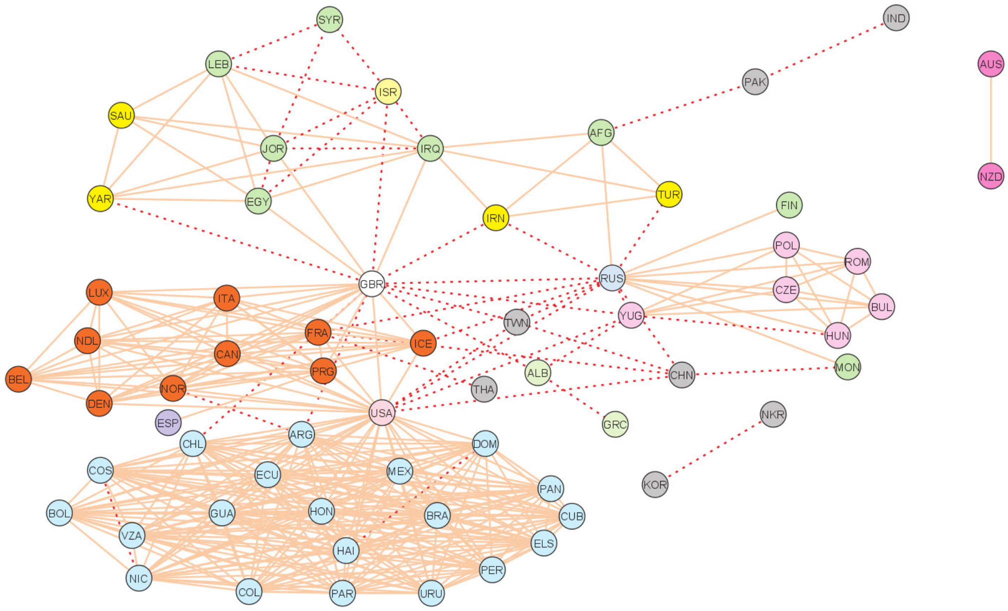
*Table 4.* The distribution of the number of times vertices are present in ‘One Negative/3’ triples

| Vertex | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fragment Count | 2 | 4 | 0 | 5 | 5 | 6 | 1 | 2 | 4 | 0 | 3 | 3 | 8 | 0 | 2 | 1 | 4 | 3 | 4 | 5 | 1 |

*Table 5.* The distribution of the number of times vertices are present in ‘Only Negative’ triples

| Vertex | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fragment Count | 1 | 3 | 6 | 9 | 0 | 4 | 1 | 0 | 0 | 3 | 0 | 7 | 1 | 4 | 6 | 0 | 2 | 7 | 4 | 2 | 0 |

*Figure 5.* The CoW signed undirected network for 1946-49
Notes: Solid lines represent positive ties with dashed lines representing negative ties




*4.2 Measuring imbalance in an undirected network*

We return to the main theme of this paper by showing how to measure imbalance in signed networks using a much larger network with undirected ties. This larger network introduces some new methodological issues as discussed in Doreian and Mrvar (2015).

This undirected signed network has 64 vertices and 362 edges. The vertices represent countries which are linked by positive and negative ties. This example is taken from the Correlates of War (CoW) project for nations in the world system following WWII.[3] This network is for the period 1946-1949. The positive ties are for joint memberships in alliances, unions and inter-governmental agreements. The tie is binary. The negative ties are for being at war, in conflict with each other without military involvement, border disputes and sharp ideological or policy disagreements. When there is a negative tie between states that otherwise have a positive tie, the negative tie is used. There are 320 positive edges and 42 negative edges. In contrast to the small network in Figure 4, there is a major difference in the number of positive and negative ties. While this raises some issues regarding the measures of imbalance, the counting of signed triples is not affected. The network is shown in Figure 5. The design of the layout reflects a blockmodel fitted according to balance theoretical ideas. The colors of the vertices represent membership in clusters (positions) determined by blockmodeling (see Doreian and Mrvar, 2015 for details).

When there are only edges in the signed network, the counting of fragments takes the form of counting signed 3-cycles with edges. The number of possible signed 3-cycle types is four. There are only two balanced and two imbalanced 3-cycles. Considering the triples in the top panel of Figure 1, but with edges instead of arcs, there is the all positive 3-cycle. All of the other triples with edges have the same structural form with two negative edges. From the bottom panel, an all negative 3-cycle is present and the other three imbalanced triples with edges have the same structural form with one negative edge. As a result, the Pajek project file with the fragments has the four networks shown in Table 6. The actual project file used is provided in the zipped file. The steps required for obtaining these signed 3-cycles are the same as for the first example only a different Pajek project file with only these four types of 3-cycles was used with the fragments. The relevant counts are shown in Table 7.

The blockmodel shown in Figure 5 through the coloring of the vertices makes it clear there are more than two positions in the world system. The appropriate measure of balance, given the Davis (1967) formulation, is 0.966 (1593/1656). Were the all-negative triple considered as imbalanced, the measure of balance would

[3] See http://www.correlatesofwar.org/. The data were provided kindly by Daniel Halgin of the Links program at the University of Kentucky. They were constructed as part of a larger project on signed networks. We appreciate greatly his generosity.

be 0.954 (1579/1656).[4] Either way, the signed network of nations following WWII was highly balanced. By itself, this is of modest interest. Whether balance (or imbalance) changed over time has greater interest value. Even more important is how – and why - the measures of balance/imbalance changed over time. We consider this in Section 5.

## 5. Measuring and tracking imbalance through time

The larger data set has signed networks for 51consecutive time points. The network expanded from having only 64 nations to a maximum size of 155 because new nations joined the world system through gaining independence or being formed through dissolution of states, especially the USSR and the former Yugoslavia. Nations having few ties can drop out when these ties are severed or can join the international network when new ties involving them are created.

In terms of identifying fragments and counting them, the above procedure is repeated for each time point. However, as the same commands are going to be repeated for every time point the procedure can be made more efficient by using Pajek's 'Repeat last command' feature. The modified Pajek commands are:

- Load all 51 networks and 4 fragments in Pajek. This can be done most easily by having all of the networks stored in a Pajek project file as they will be loaded in one step.
- Select the first fragment (from the fragments project file) as the First Network.
- Select the first loaded network as the Second Network.
- Run Fragments searching as described above.
- Check 'Repeat Last Command'. (This will open another small dialogue box with further options appearing.)
- Check the 'Fix (First) Network' button in this dialog box. Doing this sets Pajek up to search for the same fragment in all of the rest of networks, starting with the second network.
- Check the 'Repeat Last Command' button and, when asked for the number of repetitions, enter 50 (as there are 50 more networks for which first fragment should be found). In general, this entered number will change depending on the number of networks in which fragments are sought. Pajek then searches for this fragment in all of the networks that were loaded.
- To search for other types of fragments (as loaded from the fragment Pajek project file) in all of the networks (i.e. in this case all 51 time points) execute the above sequence of commands for each of the remaining fragments.

*Table 6*. The four network fragments defined by 3-cycles

| Balanced 3-cycles | Imbalanced 3-cycles |
|---|---|
| *Network Only Positive Undirected<br>*Vertices 3<br>*Edges<br>1 2 1<br>1 3 1<br>2 3 1 | *Network Only Negative Undirected<br>*Vertices 3<br>*Edges<br>1 2 -1<br>1 3 -1<br>2 3 -1 |
| *Network Two Negative Undirected<br>*Vertices 3<br>*Edges<br>1 2 1<br>1 3 -1<br>2 3 -1 | *Network one Negative Undirected<br>*Vertices 3<br>*Edges<br>1 2 -1<br>2 3 1<br>1 3 1 |

Note: The four fragments are stored after each other in one column in Pajek, not in two panels

[4] The corresponding measures of imbalance are 0.034 and 0.046 respectively.

*Table 7*. Counts of signed 3-cycles for the undirected signed network

| Balanced | | Imbalanced | |
|---|---|---|---|
| Triple type | Count of triples | Triple type | Count of triples |
| Only positive edges | 1556 | One negative edge | 63 |
| Two negative edges | 23 | Only negative edges | 14 |

One additional result of the 'Repeat Last Command' is a Vector called 'Number of Fragments' in which counts of all fragments for all 51 time periods are stored. The counts of fragments can be stored and organized by the time points. Figure 6 shows the results of computing the proportions of balanced signed triples for each time point. Clearly, there were huge changes in the levels of balance (and imbalance depending how the system is viewed.) Of course, the next task for a broader project is to account for the changes by coupling them to events taking place in the world over time. This will be no easy task but, for our purposes here, the task of tracking changes in balance has been completed. A preliminary effort at doing this is contained in Doreian and Mrvar (2015).

Figure 6 makes it clear that the level of imbalance varied greatly over time. One of the empirical hypotheses espoused by structural balance theorists was that signed networks moved towards a balanced state. Even with the early small group datasets that were examined, the empirical evidence tended not to be consistent with this hypothesis. See, for example, Doreian et al. (1996) and Hummon and Doreian (2002). The hypothesis of movement towards balance, even though Heider's initial formulation made it seem very plausible, was not a fruitful longer-term hypothesis for the field: it led to a one-directional view regarding change in signed networks towards balance and obscured a more important question. See Doreian and Mrvar (2015). A more fruitful line of inquiry is to ask about the conditions under which signed systems do move towards balance and the conditions under which they move away from balance.

Another issue addressed by Doreian and Mrvar (2015) is the utility of the proportion of balanced triples when the number of positive ties far exceeds the number of negative ties. The same issue would occur if the number of negative ties exceeded the number of positive ties by a wide margin. This issue has been obscured by the ways in which data have been collected hitherto. For a comparison with the blockmodeling approach when there are disproportional numbers of signed ties, we argue the best comparison is between the *number*[5] of imbalanced triples and the line index of imbalance. The temporal plot of imbalance using this measure is shown in Figure 7. The correlation between the line index of imbalance and the number of imbalanced triples is 0.91. The contrast between the trajectories shown in Figure 6 and 7 is discussed further in Doreian and Mrvar (2015).

While there is no reason to expect a perfect correspondence between these two measures, they are tracking something in a similar fashion. One reason for the slight difference between these measures is that the line index is constructed for the networks as a whole while counting triples or 3-cycles is far more local. Longer cycles and semi-walks are not counted when only triples are considered. However, as noted above, for studying the balance theoretic dynamics of signed networks, such longer fragments have far less utility. For a blockmodeling analysis, the line index is preferable as it is integral to the delineation of the blockmodel structure of a signed network. But if all that is required is a useful measure of the change in balance of a signed network, then using triples provides a simple measure that is far easier to use than conducting blockmodeling for as many networks as were considered for the CoW data.

Regardless of how this issue of the difference between using proportion or number of imbalanced triples to measure imbalance is resolved, the role of counting fragments is clearly useful. The debate will be one of examining the relative merits of the number of imbalanced triples and the proportion of them and will depend on the signed networks that are studied. This will hinge on the relative number of positive and negative ties in the signed network.[6]

## 6. Conclusion and extensions

A simple method for tracking change in the levels of structural balance (or imbalance) of a signed network was

[5] A very strong case can be made for discounting the presence of the all-positive triples as they are the most frequent type of triple in these data. The real interest in terms of balance theoretic phenomena involves the negative ties and how they are changed over time.

[6] For readers interested in analyzing the temporal data, they can be found at the following link: http://mrvar.fdv.uni-lj.si/pajek/SVG/CoW/. A zipped version containing all of the data files can be found at: http://mrvar.fdv.uni-lj.si/pajek/SVG/CoW/cow.zip. The data file for the network shown in Figure 5 is N46.net. The other networks for successive periods are numbered in a similar fashion.

presented for signed networks through using fragment identification and then counting them. If needed, this approach can be applied to much larger networks than the examples presented here. Of equal importance, the idea of fragments is far more general than this application for signed networks might suggest. Our hope is that it will be used more often in social network analysis as a way of characterizing network structure depending on the substantive concerns of researchers.

There is another possible way in which imbalance could be measured. It is the number of vertices whose removal creates a balanced network. This is also an NP-hard computational problem. It may be that the distributions of vertices in imbalanced triples could be used to address this issue. Also, further exploration of coupling of global imbalance with the local imbalance at vertices merits further attention.

The data for the network in Figure 5 is the first of a sequence of 51 networks. Over time, this network expanded considerably. This raises the issue of considering the impact of changing system size on the number of fragments present in the network. Doreian and Mrvar (2015) showed that the number of signed triples with negative edges did not expand greatly save for the all-positive triples which exploded. This was due to the expansion of positive ties which were far less costly

*Figure 6*. Tracking the proportion of imbalanced triples through time for a changing network.

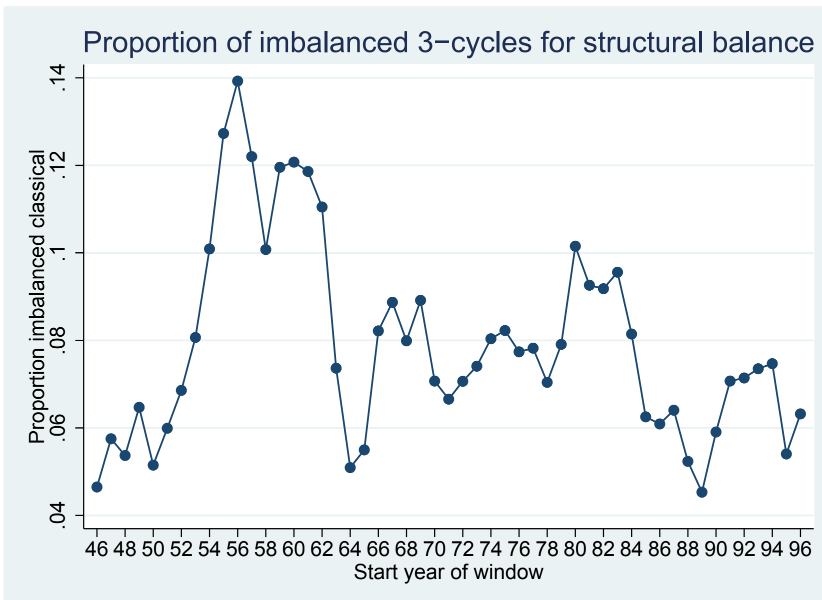
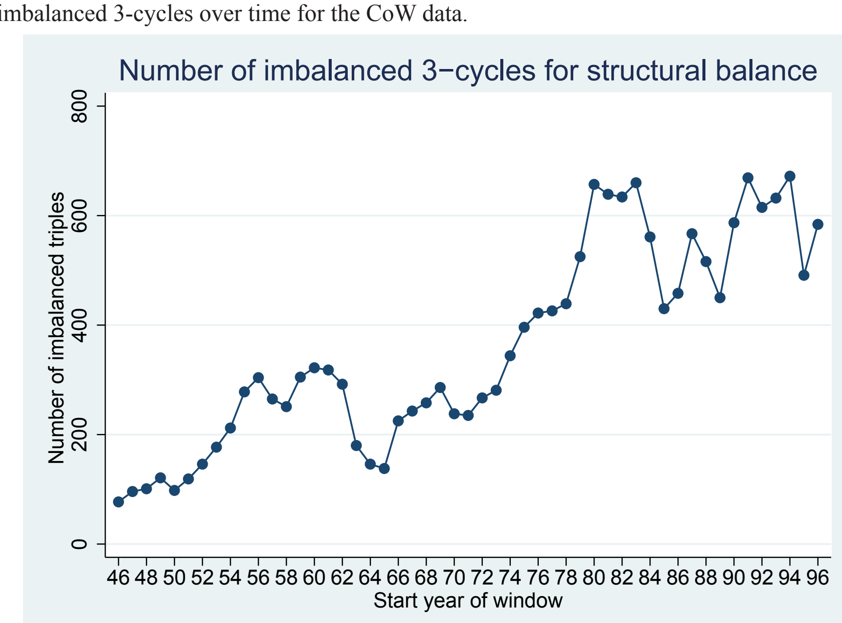



*Figure 7*. The number of imbalanced 3-cycles over time for the CoW data.



to maintain than the negative triples for countries. The impact of extreme disproportions in the numbers of positive and negative ties may be more consequential than changes in the number of units in the network.

Regarding balance, a more general problem occurs when signed networks (or their closest to balance form) do not conform to the blockmodel structure implied by the structure theorems. The CoW data have positive blocks off the main diagonal and negative blocks on the main diagonal of the blockmodel. The coloring of the vertices in Figure 5 comes from a blockmodel fitted according to relaxed structural balance (Doreian and Mrvar, 2009). Within the blockmodeling approach to signed networks there are two general concerns. One is the delineation of the blockmodel structure with the other being establishing a measure of imbalance for the network as a whole. The correspondence between the line indices from such blockmodels and the counts of triples has not been explored. Examining this relationship is ongoing. However, for signed networks with forms close to those anticipated by the structure theorems, using measures based on identified triples and 3-cycles will be fully appropriate. They may be more practical measures of balance or imbalance if blockmodeling becomes impractical or too time consuming. Moreover, their simplicity makes them easy to interpret.

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# Who Says Networks, Says Oligarchy? Oligarchies as "Rich Club" Networks

**Christopher Ansell**
*University of California*
*Berkeley, CA, USA*

**Renata Bichir**
*University of São Paulo*
*São Paulo, Brazil*

**Shi Zhou**
*University College London*
*London (UCL), UK*

**Abstract**
Departing from Roberto Michels's classic analysis of oligarchy, we provide a structural analysis of the concept based on social network analysis. We define oligarchy as a social network that exhibits three structural properties: tight interconnections among a small group of prominent actors who form an "inner circle"; the organization of other actors in the network through the intermediation of this inner circle; and weak direct connections among the actors outside the inner circle. We treat oligarchy as a global property of social networks and offer an approach for measuring the oligarchical tendencies of any social network. Our main contribution is to operationalize this idea using a "rich club" approach. We demonstrate the efficacy of this approach by analyzing and comparing several urban networks: Sao Paulo urban infrastructure networks and Los Angeles and Chicago transportation policy networks.

*Keywords*: *oligarchy, rich clubs, policy networks, urban networks*

**Authors**
***Christopher Ansell***, *Department of Political Science, University of California, Berkeley, California, USA.*
***Renata Bichir***, Center for Metropolitan Studies, Center of Arts, Sciences and Humanities, University of S*ão Paulo, São Paulo, Brazil.*
***Shi Zhou***, *Department of Computer Science, University of College London (UCL), London, UK.*

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*Correspondence concerning this work should be addressed to Christopher Ansell by email: cansell@berkeley.edu*

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## 1. Introduction

The concept of oligarchy has a long history in the social sciences and in the popular imagination, from Aristotle’s description of oligarchy as rule by the few, to Roberto Michel’s “Iron Law of Oligarchy,” to the colloquial description of post-Soviet capitalist grandees as “oligarchs.” The term has various connotations in the social sciences, from the “bureaucratic conservatism” of social movements (Voss and Sherman 2000), to the control of the economy by “industrial tycoons” (Guriev and Rachinsky 2005), to the domination of politics by “major producers” (Acemoglu 2008). Most of these references, however, share the idea that an oligarchy is a regime controlled by cooperation or collusion among a small group of powerful elites.

Given the long history and ubiquitous use of the idea of oligarchy and the potential importance of oligarchical control over social movements, economies, and political systems, it is surprising that there is so little theoretical and empirical attention paid to the concept of oligarchy. Many authors make reference, of course, to Roberto Michels’s work, *Political Parties*, which provides the classic theoretical treatment of the concept. But since the publication of this important work in 1910, there has been limited theoretical analysis of the concept of oligarchy. Taking Michels’s claim that oligarchies were inevitable seriously, subsequent scholarship has mostly sought to identify the conditions under which organizations and social movements do *not* become oligarchical (Lipset, Trow, and Coleman 1977; Voss and Sherman 2000). In this paper we build on, but go beyond Michels’s classic treatment by analyzing the structural bases of oligarchy, which we operationalize using social network analysis. We treat oligarchy as a global property of social networks and offer an approach for measuring the oligarchical tendencies of any social network.

We begin by briefly reviewing Roberto Michels’s classic analysis of oligarchy, pointing to how it provides the basis for our own structural analysis. A protégé of Max Weber’s, Michels analyzed the development of oligarchy in complex bureaucratic organizations. His central insight was a synthesis of the “elite theory” of fellow Italians Gaetano Mosca and Vilfredo Pareto with Weber’s expectation that modern bureaucracy could become an “iron cage.” He argued that organizational differentiation and stratification produced a distinctive, self-perpetuating elite (“Who says organization, says oligarchy”). Though formally sovereign, the “masses” were unable to organize themselves and as a result become dependent on the elite group to direct them. While the elite group is composed of a stable “inner circle” that monopolizes control over organizational offices, the average member has a narrow and unstable relationship with the organization. Consequently, the elite’s advantages allow them to transform their “inner circle” into a “closed caste.” This closure is essential if elites are to prevent a challenge to their position by the rank-and-file. In sum, an oligarchy has three aspects: the elite are tightly interconnected among themselves, forming an “inner circle”; the masses are organized through the intermediation of this inner circle; and the masses are poorly interconnected among themselves.

Literature in the Michelsian tradition has focused on the organizational aspects of oligarchy.[1] By contrast, we focus on the relational character of oligarchy, as it might develop within a social network. A social network perspective has two important advantages for the study of oligarchy. First, it frees us from the confines of a single organization and allows us to examine how relationships might structure the organization of elites spanning organizational or institutional boundaries (see Marques (2000, 2003, 2008, and 2012) on the permeability of the “State fabric”[2]). Second, a social network perspective may be used to capture the informal relational basis of oligarchy—the proverbial ‘old boys network.’

An earlier generation of scholars made much the same argument and closely dissected the structure of relationships among “ruling elites” (Hunter 1953, Mills 1956, Dumhoff 1967). But this scholarship got bogged down in debates between “elite theorists” and “pluralists” (Polsby 1960, Dahl 1961). Although this debate generated new insights, it tended to be structured in dichotomous terms as an issue of whether or not a ruling elite existed. In the 1970s, work in this tradition shifted its attention to one specific type of network—“interlocks” between the boards of corporations. As this corporate interlock literature developed, it increasingly focused on how links

1 See Leach (2005) for a review and critique. He defines oligarchy as the “concentration of entrenched illegitimate authority and/or influence in the hands of a minority...” (2005, 329).

2 This concept refers to the relational patterns formed by both institutional and personal relationships that structure state organizations. According to Marques: “The state fabric is created and changed by networks among people and organizations, both inside the state and in the larger environment of policy communities. The contacts are both personal and institutional and are based in old and new ties, constantly re-created. These midlevel structures control several resources and affect preferences, restrict choices and strategies, and change political results” (2012, 33).

between corporate boards shaped the flow of influence and resources between them (Mizruchi 1996). These studies usefully widened the discussion of the role of corporate interlocks, but also gradually shifted attention away from the regime-like characteristics of interlocking directorates.

We have no interest in resurrecting the old elite-pluralist debate. Our relational approach to oligarchy suggests that the structure of social networks is likely to affect the flow of information, the distribution of resources, patterns of decision-making and influence. But to be clear, a structural analysis of networks alone does not provide sufficient behavioral evidence that a ruling elite monopolizes power and influence; it can only demonstrate that the relational basis for such control or influence exists. In addition, as our analysis will show, we depart from the more dichotomous inclinations of the elite-pluralist debate, focusing instead on how to measure oligarchical tendencies in networks.

Why is a relational concept of oligarchy useful? One way to approach this question is through the idea of brokerage. Brokerage is a form of intermediation where a focal actor, the broker, mediates the relationship between some other set of actors. Social network analysis has a well-established tradition examining this brokerage role (Simmel 1950; Gould and Fernandez 1989; Burt 2005; Obstfeld 2005; Stovel and Staw 2012). The focus of this tradition has been to understand the position and power of individual brokers, and the advantages that accrue to them or those they connect. However, in many cases, it is also interesting or valuable to understand the collective pattern of mediation in a network. The concept of oligarchy, we suggest, *points to the collective mediation of a network by a small but cohesive subgroup*. To explain this point, recall the three aspects of oligarchy that we drew from Michels: the elite are tightly interconnected among themselves, forming an “inner circle”; the “masses” are organized through the intermediation of this inner circle; and the masses are poorly interconnected among themselves. An oligarchy describes a network where a cohesive subgroup monopolizes the intermediation of relationships in the network as a whole. As in the work on individual brokerage, Michels suggests that advantages accrue to the inner circle. But the concept of oligarchy is about the collective, rather than individual intermediation of the network.

Pure oligarchies may rarely exist. Nevertheless, many kinds of social networks may have oligarchical tendencies. It is well established in the social network literature that some nodes are often much more central than others and that these central nodes may play an important brokerage role, often by spanning “structural holes” in the network. We also know that subgroups form within networks, often among well-connected actors, and that networks often exhibit center-periphery patterns. Work on “small world” networks has also found that a small group of “hubs” can link a sparsely connected network together (Watts 1999). When taken together, these findings suggest the possibility for cohesive subgroups to dominate or monopolize the intermediation of the network as a whole. It is more useful, however, to understand the degree to which a social network is collectively intermediated than to become fixated on whether or not a network has a ruling elite.

In the following section, we develop a strategy for measuring the oligarchical tendencies of a network using a “distribution of degree” approach. In later sections of the paper, we demonstrate the value of this approach by analyzing several social networks.

## 2. Three Network Metrics

How should we identify the tendency of a social network to be oligarchical? The tool kit of social network analysis offers several possibilities. In this paper, we introduce a method based on work in physics and computer science that focuses on how ties are distributed across the network. We use the concept of “rich clubs” (Zhou and Mondragón 2004; Zhou and Mondragón 2007, Mondragón and Zhou 2009) as our basic measure of the oligarchical tendencies of a network, and supplement it with an analysis of the “mixing properties” of networks (Newman 2002) and the degree distribution of ties (Barabasi and Albert 1999). Taken together, these measures identify the tendency of social networks to exhibit the key features of oligarchy that we have identified: the existence of a small, cohesive group that monopolizes the intermediation of the rest of the network.

### *2.1 Power-Law Degree Distribution*

Many real networks – especially large and complex ones – may display a skewed degree distribution known as the “power law,” or $P(k) \sim k^{-\gamma}$, where degree $k$ is defined as the number of links a node has (Barabási and Albert, 1999; Xu, Zhang and Small, 2010). A power-law network is called ‘scale-free’ because it is not the average degree, but the exponent of the power-law distribution, that characterizes the network's connectivity.[3]

In a power-law network, most nodes have only a few links, and the network is guaranteed to have a small set of nodes with very high degrees, order(s) of magnitude higher than the average degree expected from a random process. Thus, for power-law networks, it is particularly important to examine the role of the high-degree nodes in organizing the network's global structure.

### *2.2 Network Mixing Patterns*

Newman (2002) identified different mixing patterns in networks. A network is *assortative* if nodes of similar degrees tend to be connected to one another and *disassortative* if nodes tend to be connected to nodes of different degrees. To measure these different mixing patterns, Newman proposed the assortative coefficient r, which ranges from -1 to 1. When r = 1, there is perfect assortative mixing in the network, i.e., every link connects two nodes with the same degree; when r = -1, there is a perfect disassortative network, i.e., every link connects two nodes with different degrees; when r = 0, there is a neutral mixing network.

### **2.3 Rich-Club Coefficient**

The "rich club" concept proposed by Zhou and Mondragon (2004, 2007 and 2009) complements this discussion of network mixing patterns. In doing so, it addresses the following ambiguities. For example, if a network displays assortative mixing where high-degree nodes tend to link with other high-degree nodes, does this mean the high-degree nodes are tightly (or fully) interconnected with each other? Or, if a network is disassortative and high-degree nodes (on average) tend to link with low-degree nodes, does this mean the high-degree nodes do not link with themselves at all?

"Rich" nodes are defined as a group of nodes with the highest degrees in a network, specified either as the top **n** best-connected nodes or as the nodes with degrees larger than or equal to a given degree **k**. For a given group of rich nodes, any member of the group has a degree higher than or equal to any node outside the group. More nodes with lower degrees are included when the size of the group increases.

The rich-club coefficient Ø is defined as the ratio of the actual number of links to the maximum possible number of links among a group of rich nodes (Zhou and Mondragon 2004, 2007).[4] It is a quantitative measure of the density of connectivity among a given group of rich nodes. When Ø=1, the rich nodes are fully interconnected, forming a clique. When Ø=0, the rich nodes have no direct link among themselves (although each of them may have a large number of links with nodes outside the group).

For simplicity, a network is said to contain a *rich club* if the richest nodes (e.g. the top 5% best-connected nodes) have a high value rich-club coefficient (say, Ø > 0.5). No a priori definition exists to determine which nodes are in the rich club. The rich-club coefficient is usually calculated for all groups of rich nodes so that this structural property can be examined across all levels of network hierarchy.[5] The rich-club coefficient has been found to be critically relevant to the redundancy and robustness of a network (Zhou and Mondragón 2004b) and to its routing efficiency in terms of shortest paths between nodes (Zhou 2009).

Zhou and Mondragon (2007) shows that a network's rich-club coefficient is not trivially related with the network's degree distribution or mixing pattern. For example, networks having exactly the same degree distribution can have a vastly different rich-club coefficient; and high-degree nodes in an assortative network are not necessarily more interconnected than those in a disassortative network.

### *2.4 Debate on the Rich-Club Phenomenon*

There has been a debate on the rich-club phenomenon with respect to how to determine whether the rich nodes in a network show a tendency to form a tightly interconnected club. Colizza et al. (2006) propose to compare the rich-club coefficient of a real network against a null model defined as the average of a maximally randomized version of the real network. The logic here is analogous to the difficulty of determining whether a person is "tall" or "short" without comparing their height to the average height of the group of people that the person belongs to. One "surprising" result is that the Internet (AS graph), which is considered to exemplify a strong rich-club phenomenon, would have a slightly lower rich-club

3 This property derives from two main mechanisms of the power-law networks identified by Barabási and Albert (1999, p.509): (i) networks expand continuously by the addition of new vertices, and (ii) new vertices attach preferentially to sites that are already well connected. In other words, the authors showed that large networks self-organize into a scale-free state, a feature unpredicted by previous random network models.

4 The maximum possible number of links among n nodes is n(n-1)/2.

5 When the group of rich nodes is given by the node rank n, the most exclusive group contains only the top 2 best-connected nodes (n=2), and the largest group is the whole network (n=N). When the group is given by degree k, the smallest group has nodes with k=kmax where kmax is the largest degree in the network, and the largest group contains all nodes with k >= 1.

coefficient when the network is randomly rewired (while preserving the original degree distribution). However, this method cannot be used to compare between different real networks – because a “short” person on a basketball team may be taller than a “tall” person in a primary school class.

Amaral and Guimera (2006) relate the rich-club phenomenon to a monotonic increase of the rich-club coefficient as a function of degree. They conjecture that the monotonic increase may be “a natural consequence of a stochastic process” and comment that “… an oligarchy will always appear to be present, even if the network is random.” However, it is widely known that the rich-club coefficient is not a monotonic function in most real networks (McAuley et al 2007; Opsahl et al 2008). The rich-club coefficient can even be a bell-shaped function in some networks (Zhou and Mondragon 2007).

Mondragon and Zhou (2007) argue that the rich-club coefficient is an absolute measure of the density of interconnectivity among a group of rich nodes. It is calculated without any assumption and judgment about the rich-club phenomenon. In other words, it is measuring a person’s height without judging whether a person is tall or not. In this paper we use the rich-club coefficient as a network metric and avoid referring to the rich-club phenomenon.

## 3. Oligarchy as a Global Property of Networks

Assortative mixing is common in social networks, but is not associated with “oligarchical” networks. An oligarchy is a rich club with disassortative mixing. In other words, the “rich” nodes are interconnected, but they are also connected to the “poor” nodes who are not strongly interconnected among themselves.

The idea that the power of well-connected people is derived from their connections to other well-connected people is well established in social network analysis, and typically measured using eigenvector centrality (Bonacich 1972) or, in a form that allows you to vary the relative importance of indirect ties, “power centrality” (Bonacich 1987). One difficulty with the later measure, however, is that it requires an arbitrary decision on the part of the analyst about whether people gain more power by being tied to other “rich” nodes or by being tied to more “impoverished” nodes. Following this tradition of measuring centrality and power in networks, some authors have recently developed new measures for identifying “leadership insularity” (Abersman & Christakis, 2010) or “organizational influentials” (Cole and Weiss, 2009).[6] Similarly, classic strategies of detecting cohesive subgroups (Wasserman and Faust 1994), such as clique analysis and its variants, or newer methods of “community detection,” such as the Girvan-Newman method (Newman 2004) may be quite useful for identifying the “inner circles” of oligarchies.

The rich-club approach has a different focus and purpose than these techniques. First, it expands the analytical focus beyond identifying well-connected leaders or important subgroups. “Rich” nodes form a cohesive group among themselves, but they also maintain ties to more “impoverished” nodes—e.g., their clients. It is these ties with non-rich nodes that makes rich nodes “rich.” Second, the rich-club approach aims to characterize the oligarchical tendency of entire networks as opposed to identifying the oligarchs themselves.

The rich-club approach uses the “mixing properties” of the network to evaluate whether rich nodes merely affiliate among themselves, or whether they also affiliate with non-rich nodes. If a network is “assortative,” rich nodes affiliate primarily with other rich nodes, while non-rich nodes affiliate primarily with other non-rich nodes (in an assortative network, nodes of similar degree associate with each other). If a network is “dissassortative,” by contrast, nodes of dissimilar degree associate together. While the “rich club” measure captures the way a core group monopolizes ties, the disassortative measure guarantees that this core is not segmented off from the rest of the network.

In addition to knowing that there is a group of rich nodes who are tied together, but also linked to a wider network of clients, the concept of oligarchy also presumes that the “rich club” at the core of the network is small relative to the network as a whole. One way to evaluate whether the “rich club” is small is to examine the degree distribution of the network. If the rich-club is small, we should expect the degree distribution to resemble a power law.

To summarize, an oligarchical network can be characterized as having a “rich club” (a group of well-connected nodes who are connected to one another), but the overall network exhibits mixing properties that are disassortative (where each rich node is strongly connected to the poor nodes) and a power-law degree distribution (few well-connected nodes and many poorly-connected nodes). Taken together, these three properties capture the degree to which a small group dominates the collective intermediation of the network as a whole. In

6 Looking for the most influential individuals in school networks, Cole and Weiss (2009, 4) propose four methods: 1) absolute cut score (in-degree score); 2) fixed percentage of population is defined as influential; 3) degree standard deviation; 4) random permutation.

Michels’ terms, the rich club is a cohesive “inner circle” that organizes the weakly organized “masses.”

One alternative way to identify an oligarchical network regime is to develop a core-periphery analysis. Much like the concept of an oligarchy, a core-periphery structure is a “core” of people who are tied together and a “periphery” of less well connected actors (Laumann and Pappi 1976). Breiger describes a core-periphery network as follows: “a coherent set of active members (or a “leading crowd”) is surrounded by isolated individuals who have interchange both to and from them” (1979, 29). Consistent with this definition, Borgatti and Everett (1999) developed a partitioning algorithm for analyzing core-periphery structure that assigns those who are closely connected to each other (1-block) to the “core” and those who are not connected to each other (0-block) to a “periphery.” They then develop a “fitness measure” to evaluate how closely the derived assignment corresponds with an idealized core-periphery structure. However, there are several limitations of using a core-periphery analysis as measure of oligarchy:

1. The core-periphery algorithm partitions a network into a core that is tightly interconnected (1-block), but this measure does not directly capture the degree to which this core is a “rich-club” (as measured by the rich-club coefficient);
2. The core-periphery measure says that the core is tightly interconnected and the periphery is weakly interconnected; it says less about the link between core and periphery (only that it expects an imperfect 1-block). The rich club approach directly measures how rich nodes are tied to non-rich nodes (assortative and disassortative mixing).
3. The “core” of a core-periphery structure might be very large, while we are assuming that the “rich club” is a small group (as measured by the power law distribution).

Thus, while core-periphery measures may also provide an approximate measure of oligarchical structure, the rich-club approach offers a more direct and discriminating measure of oligarchy. In the next section, we will analyze several social networks using this rich-club approach: urban infrastructure policy networks in São Paulo, Brazil over six mayoral administrations and transportation policy networks in two U.S. cities, Chicago and Los Angeles. These networks allow us to compare urban policy regimes across time in the same city (São Paulo) and across city for the same kind of policy domain (Chicago and Los Angeles), and across urban regimes in two countries (Brazil and the U.S.).

## 4. Description of the Networks

### *4.1 São Paulo Urban Infrastructure Networks*

São Paulo is the largest and most important metropolis in Brazil and South America, with roughly 11.9 million municipal inhabitants and 20 million in the metropolitan region. Besides shaping the urban space in São Paulo, urban-infrastructure policy is at the core of municipal politics and policies, and receives a large share of the municipal budget – 13% on average during the period 1975-2000 (Bichir, 2005). Thus, it is an influential and important policy domain.

Policy network data was collected by Eduardo Marques and Renata Bichir in order to investigate the policy dynamics of the Secretariat of Public Roads (“Secretaria de Vias Públicas” – SVP), the São Paulo municipal agency responsible for urban infrastructure policy (Marques, 2003).[7] Based on an examination of contract notices published in the official press, this research analyzed spatial, relational, and political dynamics of urban-infrastructure policy in the city of São Paulo from 1975 to 2000.[8]

7 Urban infrastructure policy is a part of a broader “urban engineering” community that encompasses several policy domains, including infrastructure, maintenance of the built environment and services, urban transportation, and cleaning (Marques, 2003). The municipal agency responsible for urban infrastructure policy depends on the municipal budget, does not have strong institutional boundaries or civil service career patterns, and experiences strong migrations from and to other parts of the government and the private sector (Marques, 2003). These institutional features affect the policy network and the way policy is formulated and implemented.

8 In Brazil, all government contracts have to be published in official daily publications called “Diários Oficiais.” To obtain information on the patterns of investment in urban infrastructure, the data set includes information on almost 5500 urban public works project contracts (road and drainage work, river canalization, bridges and tunnel construction etc.) from 1975 to 2000.

To recreate the policy network from 1975 to 2000, the researchers conducted 26 in-depth interviews with career officials, technicians, and members of the community of engineers associated with SVP. These interviews sought to characterize the policy and political dynamics in the city over time, as well as to investigate the continuity of the networks.[9] The interviews used a name generator – based on official data of all incumbents of the main institutional positions of the Secretariat over time – and snowballing techniques, to identify the complete network. The network data analyzed in this paper is the data set produced by the Marques team using this data collection process.

This policy network was constructed with the aim of analyzing the power dynamics inside this bureaucracy under different mayors with different political inclinations. The study focused on the differences between right-wing and left wing parties, since this is a policy area traditionally associated with the right in the city of São Paulo.[10] The relations among different groups of the Secretariat, the broader political environment (political parties, other public agencies), and private companies responsible for public works were investigated. The analysis found that this policy community is characterized by the importance of personal ties among state actors and between state and private sector actors (Marques, 2003, 2012). The infrastructure policy network in São Paulo became more dense and complex over time, from approximately 75 interconnected people prior to 1975 to more than 250 people in the administration of Celso Pitta (1997-2000). Marques (2003) found a hegemonic group in control of policy across this period, which was stable even during the two left-wing administrations (Covas and Erundina) despite their attempts to change the power dynamics in this policy domain by introducing new players into the policy network. These new actors, however, failed to displace or break the hold of the hegemonic group.

*Chicago and Los Angeles Transportation Policy Networks*

Weir et al. (2009) collected data on the transportation policy networks of the second and third largest U.S. metropolitan regions — Los Angeles (13 million people) and Chicago (9 million people). The purpose of the study was to investigate whether the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) had created conditions for collaboration on transportation policy issues among groups operating on an urban and regional scale. ISTEA also sought to encourage the participation of new groups typically excluded from previous planning regimes. In addition to their size, L.A. and Chicago were selected because they represent contrasting urban political dynamics. L.A. is traditionally regarded as having a very fragmented urban and regional politics, while Chicago's active business and civic community and centralized political regime make it an example of more organized and cohesive policy-making.

Semi-structured interviews were conducted in 2003 with 41 groups active in transportation issues in the Los Angeles region and in 2005 with 35 groups active in the Chicago region. During these interviews, groups were shown a list of organizations involved in transportation issues and asked to "check every name on the list that your organization has worked with as part of its transportation work." A follow-up question then asked respondents to indicate which of these groups they had worked with "closely." The questions were intended to capture the difference between "weak" and "strong" network ties.

The study found that ISTEA had encouraged the creation of new groups and that these groups brought new perspectives to the urban and regional transportation policy process. It was also found that these groups were engaged in active networking within their regions. The interviews, however, also indicated that the groups

9 Since this is a relatively stable and close community-many of the technicians studied together in the same universities, have common business associations outside the public sector and are co-members of professional associations-the research team assumed that most people would know each other, forming a one-mode network. Information on all types of contacts inside the policy community was considered, and not only information on ties associated with some specific policy issues or contracts. In this sense, the relationship between two nodes may represent several types of ties, including work ties, friendship ties, business ties, etc. The researchers did not exclude people from the network due to retirement, only when someone died or went to a completely different sector. The interviews revealed that the retired public servants usually went to the private sector and stayed as formal and informal consultants for the public sector. Additional interviews were then conducted in order to separate contacts into different periods and to differentiate the types and strength of ties (indicated by the frequency of citation of each dyad). These interviews allowed the construction of the network of relationships between individuals, entities and private companies in each mayoral administration from 1975 to 2000.

10 The study characterized "right-wing" politicians as belonging to the party that supported the military regime (Arena) and the parties that were created after it (PPB and PDS), including a party aligned with them at the municipal level (PTB). Thus, Olavo Setúbal (in charge of the municipality from 16/04/1975 to 12/07/1979), Reynaldo de Barros (12/07/1979 to 13/05/1982), Salim Curiati (13/05 / 1982 to 13/05/1983), Jânio Quadros (1986 to 1988), Paulo Maluf (1993 to 1996) and Celso Pitta (1997 to 1999) were classified as "right-wing." "Left-wing" mayors were those belonging to the opposition to the military regime – the MDB – and their descendants after the political opening: Mario Covas (13/05/1983 to 31/12/1985) and Luiza Erundina (1989 to 1992), who belonged to the PMDB and the PT, respectively.

felt that they were still not fully included in a planning process now dominated by the Metropolitan Planning Organizations (MPOs) also created by ISTEA. Of the two cities, Chicago groups were more successful in getting their MPO to be responsive to their input.

## 5. Comparison of the Networks

As indicated in Table 1, the policy networks vary significantly across the three cities. The São Paulo networks are much larger than the U.S. networks, but also much sparser (e.g., less dense). Since density often declines as networks become larger, this is not surprising. As the comparison of the "strong" and "weak" tie networks in Chicago and L.A. suggests, density is also a reflection of the kinds of social relations elicited by interviews and surveys. If you ask people to specify only the people they work with closely ("strong ties") then you will generate a sparser network than if you ask them whom they have worked with ("weak ties"). The differences between the networks indicate that it is important to exercise caution when making comparisons, since many network measures are sensitive to the size and density of the network. In the analysis that follows, we attempt to normalize our measures where possible.

### *5.1 The Rich-Club Coefficient*

When we look at the distribution of the rich-club coefficient as a function of degree (Figures 1 and 2), we can see that all the policy networks show a rich-club pattern. According to Zhou and Mondragón's (2004) definition, rich nodes are those with the highest degrees (much larger than the average degree). The figures show that the people with the highest degree are also interconnected with each other--the higher the degree, the greater the rich club coefficient.[11]

*Table 1*: Degree, Clustering and Mixing Properties

| Dataset | Density | Number of Nodes | Number of Ties | Average Degree | Maximal Degree | Shortest Path Length Between Nodes | Clustering Coefficient | Assortative Coefficient |
|---|---|---|---|---|---|---|---|---|
| *São Paulo* | | | | | | | | |
| Reynaldo | 0.030 | 162 | 429 | 5.3 | 42 | 3.18 | 0.279 | -0.23 |
| Covas | 0.028 | 198 | 562 | 5.67 | 47 | 3.23 | 0.299 | -0.196 |
| Janio | 0.024 | 236 | 686 | 5.81 | 51 | 3.32 | 0.286 | -0.169 |
| Erundina | 0.026 | 209 | 584 | 5.59 | 49 | 3.37 | 0.312 | -0.179 |
| Maluf | 0.028 | 196 | 551 | 5.62 | 49 | 3.24 | 0.321 | -0.191 |
| Pitta | 0.028 | 204 | 586 | 5.75 | 49 | 3.25 | 0.305 | -0.175 |
| | | | | | | | | |
| *Chicago* | | | | | | | | |
| Chicago – Weak | 0.403 | 35 | 240 | 13.71 | 29 | 1.62 | 0.62 | -0.16 |
| Chicago – Strong | 0.106 | 33 | 63 | 3.82 | 9 | 2.91 | 0.413 | -0.013 |
| | | | | | | | | |
| *Los Angeles* | | | | | | | | |
| LA – Weak | 0.359 | 37 | 239 | 12.92 | 29 | 1.69 | 0.519 | -0.114 |
| LA – Strong | 0.156 | 38 | 103 | 5.42 | 12 | 2.49 | 0.274 | 0.006 |

11 MISSING FOOTNOTE

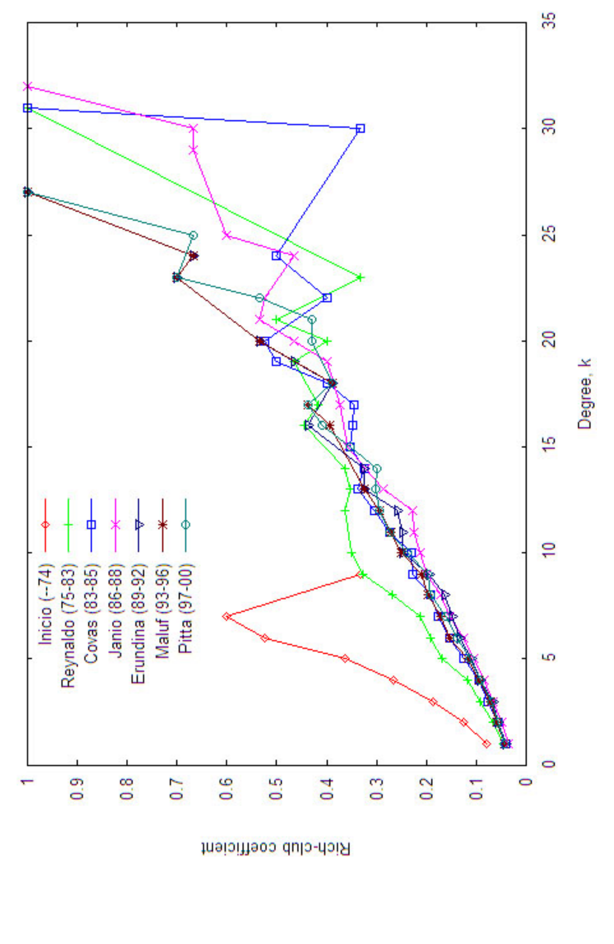


*Figure 1*: Rich Club Coefficient as a Function of Degree: São Paolo

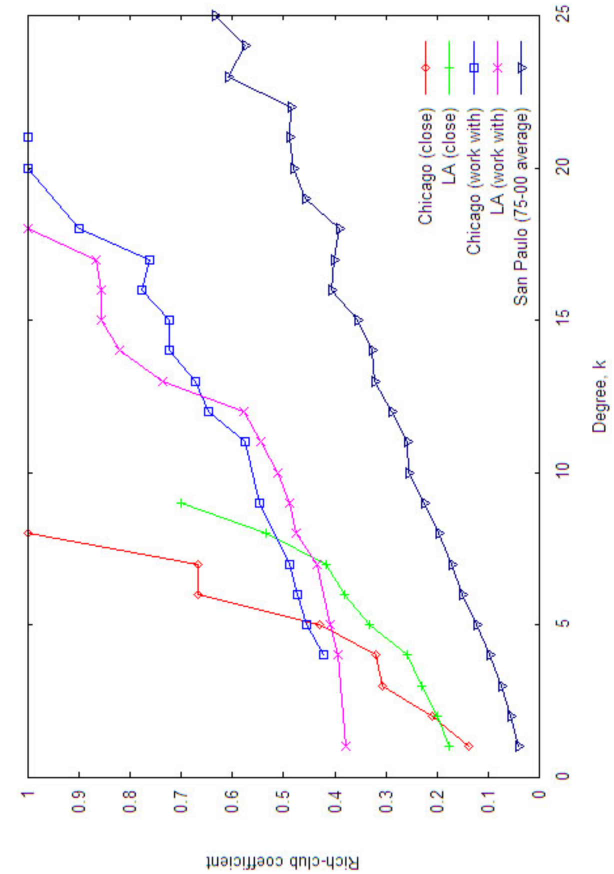


*Figure 2*: Rich Club Coefficient as a Function of Degree: Chicago and LA

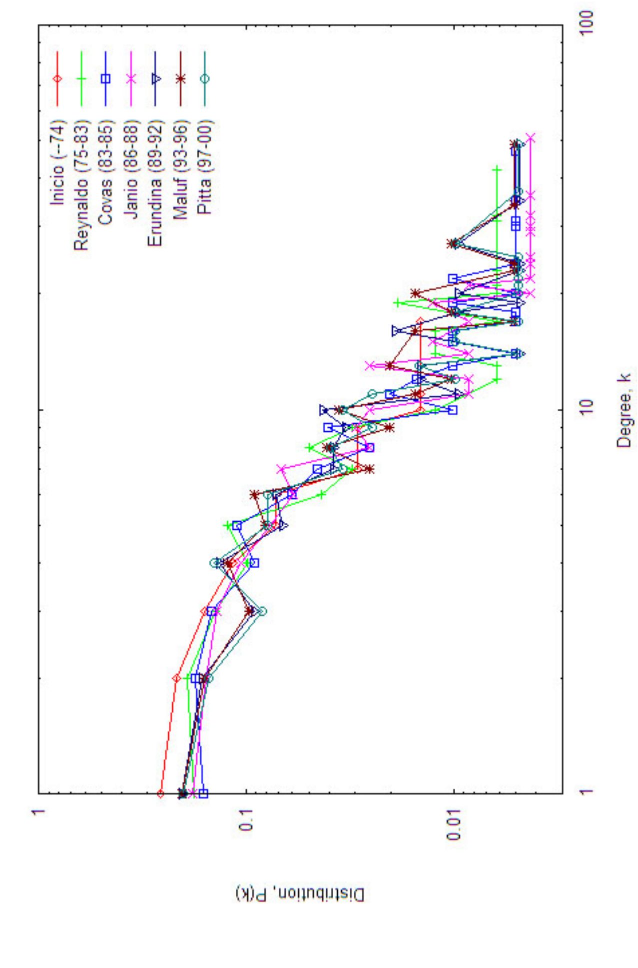


*Figure 3*: Degree distribution: São Paolo networks

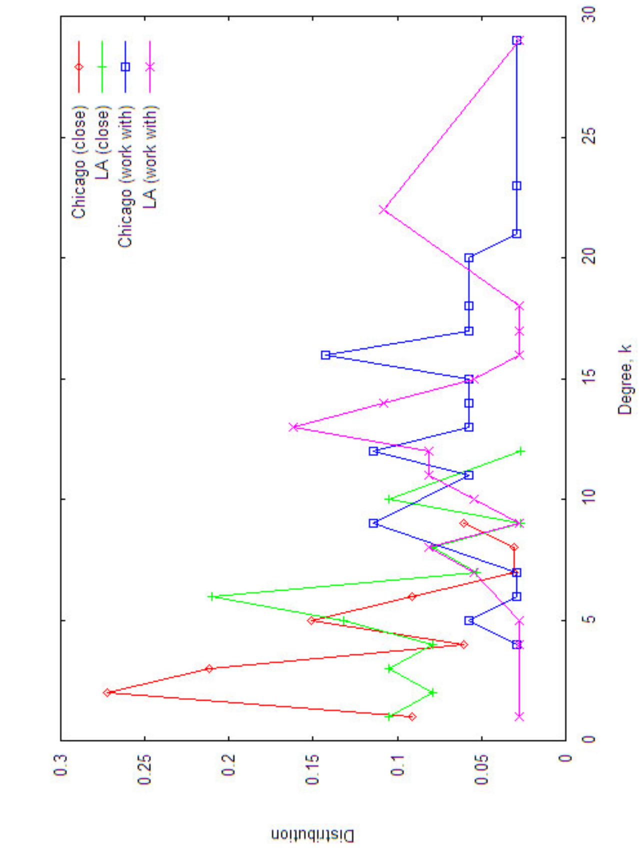


*Figure 4*: Degree distribution: Chicago and LA networks

*5.2 Mixing Properties*

Table 1 also shows the findings for the assortative coefficient and several other related measures.[12] With the exception of the Los Angeles strong tie network, all the networks are disassortative ($r < 0$). This means that nodes with dissimilar degree tend to be connected to each other, i.e. well-connected nodes tend to be connected to poorly-connected nodes and vice-versa (Zhou and Mondragón, 2007; Colizza et al, 2006). In the case of São Paulo, it is interesting to note that the Reynaldo regime is the most disassortative ($r = -0.230$), which is consistent with Marques's finding that a hegemonic group is first established during this administration. The disassortative coefficients, however, are quite similar across the different administrations in São Paulo, regardless of their ideological inclination. This finding is consistent with the argument that the hegemonic group, once established, is quite stable (Marques 2003).

*5.3 Degree Distribution*

We can also contrast the São Paulo networks with the US networks by looking at degree distribution in these networks. The degree distribution is indicative of a network's global connectivity, although different properties/mixing patterns may be found in networks sharing the same degree distribution (Zhou and Mondragón, 2007). One important type of degree distribution is a "power law" distribution, in which many nodes have only a few links and a small number of nodes have a very large number of links (Zhou and Mondragón, 2007).

When we look at Figures 3, we see the degree distributions approximate a power law, where there are few nodes with a large number of connections, but most nodes have few connections. Compared with the Chicago and LA networks (Figure 4), the São Paulo networks more closely resemble a power law distribution.

**6. Analysis**

Four bases of comparison are presented by our three urban policy networks. The São Paulo data allows us to examine regime-level properties over time — across different municipal administrations. The Chicago and Los Angeles data allow us to compare policy network regimes in two different American cities, while holding policy sector constant. The Chicago and Los Angeles data also allows us to compare weak and strong tie networks within each city (and, to some degree, to draw generalizations about the character of weak and strong ties in both cities). Finally, we can cautiously contrast a Brazilian urban policy network against U.S. urban policy networks.

All three policy networks show some tendencies towards oligarchical organization. All of them demonstrate a "rich-club" organization, where the best-connected individuals or organizations are connected to other well-connected people and groups. With the exception of the Los Angeles strong tie network, however, all the networks are disassortative, meaning that the well-connected are also connected to the less well-connected. This is to be expected in an oligarchic network, where the inner elite collectively intermediate the social network as a whole. While all these networks may have oligarchical tendencies, the São Paulo networks are more clearly oligarchical than either of the American networks. The São Paulo networks are more disassortative than the American networks, particularly the strong tie networks. This means that the São Paulo elite has strong links to the entire policy network, while elites in the American networks are less broad-based. To some degree, this makes us reflect upon the concept of oligarchy we have embraced. Is a regime more oligarchical if the elite (e.g., the well-connected) organize the broader network or ignore it? In the Michelsian tradition, the former qualifies, but we might consider whether the latter case also represents a form of oligarchy. The fact that the strong tie networks in the American cities are less disassortative than the weak tie networks suggest that when it comes to the closest ties, the American networks are more clubbish.

There is another more important reason, however, to question the oligarchical qualities of the American networks. The well-structured power law distribution of the São Paulo networks indicates that there is a small "inner circle" that monopolizes most of the network. By contrast, in the American cities, this "inner circle" is not well differentiated. In the weak tie networks, in particular, a rather large group of institutions are well-connected, suggesting more of a pluralist than an oligarchical regime. In other words, there are well-connected organizations but no small group of elite that monopolize ties. The strong tie networks appear closer to power law distributions, suggesting a more distinct elite. But even these networks do not differentiate between a small well-connected elite

12 Each of the São Paulo networks contains multiple components. In the rich club analysis, we only considered the giant component, which is the largest component in a network. The giant component contains more than 90% of the nodes in these networks. All other analyses consider entire networks.

and a less well-connected periphery.

Our analysis concludes that the São Paulo networks come much closer to being oligarchies than do the American networks. While the American networks have some oligarchical tendencies, they ultimately appear more pluralistic. Well-connected organizations in the American networks are clubbish, but the analysis does not suggest that this elite is very well differentiated. Without studying other Brazilian cities, it is difficult to confidently conclude that these contrasts represent national differences in urban policy networks. But the contrast suggests that this is a distinct possibility. One thing that is clear from the data, however, is that the Brazilian oligarchy appears to be stable across municipal administrations, a point that reinforces the argument made by Marques (2003) about these networks. Different political parties were in charge during these different administrations, so it is striking to find this stability. There is a sharp disjuncture in the distribution of the rich-club coefficient at higher degrees during the first left-wing administration (Covas) that probably reflects an attempt to destabilize the oligarchy. But the distribution returns to the prior pattern under the next left-wing administration (Erundina).

The contrast between Chicago and Los Angeles was less striking than we anticipated, though in the expected direction. As mentioned, Los Angeles is reputed to be a civically fragmented city, while Chicago has a reputation for more civic cohesion. The distribution of the rich-club coefficient by degree (Figure 2) is very similar: in both cities, the well-connected are strongly linked to one another. The Los Angeles networks are less disassociative than the Chicago networks, suggesting that that the well-connected organizations in Los Angeles are less well-connected to the wider network. This could be one indicator of greater fragmentation in the Los Angeles networks. For the strong tie networks, Chicago also appears somewhat closer to a power law distribution (many organizations with few ties; a few organizations with many ties) than the Los Angeles network; in Los Angeles, many organizations have a medium range of ties. Our conclusion is that there is a less distinctive elite in Los Angeles. For the weak tie networks, however, this contrast is less clear.

## 7. Conclusion

The concept of oligarchy has an illustrious history in the social sciences, but is only weakly developed as an analytical concept. Though it is not uncommon to hear the word used to describe political and economic regimes in organizations, social movements, and nations, the precise meaning of the concept is often suggestive rather than precise. In this paper, we provide a structural analysis of the concept based on social network analysis. Building on the classic treatment of oligarchy by Michels, we begin with a conception of oligarchy as a social structure organized and dominated by a small inner circle of prominent actors tightly interconnected among themselves. These "oligarchs" are linked to less prominent actors in the network, who are only weakly interconnected among themselves. The power of an oligarchy lies in the cohesion of the oligarchs, their ability to organize less prominent actors, and the weakness of these less prominent actors to organize themselves.

Our main contribution is to operationalize this idea using a "rich club" approach. The social network concept of a "rich club" captures the idea that well-connected actors (high degree) are also connected among themselves. The "mixing properties" of a rich-club network indicate whether well-connected actors are only connected to each other (assortative) or to less well-connected actors (disassortative). Finally, by evaluating whether the network fits a power law distribution (few actors of high degree; many actors of low degree), we can determine whether the inner-circle is a small or large group relative to the size of the network.

We demonstrate the efficacy of this approach by analyzing and comparing several urban networks. Our analysis of São Paulo, Chicago, and Los Angeles suggests that policy networks have oligarchical tendencies, in the sense that well-connected actors in all three cities tend to be connected to other well-connected actors. The São Paulo networks, the weak tie networks in Chicago and Los Angeles, and the Chicago strong tie network are also disassortative, meaning that the well-connected actors are connected to less well-connected actors. However, only the São Paulo networks demonstrate a clear power law distribution, indicating a small coterie of well-connected actors. We conclude that the São Paulo networks come closest to being oligarchical regimes, while the Chicago and Los Angeles networks are more pluralist. Remarkably, the oligarchical structure of the São Paulo networks is stable across several municipal administrations, suggesting that oligarchy, once formed, may be a robust form of political organization.

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# Social Exchange Networks: A Review of Experimental Studies

**Sabine Neuhofer**
*University of Vienna*
*Vienna, Austria*

**Ilona Reindl**
*University of Vienna*
*Vienna, Austria*

**Bernhard Kittel**
*University of Vienna*
*Vienna, Austria*

**Abstract**
This article surveys laboratory experiments on social exchange networks. The method of laboratory experiments is prominent in this field. The various theoretical perspectives informing the experiments are grouped into three approaches: the first, dominated by network-exchange theory, is mainly concerned with power and structure, the second discusses social-psychological approaches and emphasizes behavioral and psychological dimensions such as reciprocity, emotions and cohesion, and the third is concerned with game-theoretic experiments embedded in network structures.

**Keywords**: *social exchange; network; laboratory experiment*

**Authors**
***Sabine Neuhofer*** *is a researcher in the Department of Economic Sociology, University of Vienna, Vienna Austria.*
***Ilona Reindl*** *is a researcher in the Department of Economic Sociology, University of Vienna, Vienna Austria.*
***Bernhard Kittel*** *is a professor in the Department of Economic Sociology, University of Vienna, Vienna Austria.*

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*Correspondence concerning this work should be addressed to Bernhard Kittel, Department of Economic Sociology, University of Vienna, Oskar-Morgenstern-Platz 1, 1090 Wien, Austria or by email: bernhard.kittel@univie.ac.at*

## 1. Introduction

Social exchange theory focuses on the distributive and allocative effects of human interactions within boundaries determined by the structure of the network. It is closely linked to social network analysis, which studies relational and structural aspects of networks. By providing theoretical explanations for behavioral patterns in network settings, social exchange theory complements and extends the scope of classical social network analysis. Over the past 40 years, theoretical and experimental studies have shed light on the variety of factors, which influence exchange in networks. Structurally induced power differences, emotions, commitment, trust, fairness preferences, status, coalition formation and the sequence of exchange are only a few of the factors that have been considered. The experimental evidence presented in this article underlines the potential benefit of considering the social and behavioral preferences of agents in a network. Furthermore, social exchange research provides insights with respect to explaining why networks observed in the real world assume specific forms, why some links are used more often than others and some are dropped entirely, and how networks can be influenced through institutions in order to manipulate the flow of resources, specifically knowledge and information. The diversity of theories having been developed and tested experimentally thus complements classical social network analysis.

We organize the literature along three broad categories: 1) *Network Exchange Theory* and its variants, 2) theories with affinity to social psychology, and 3) theories using a game theoretic approach. The first

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category of theories and experiments focuses mainly on structure and power in networks. Their research interests and the concepts they use are relatively close to classical social network analysis. The second category is concerned with emotions, cohesion, and other dynamics within networks, thus shifting the main focus away from the global structure of the network to the level of the individual. The studies summarized in the third category use game-theoretic concepts to study social exchange in networks. They focus on strategic choices and network formation and put again more emphasis on the structure of the network. This categorization is neither chronological nor exact. On the one hand, some of the more social-psychological approaches are also advancements of Network Exchange Theory. On the other hand, over the decades, some scholars carried out their research in different directions.

The empirical evidence presented in this article has been gathered exclusively in laboratory experiments. Social exchange research is thus among the pioneers in sociology in using this method for whole research programs. Laboratory experiments are well suited to examine social exchange network as they allow for highly controlled circumstances and exact comparison.

In the following, we first introduce the basic concepts, the standard experimental setting and the historical development of social exchange theory in section 2. Section 3 to 5 summarize the existing empirical work divided into the three aforementioned categories and section 6 concludes.

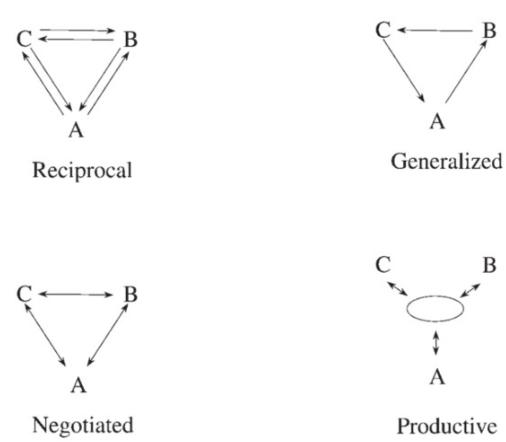
## 2. Basic Concepts

Social exchange takes place between two or more agents, each controlling resources which others value and seek to obtain.[1] Agents provide each other with the valued resources through some form of exchange and exchange is recurring over time. Resources can range from tangible goods to intangible goods such as status or approval. Most variants of exchange theory assume homogenous and self-interested agents who seek to maximize their utility within the constraints of the network structure (Molm, 2007). Some of these basic assumptions have been relaxed in more recent studies, for example by allowing for heterogeneity in the values of edges or in agents' characteristics.

### *2.1 Forms of Exchange*

Exchange in networks can either take the form of *direct*, *indirect*, or *productive exchange*. Direct forms of exchange are further differentiated into *negotiated* and *reciprocal* exchange. In negotiated exchange, agents jointly agree on the terms of exchange and these agreements are strictly binding. In reciprocal exchange, agents initiate exchange unilaterally and independently "without knowing whether, when, or to what extent the other will reciprocate" (Molm, 2003a, p. 35). From a game theoretic point of view, negotiated exchanges in which agents decide jointly, are cooperative games (see also Bienenstock & Bonacich, 1992), while reciprocal exchanges in which agents decide individually are non-cooperative games. Both negotiated and reciprocal exchange can be found in a variety of different settings such as negotiating division of task in a team or doing favors unilaterally (Molm, 2003a, 2003b, 2007; Molm, Takahashi, & Peterson, 2000). In *indirect exchange*, which is also referred to as generalized exchange, three or more agents exchange by giving benefits to one agent and receiving benefits from another, but not the same agent (for example, feedback chain in a department). An agent's outcome thus depends *indirectly* on another agent's behavior, while in direct exchange an agent's outcome depends *directly* on another agent's behavior. In *productive exchange*, a form that has been largely neglected in the literature (Lawler, Thye, & Yoon, 2000, p. 617), all agents have to contribute their share in order to obtain benefits (for example, coauthoring a book). Defection of one group member thwarts the exchange, characterizing productive exchange as a coordination problem. Productive exchange can comprise elements of negotiation and reciprocity (see Fig. 1).

*Figure 1*: Forms of exchange (Lawler, Thye, and Yoon, 2008, p.525)




1 The terms agent, actor, and subject are used interchangeably in the literature.

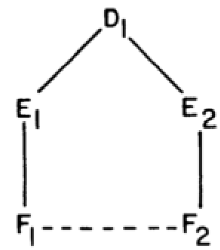
Just as in social network analysis, exchange theorists usually assume dyadic exchange relations to be embedded in a broader *exchange network*. Exchange networks are defined as a set of at least three agents. Each agent is connected to at least one other agent in the network, a precondition for engaging in exchange. The dynamics of exchange depend crucially on whether network *connections* are positive or negative, a distinction proposed by Emerson (1972a, 1972b), which is also used in network analysis. In *positively* connected (or inclusionary) networks, exchange in one relation is independent from exchange in another relation. This means that agents are allowed to exchange with more than one of their connections per round. In *negatively* connected (or exclusionary) networks, exchange in one relation is contingent on *non-exchange* in another relation, that is agents can only exchange with one of their connections per round (Cook & Emerson, 1978; Molm, 2001). While most theoretical models in this field provide outcome predictions for negatively connected networks, only few models are designed to predict outcomes in positively connected networks as well. Following the theoretical focus, most experimental studies deal with negatively connected exchange networks.

*2.2 Experimental Setting*

The formalization of social exchange theory in networks allows testing its propositions in controlled settings such as laboratory experiments. The experimental design developed by Cook, Emerson, Gillmore, and Yamagishi (1983) became the standard setup of many subsequent experiments on negotiated exchanges in negatively connected exchange networks. At the beginning of the experiment, agents are randomly assigned to a position in the network which they keep throughout the experiment. During the experiment agents may negotiate on how to divide a fixed amount of resources. Agents send offers and counter-offers until either an agreement or a time limit is reached. If two agents fail to agree, both agents gain nothing. The information available to the agents varies across studies. They may or may not be informed about the profit of others, the form of the network, or their position in the network. Cook et al. (1983), for example, use a restricted-information setting in order to limit the effects of agents' equity preferences on bargaining outcomes in a five-node network (see Figure 2). Many subsequent experiments relax this information restriction and instead use a full-information setting, that is, agents are informed about the constant sum to be divided, the shape of the network, and their position in the network.

Once the focus shifted away from explaining behavior and the outcome of exchange solely in terms of network structure, not only the theoretical models but also the experimental settings became more diverse and sophisticated. For example, "[t]he rules about the form of exchange, who can exchange with whom, for how long, whether individuals can choose their partners or not, [...] and other aspects of the exchange interaction" (Cook, Cheshire, Rice, & Nakagawa, 2013, p. 80) were varied.

*Figure 2*: 5-node network with restricted information (Cooket al., 1983, p. 280)




*2.3 Historical Development*

George Homans (1961) was among the first sociological theorists who focused on interpersonal exchange, emphasizing individual behavior. He described behavior as a function of payoffs obtained from other humans or non-human agents. In the tradition of behaviorism, he incorporated the principle of reinforcement according to which A's behavior is reinforced by B's behavior and B's behavior is in turn reinforced by A's behavior. Homan's main interest was social behavior that emerges over time from this social process of mutual reinforcement. He framed his ideas in terms of rewards and punishment and discussed the conditions of exchange behavior. Homan's focus on the individual in the explanation of processes in social groups was criticized as reductionist by Peter M. Blau (1964) because of the use of psychological principles to explain social behavior (Cook et al., 2013, p. 62). Instead, Blau proposed a more economic and utilitarian view on behavior. In the utilitarian tradition, he assumed agents to be forward-looking and acting in anticipation of future rewards, as opposed to the more backward-looking agent assumed by Homan's reinforcement principle. Blau focused mainly on reciprocal exchange of extrinsic benefits and the thereby created social structure (Cook et al., 2013). His work on the structure of social exchange and emerging social processes in groups influenced Richard M. Emerson's *Power-Dependence Theory* (1972a; 1972b), which combines the work of Homans and Blau. He moved the focus from the individual agent in a dyadic exchange relation to larger networks and shifted the emphasis to the relations between agents and the *structure* of the exchange network. He defined an exchange network as a set of directly connected exchange relations mutually influencing each other. From then on, research on social exchange generally moved to a more formal and analytical approach (Cook et al., 2013; Molm, 2007).

**3. Structure, Power and the Form of Exchange**

Early social exchange theories assume that the static structure of a network determines individual bargaining power. These exchange theories can be divided into three branches. The first branch originates in Emerson's *Power-Dependence Theory* and has mostly been pushed forward by a group of researchers around Karen Cook. The second branch is *Network Exchange Theory (NET)*, associated with David Willer, Barry Markovsky, and others. The third branch is the extensive research program of the group around Linda Molm, which analyses different forms of exchange.

*3.1 Network Structure and Power*

The first branch of early social exchange theories was initiated by Cook and Emerson in the 1970s and 1980s. Cook et al. (1983) and Cook and Yamagishi (1992) expand the scope of the *Power-Dependence Theor*y of Emerson (1972a, 1972b) to develop the so-called *Equi-Dependence Theory*. This theory assumes that structural power is a function of mutual dependence of agents in negatively connected networks. The maximum amount of resources an agent can gain in an exchange depends crucially on the best alternatives of her exchange partner. If an agent attempts to obtain more than this maximum, the partner will choose her best alternative instead. At the point where agents A and B are equally dependent on each other, the relation is said to be *equi-dependent*. The exchange ratio at this equilibrium is not necessarily an equal split of resources. Instead, it reflects the relative structural power of the exchange partners. Agents can thus have weak power or strong power. In a laboratory experiment, Yamagishi and Cook (1993) find that strong-power agents gain more in exchange than weak-power agents as predicted by *Equi-Dependence Theory*.

A different approach is chosen by Cook and Emerson (1978), who manipulate power by varying the *value* of exchange relations in an experimental study. In a power-balanced network, all agents dispose of the same number of equally valuable exchange relations and all agents are expected to benefit equally from exchange. In a power-unbalanced network, exchanges with the central agent are of more value than exchanges with the peripheral agents. That is, despite of having the same number of exchange alternatives available, the peripheral agents are less powerful than the central agent and are expected to benefit less from exchange. The experimental results support these hypotheses: While outcome differences between the central and the peripheral agents converge towards a very low level in balanced networks, they continue to exist in unbalanced ones. Cook and Gillmore (1984) also use differences in value to manipulate power in exchange networks. The authors assign different values to the exchange relations in a three-agent exchange network to study whether two weak agents choose to form a *coalition* against the stronger agent when given the opportunity to do so. The experimental results show that power imbalances indeed lead to the formation of "weak-against-strong" coalitions and an almost equal distribution of profits between the powerful agent and the coalition of weak-power agents. Furthermore, coalitions are more likely to form the more severe the imbalance of power in the network is. Besides these two studies, value has not been used to manipulate power in exchange networks until the late 1990s, when value has been rediscovered as a research topic in the context of social exchange theory (see Section 4).

*3.2 Network Exchange Theory*

Another branch of early social exchange theories is the so-called *Network Exchange Theory (NET)* which was developed on the basis of Elementary Theory (Willer & Anderson, 1981) as a critique of *Power-Dependence Theory* (Markovsky, Willer, & Patton, 1988). In order to assess the relative power of positions in a network, the authors develop the so-called graph-theoretic power index (GPI) which is related to structural concepts from social network analysis. Markovsky, Skvoretz, Willer, and Lovaglia (1993) further refine *NET* by introducing the concept of exclusion: an individual in a weak position is more likely to be excluded from exchange than an individual in a strong position. They introduce the path-breaking distinction between *weak* and *strong*-power networks. In weak-power networks, power and thus individual profits are distributed more evenly, compared to strong-power networks, where the structure of the network enables individuals in powerful positions to acquire more profit than others.

These predictions are tested by Skvoretz and Willer

(1993), who have been first to experimentally compare predictions of a set of different exchange theories, to which they added their own *Exchange-Resistance Theory*.[2] This theory is close to NET in its assumptions, but includes the concept of resistance. An agent is considered less likely to *resist* the terms of an agreement if she faces a high probability to be excluded from exchange. When both agents are equally resistant to their offers, the point of *equi-resistance* is reached. They identify *Exchange-Resistance Theory* as the best model explaining the observed outcomes.

Lovaglia, Skvoretz, Willer, and Markovsky (1995) further develop *NET* by combining the concept of resistance with the degree of the agent, another concept stemming from network analysis. The degree of an agent is the number of direct relations this agent has to other agents in the network. The resulting *GPI-RD* model assumes that a higher relative degree of an agent leads to a higher outcome. Further, a higher degree is assumed to bias the effect of inclusion in an exchange network: a structurally advantaged agent may gain more from a single exchange, but may exchange not as often as agents with a lower relative degree since others expect higher-degree agents to be tougher in bargaining. The authors test the same theories as Skvoretz and Willer (1993) and add the *Exchange-Resistance* model and the newly developed *GPI-RD* model, as well as a the *GPI-R* model, which is basically the same as the former, but without degree. They find that the *GPI-RD* model offers the most exact predictions.

Another model to be mentioned in this context is the *Power Model* of Yamaguchi (1996), which is applicable to positively and negatively connected networks. Yamaguchi assumes power to be the result of an agent's network position (structural causes) and the exchanges with her network partners (relational causes). The power of an agent is affected by the utility maximizing behavior of her partners. As long as a network has not reached an equilibrium stage, agents will seek alternative partners for exchange, leading to an increase in the power of those partners facing a rising demand for their resources. Using the experimental data of other studies, Yamaguchi finds experimental support for his model's predictions and claims that his model performs at least as well as *Expected Value Theory* and *Exchange-Resistance Theory*. However, the model was subject to sharp methodological criticism by Markovsky, Willer, Simpson, and Lovaglia (1997), and was not further developed.

In a comparative study, Willer and Emanuelson (2008) test ten social exchange theories that have been developed until that point. They identify the *GPI-R* model (Lovaglia et al., 1995) as the best performing theory and the *Equi-Dependence Theory* (Cook & Yamagishi, 1992) ranks ninth.[3] The authors also call for the extension of all existing theories to larger networks and contribute a paper on large scale exchange networks (Willer, Van Assen, & Emanuelson, 2012), in which the authors offer *Domain Analysis* (DA) as a tool to cut large networks into smaller, calculable networks.[4] *DA* distinguishes between domains (subnetworks which function inside and outside the large network in the same way), components (subnetworks function in the large network and outside of it in different ways) and breaks (connections which are never used) -- concepts, which are also used in network analysis. Experimental data and a simulation support their proposition of domains, components and breaks in social exchange networks. They show that power decreases as network density increases. Density is a measure for the number of connections in a network, a concept developed by social network analysists. Although DA only seems to work in networks with low density it nevertheless widens the scope of social exchange theories.

The theories presented so far share the assumption that all exchanges in a network happen simultaneously. In contrast, *Sequential Power-Dependence Theory*, developed by Buskens and Van De Rijt (2008), considers the sequential nature inherent to exchange. As soon as two agents have decided to exchange, the opportunity structure for the remaining agents in the network changes and this, in turn, may change their bargaining power. The anticipation of a potential loss of power should cause profit splits to be more equal than usually predicted in such a network. Buskens and Van De Rijt (2008) develop a measure to predict unique profit splits for every dyadic relation in every possible network type under consideration of a changing opportunity structure.

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2 Skvoretz and Willer (1993) evaluate the predictions of their Exchange-Resistance Theory as well as those of three other theories: Core Theory (Bienenstock & Bonacich, 1992), Equi-Dependence Theory (Cook & Yamagishi, 1992), and Expected Value Theory (Friedkin, 1992).

3 Tested theories: Power-Dependence Theory (Cook & Yamagishi, 1992), the GPI-R Model (Lovaglia et al., 1995), X-Net (Markovsky, 1995), Quantified Core (Bienenstock & Bonacich, 1992; Skvoretz & Fararo, 1992), Expected Value Theory (Friedkin, 1992), Rational Exchange Theory (Skvoretz & Fararo, 1992), Power Model (Yamaguchi, 1996) , Identity Theory (Burke, 1997), Network Control Bargaining Model (Braun & Gautschi, 2006), and the Expected Value-Resistance Model (Willer & Emanuelson, 2008).

4 The application of exchange theories is often limited by the size of a network. The maximum possible is at most 12 agents. Theories can be applied to small networks in a lab experiment, but not to larger networks in the field. The network size is limited because of computational complexity or the limits programs for application have (Willer et al., 2012, p. 171).

The authors refer to the data generated by Willer and Emanuelson (2008) to assess the predictive power of two variations of the *Sequential Power-Dependence Theory* in comparison to three other theories.[5] Both models outperform the predictions of *Equi-Dependence Theory* and *Expected Value Theory*. However, the *GPI-R* model still performs better and thus the conclusion of Willer and Emanuelson (2008) is supported.

*3.3 The Form of Exchange and Power*

Following the lead of the seminal experiment of Cook et al. (1983), the vast majority of theoretical and experimental studies discussed so far assumes implicitly or explicitly that exchanges are *negotiated*. However, the limitation to one form of exchange and the neglect of other forms may have led to assumptions and principles valid only for negotiated exchange and not for exchange in general since "the form of exchange affects the causal mechanisms underlying power use and the relation between network structure and power" (Molm, 2003b, p. 1). To overcome this limitation, Molm and colleagues started a series of experiments in the late 1990s to study how the *form of exchange* affects power, inequality, trust and commitment as well as the perception of fairness in exchange relations. Besides the form of exchange, Molm (1997) further distinguishes between power of coercion (that is, power based on the capacity to punish) and power of reward (that is, dependence on others for rewards).

Molm's *Theory of Coercion in Exchange* builds on Emerson's *Power-Dependence*.[6] Coercion is not induced by the structure of a network but has to be used strategically by the agents (Molm, 1997). Molm, Peterson, and Takahashi (1999) find experimental evidence that average power use is lower in reciprocal exchanges than in negotiated exchange. Powerful agents gain more from exchanging with more dependent agents in negotiated exchange, while they gain more from exchanging with less dependent agents in reciprocal exchange. In negotiated exchange, powerful agents seem to prefer the less risky strategy of exchanging continuously with a partner who is more dependent rather than choosing a more valuable but riskier strategy of exchanging primarily with the less dependent partner.

In the 2000s, Molm and colleagues set out to develop a more general theory of power in exchange networks. In a first step, Molm, Peterson, and Takahashi (2001) consider variations in the relative *value* of a resource as a further dimension, as did Cook and Gillmore (1984; see above). They argue that an agent A's dependence on B increases the more value A can obtain from B, relative to the value A can obtain from alternative exchange relations. Access to more valuable alternatives decreases A's dependence and increases A's power over B. Consequently, A's power use over B is expected to increase with the availability of more valuable alternatives, resulting in higher payoffs for A. In an experimental study, Molm et al. (2001) found that in negatively connected networks A's power over B not only increases with the value of A's alternatives to B, but that a higher value even tends to compensate for lower availability. Building on these results and results obtained in other experiments, Molm (2010) develops the *Theory of Reciprocity*. This theory will be described in the following chapter since it marks the beginning of a stronger social-psychological orientation of Molm's research agenda.

Early social exchange theories have been mainly concerned with the structural properties of a network and its consequences for the action space of its agents. The pioneering social exchange researchers focus not only on similar topics as social network analysists, that is, structure and power, but also use similar concepts to describe networks and relations. As social exchange theory evolves, the connection to network analysis decreases and the focus of social exchange research shifts gradually towards the individual agent in the network.

## 4. Social-psychological Approaches

From the turn of the century onwards, social-psychological factors and their influence on behavior in social exchange networks have attracted more attention. In contrast to purely network analytical approaches, these theories explain behavior in exchange networks and outcomes of exchange on the basis of preferences and emotions. In this section we will present the research program which led to the development of the *Theory of Reciprocity* as well as other social-psychological theories of exchange. Social-psychological approaches consider exchange relationships to exceed the exchange of material goods between rational profit-maximizing agents. Agents are perceived as social agents who can feel emotions (e.g. Lawler, 2001; Molm, Peterson, & Takahashi, 2003),

5 GPI-R model (Lovaglia et al., 1995), Equi-Dependence Theory (Cook & Yamagishi, 1992), and Expected Value Theory (Friedkin, 1992).
6 Molm (1997) maps the development of her Theory of Coercion in Exchange and thereby gives an excellent example of the development of theory in a theoretical research program using laboratory experiments (see Zelditch, 2014). See chapter 10 for a summary on the theory and chapter 11 on the results of the experiments.

commit to a relationship (e.g. Lawler, Thye, & Yoon, 2006; Molm, 2010), and experience cohesion within a relation or a network (e.g. Lawler & Yoon, 1998). In consequence, exchanges may be driven not only by economic rationality, but also by emotions or appreciation of a relation, thereby changing the interpretation of the dynamics observed in social exchange networks.

The role of emotions, commitment and cohesion in exchange situations have been studied for more than a decade largely in parallel by two research groups headed by Linda Molm and by Edward Lawler. Only recently, attempts of connecting and reconciling their theories and experimental findings were made (Kuwabara, 2011; Lawler, Thye, & Yoon, 2008; Molm, Melamed, & Whitham, 2013). We will first present the work of the two research groups separately and then discuss links between their research programs. Finally, we will review additional work on fairness, status and value.

### *4.1 Reciprocal Exchange and Salience of Conflict*

Molm (2010) develops the *Theory of Reciprocity* as part of an extended research program. In a first step, Molm et al. (2000) compare how *trust* and *commitment* develop in negotiated and reciprocal exchange networks. They find that trust and affective commitment (that is, positive emotions towards the exchange relation or group) are more likely to develop in reciprocal exchange relations than in negotiated exchanges. The emergence of emotions in reciprocal exchange networks depends on how the exchange partners behave. The greater the behavioral commitment (that is, recurring exchanges within the same relation) of the partner and the lower the inequality of profits, the higher the level of trust and affective commitment. These effects are not observed in negotiated exchanges. Confirming previous findings (Molm et al., 1999; see section 3) the experiment demonstrates once more that inequality of outcomes is greater in negotiated exchanges.

In another series of experiments, Molm et al. (2003) show that agents in negotiated exchanges hold their exchange partner more responsible for the outcomes of exchange even if the outcome is the same as in the reciprocal exchange situation. In addition, they are more likely to perceive their partner as being untrustworthy, unhelpful, competitive, and tough. In reciprocal exchanges, the rate of reciprocity matters, while the value of the given benefits makes no difference. In negotiated exchanges, the value of benefits determines whether the exchange is perceived as fair, while the rate of exchange is irrelevant. Molm, Collett, and Schaefer (2006) suggest, and empirically show, that the greater *salience of conflict* in negotiated exchange is responsible for these differences in fairness perceptions between exchange types. In negotiated exchange, the agents are in direct confrontation with each other, i.e. the conflict is more salient, compared to unilateral giving in reciprocal exchange.

Emotions emerge not only with respect to the behavior of the other agents, but also towards the relation as such. Reciprocal exchange can provide *symbolic value* beyond the instrumental value of exchange. Symbolic value is created through constant reciprocal behavior of the other agent which triggers affection for an exchange relation (*expressive value*) and reduces uncertainty with respect to that relation. The authors show experimentally that agents primarily consider the expected instrumental value of exchange and less its symbolic value when choosing between two exchange relations of different instrumental and symbolic value. A potential explanation is that the instrumental value of an exchange relation is obvious right from the beginning, while the symbolic value of a relation becomes salient only after repeated exchange (Molm, Schaefer, & Collett, 2007).

Summarizing this research program, Molm (2010) suggests that the *Theory of Reciprocity* consists of three core elements: the risk of non-reciprocity, expressive value, and salience of conflict. These mechanisms jointly affect the development of integrative bonds of trust in an exchange relation, affective commitment, and relational cohesion.

### *4.2 Relational Cohesion and Jointness of Action*

Independent of, but parallel to the group headed by Linda Molm, Edward J. Lawler and his colleagues also study emotions and cohesion and their interaction with structural factors. Over a period of two decades, they have developed *Relational Cohesion Theory,* the *Affect Theory of Social Exchange, Network-to-Group Formation Theory* and the *Choice Process Theory of Commitment*.

Lawler and Yoon connect *NET* (see Section 3) with *Relational Cohesion Theory*, a theory developed and tested in a series of experimental studies (Lawler & Yoon, 1993, 1996, 1998).[7] The authors assume that the frequency of exchange affects an agent's relational cohesion and commitment to a relation. Two complementary processes are considered responsible

7 Initially, their focus is on the dyadic relation embedded in a minimal exchange network (i.e. agents have only one exchange alternative) or a small exchange network (e.g. kite or branch) and later they extend their theory to the entire network, i.e. multi-agent networks.

for the development of commitment in dyadic exchange relations. If exchange is repeated successfully between two agents, positive feelings emerge (emotional process) and the predictability of exchange with this partner increases (uncertainty reduction process). Consequently, agents perceive these relations as more cohesive and develop greater commitment to this exchange relation which results in a more favorable treatment of the exchange partner. Lawler and Yoon (1996) consider three forms of commitment behavior and compare them experimentally: (1) Agents stick to an exchange relation even if better alternatives exist (*staying behavior*), (2) unilateral and non-contingent *gift-giving* to the exchange partner in form of tokens, and (3) *contributing* to a group project when the profits from the project are divided equally among agents. The results support *Relational Cohesion Theory* by showing that the perception of relational cohesion stimulates all three forms of commitment. In later versions of the model, starting with Lawler et al. (2000), both the emotional process and the uncertainty reduction process are incorporated as complementary processes operating independently.

However, Lawler and Yoon (1998) notice differences in the level of relational cohesion and commitment between structurally induced equal-power relations and unequal-power relations. The relatively higher frequency of exchange in equal-power relations triggers stronger positive feelings and thus higher relational cohesion. These relations are also more likely to persist when agents are provided with a second and better exchange alternative after having exchanged with the same agents for some time. Lawler and Yoon interpret this staying behavior as a sign of commitment to the exchange relation.

In the same experimental study, Lawler and Yoon (1998) also test the effect of an overarching *group identity*, which is imposed *exogenously* on the network. They assume that relational cohesion and behavioral commitment in individual dyads are weakened by framing the whole exchange network as a group with a common identity. In this case agents are expected to keep exchanges balanced across all potential exchange partners. However, the experimental results show no evidence for a weakening of cohesion and commitment on the dyadic level in the group-treatment. Following up on this work, Lawler and colleagues (Lawler et al., 2000; Thye, Lawler, & Yoon, 2011) examine whether the endogenous processes underlying *Relational Cohesion Theory* (uncertainty reduction and emotional processes) may induce agents to develop a sense of cohesion not only on the level of the dyad but also on the level of the group or network in a productive exchange setting. Comparing the results of the triadic productive exchange experiment (Lawler et al., 2000) with the results of the earlier experiment on the dyadic level (Lawler & Yoon, 1996), the authors find that multi-agent exchanges exacerbate the development of cohesion and commitment behavior. However, although fewer positive emotions are created, the perceived group cohesion reaches the same level in triads as in dyads.

Emphasizing the crucial role emotions play for the development of cohesion and commitment, Lawler (2001) develops the *Affect Theory of Social Exchange*. The author assumes that emotions triggered through participation in exchange can be attributed to the relevant social unit (relations, groups, networks). His basic proposition is that the greater the *jointness* (joint action) of the exchange task, the greater the agents' perception of *shared responsibility* and the more likely agents will attribute their emotions to the relevant social unit, which in turn leads to stronger commitment and cohesion. The perception of jointness and shared responsibility depends crucially on the form of exchange, as experimental results show (Lawler et al., 2008). Productive exchange triggers the strongest emotions since tasks are highly interdependent and the degree of shared responsibility is high. In negotiated exchanges the shared responsibility for an exchange task is also relatively high since agents have to agree on binding terms of exchange. However, there is potential for conflict if structural power is unequally distributed. In reciprocal exchanges, Lawler finds that emotions resulting from a successful exchange are weaker since agents do not carry out a joint task and the perception of shared responsibility is lower. In generalized exchange, reciprocity is indirect and agents are unlikely to develop a strong sense of shared responsibility. According to Lawler generalized exchange thus lacks an emotional foundation.

### *4.3 Connecting Salience of Conflict and Jointness of Action*

At this point, the research agendas of the groups around Lawler and Molm start to converge. Both study emotions and relational cohesion, but while Molm locates the strongest emotions in reciprocal exchange, Lawler finds them in negotiated exchange. In a first attempt to explain their diverging findings, Lawler tentatively traces them back to the use of different concepts, namely *salience of conflict* and *jointness of task*. Depending on which concept is used and presented to the agents in the experimental questionnaire the findings may differ (Lawler et al., 2008, p. 539).

Kuwabara (2011) proposes to reconcile the divergent claims of Lawler and Molm by assuming that the *subjective context* of exchange determines whether negotiated exchange strengthens (Lawler's position) or weakens (Molm's position) relational cohesion. If agents perceive the exchange task as cooperative (competitive) and their exchange partner as positive (negative), they will develop more (less) cohesion, trust, and affective regards towards this exchange relation. These predictions are tested in two experiments. In the first, unilateral reciprocal exchange (i.e. gift-giving) is compared with two types of negotiated exchange with different levels of conflict. In competitive negotiated exchange, the salience of conflict is high, while it is low in cooperative negotiated exchange. The results concerning cohesion are unambiguous: in competitive negotiated relations, cohesion is lowest, reciprocal exchange ranges in the middle and cooperative negotiated exchange yields the highest level of cohesion. These findings are in line with both Molm's and Lawler's position, as Kuwabara (2011, p. 577) finds both "the mediating effect of perceptions of cooperation (Molm, 2010) and the moderating effect of joint action (Lawler et al., 2008)."

In their most recent work, Molm et al. (2013) also intend to reconcile *Affect Theory of Social Exchange* and their own *Theory of Reciprocity* by 'embedding' one form of exchange in the other. The experimental study shows that embedded negotiated exchange relations generate higher commitment and lower inequality compared to pure negotiated exchange relations while embedded reciprocal exchange relations do not trigger such effect.

### *4.4 Cohesion and Structure*

Even though Lawler and his collaborators focus their research mainly on emotions, commitment, and cohesion, they do not neglect the structural aspect of networks. Lawler et al. (2006) study the development of cohesion and commitment in structurally *enabled* and structurally *induced* relations. In a structurally enabled relation, agents mutually prefer to exchange with one another, while in a structurally induced relation they have other preferences but no alternative to exchanging with each other. The *Choice Process Theory of Commitment* (Lawler, 1992, 1997) suggests that agents are more likely to commit to exchange relations that give them a stronger sense of control, meaning that agents prefer enabled over induced exchange relations. In line with their expectations the authors find (1) stronger positive emotions, (2) greater perceived cohesion, (3) greater perceived relation value, and (4) greater commitment in structurally enabled than in structurally induced relations.

In a related experimental study Thye et al. (2011) study whether relational ties and the sense of shared experience resulting from frequent exchange are strong enough to induce agents to perceive *competitive* exchange networks as a group (Lawler et al., 2000). They develop the *Network-to-Group Formation Theory*, combining the concept of relational cohesion with the concept of structural cohesion from early social exchange theory (Cook et al., 1983). This theory distinguishes between cognitive and behavioral group formation. The first requires agents to perceive the network as a group, and the second can be observed when agents share resources even if this countervails their self-interest. Thye et al. (2011) find evidence that networks with a higher level of structural cohesion induce more frequent exchanges and, consequently, higher levels of cognitive group affiliation. The experimental results also indicate higher levels of behavioral group affiliation for agents in strong-power positions, but not for agents in weak-power positions.

In another related study, Yoon, Thye, and Lawler (2013) compare cohesion, emotions and variance of profits explicitly between dyads and triads based on two distinctions introduced by Simmel (1964). First, triads create the conditions for the existence of a 'tertius gaudens', i.e. a third person who may profit from the competition between the other two agents. Second, triads necessarily require the exclusion of one agent for structural reasons if agents are connected negatively. Agents take exclusion in a dyad more personally than in triads, since no structural force makes exclusion necessary. The elementary core of Simmel's reasoning is that "triads reduce variability" in behavior and thus in profit (Yoon et al., 2013, p. 1458). The authors find evidence for three hypotheses derived from Simmel's reasoning: 1) Exchange frequency and variance in profit converge in triads rather than in dyads, 2) cohesion is higher in triads, and 3) these results are driven by the fact that emotions have a stronger effect in dyads and the uncertainty reduction process is more important for triads. These findings contradict earlier social exchange theories (see Section 3), which predict more cohesion in dyads than in triads due to the power of exclusion in triads and the lack of other options in a dyad. The question is how exclusion from exchange in the dyad and profits can be distributed (equally) within the triad in repeated exchange settings.

### *4.5 Emotions and the Perception of Justice*

Various scholars study exchange in networks with a focus on justice and the perception of justice (Hegtvedt & Markovsky, 1995; Leventhal, Karuza, & Fry, 1980; Lind & Tyler, 1988; Tyler & Lind, 1992). Hegtvedt initially uses vignette-studies to address her research questions, but later turns to laboratory experimental methods.

How negotiations affect the perception of procedural and distributive justice, which in turn influence emotions and the distribution of outcomes, is examined in an experiment by Hegtvedt and Killian (1999). While procedural justice refers to the process of distribution, distributive justice refers to the resulting distribution of resources. The design of the experiment differs from previous designs. Participants divide points not only between themselves, but also a third party, who does not perform the same task as the other two agents. A positive correlation between procedural justice and distributive justice is found, but the types of justice trigger different emotional reactions. The perception of procedural fairness generates positive emotions, but is negatively affected by the emergence of conflict in negotiations. The perception of distributive fairness, on the other hand, is affected by the observed levels of profit and agents' performance levels. High performing agents perceive their own profit as more fair than low performing agents who perceive their lower income as less fair. Hegtvedt and Johnson (2000) conclude that individuals perceive different distributions as just and that an individual's view of justice can also be influenced by the groups' legitimization and endorsement of a distribution. Critically echoing the title of Molm et al. (2003), they claim that procedural and distributive justice "is not simply in the eyes of an individual beholder, but it is in the eyes of a community, however defined" (Hegtvedt 2005, p. 25).

Hegtvedt's work has only recently been recognized in the social exchange research community. Based on Hedtvedt's findings, Park and Melamed (2015) investigate the relation between reward and fairness perception in a productive exchange situation. They find a positive correlation between the stability of rewards and both the justice evaluation of the situation as well as the commitment of an agent to her group.

*4.6 Status and Value*

While Molm et al. (2001) treat value as a further dimension of network structure, Thye (2000) suggests that the value of a resource depends on the status characteristics of the negotiating agents. He develops the *Status Value Theory of Power*, suggesting that status value spreads from agents to resources if agents differ in their status characteristics (e.g. gender, race, education). Resources held (and sought) by high-status agents are perceived as more valuable than the same resources held (and sought) by low-status agents. As a consequence, exchanges with high-status agents are preferred and the *Status Value Theory of Power* predicts that positive status characteristics are accompanied by power advantages and higher profits in social exchange relations (Thye, 2000). The authors find support for these predictions in a laboratory experiment where participants are led to believe that they are exchanging with a partner of higher, equal or lower status. These results hold true in both equal-power structures and weak-power structures, suggesting that a higher status may even compensate for the disadvantages of a weak-power position.

Status also alters the expectations regarding the performance of an agent. The *Status Influence Theory of Power* developed by Thye, Willer, and Markovsky (2006) builds on *Status Characteristics Theory* (Berger, Norman, Balkwell, & Smith, 1977; Wagner & Berger, 1993; SCT) and on NET, from which the concept of exclusion is borrowed. SCT suggests that people expect agents with a higher level of status characteristics to be more competent, perform better and obtain better outcomes when negotiating with agents of lower status. In line with these theories, the authors find that high-status agents are perceived as more competent and influential by low-status agents. Consequently, high-status agents obtain higher profits from exchange.

*4.7 Identity*

A different perspective is taken by the *Identity Model* of Burke (1997), which focuses on the identity of a typical agent participating in a network exchange experiment. Contrary to most other theories, Burke's model does not assume that agents seek to maximize their profits from exchange. Instead, agents aim at participating in as many exchanges as possible. They try to avoid getting low profits from exchange as well as taking a long time to match offers which increases the likelihood of being excluded from exchange. What the agents are trying to accomplish is defined by their identity standards, while what they are actually able to accomplish depends on the structure of the network. Participants are motivated by the desire to be included in exchange and weak positions will make higher offers in order to be included. Power therefore emerges over time. Agent-based computer simulations are used to predict power and profit splits in different exchange networks.

The socio-psychological approaches summarized in this section show that not only the structure of a network, but also the behavior of others and individual preferences influence an agent's behavior. Positive and negative emotions play a role in the choice of an exchange partner, just as the status of the partner, the value of the exchanged goods and the relation itself. By adding socio-psychological concepts to the analysis of social exchange, the interpretation and prediction of agents' behavior in a network has changed. The main focus shifted from the structure of the network to the individual behavior of agents and the research interests of social exchange theory and social network analysis are less aligned.

## 5. Game-theoretic Approaches

We now turn to approaches applying game-theoretic principles, which are more common in economics, to social exchange networks. Bienenstock and Bonacich (1993, p. 117) comment, "[t]here is much overlap in what is studied in the social sciences. Different disciplines have different theoretical orientations and different approaches. Not infrequently, in two fields the same work may be under investigation with two distinct theoretical bases and two separate vocabularies." From a game-theoretic perspective, exchange can pose coordination problems and social dilemmas comparable to games such as the Prisoner's Dilemma, the Privileged Game, the Chicken Game (Borch & Willer, 2006, p. 78) or the Trust Game (e.g. Buskens, Raub, & van der Veer, 2010; Raub, Buskens, & Frey, 2013). The first attempts to analyze networks with game-theoretic methods took place in the early 1990s. From the mid-2000s onwards, a general movement of network exchange research towards game-theory can be observed.

### *5.1 The Pioneers*

The pioneers of game-theoretic research on social exchange networks stress how structure affects power and the distribution of outcomes (Bienenstock & Bonacich, 1992; Friedkin, 1992). In addition, they take the value of exchange into consideration (Friedkin, 1995; Skvoretz & Fararo, 1992). Bienenstock and Bonacich (1992) describe exchanges in negatively connected networks as N-person cooperative games with transferrable utility. They use the game-theoretic concept of the 'core' to predict the distribution of outcomes and the stability of exchange relations in the network.[8]

The core is based on the assumptions of individual, coalition and group rationality. Individual rationality implies that an agent will not accept an exchange providing her with fewer resources than she could earn by not exchanging. Coalition rationality implies that two agents only exchange when the sum of profits they obtain from exchanging with each other equals at least the profit they could obtain from exchanging with other partners. Group rationality entails that the total profit of all agents in the network realized by exchange is as least as high as the profit obtained in alternative exchanges (see Lovaglia et al., 1995). In networks with a core, the division of profits between agents satisfies individual, coalition and group rationality and is predicted to be stable. In networks without a core, agents are expected to have difficulties reaching an agreement and these networks are expected to be unstable. In a lab experiment Bienenstock and Bonacich (1993) show that their game-theoretic solution predicts relative power in exchange networks just as well as did *NET* and *Power-Dependence Theory* (see Section 3).

Friedkin (1995) uses the experimental data obtained by others (Bienenstock & Bonacich, 1992; Markovsky et al., 1993) to test the theoretical predictions of his own models. In the *Expected Value Theory* Friedkin (1992, 1993, 1995) takes into account not only the structure of the network, but also the value of the available exchange relations. He assumes that rational agents seize every exchange opportunity they have. Exchange outcomes are thus the result of the opportunity structure provided by the network and an agent's bargaining activities. He further assumes that an agent's exchange offer is a function of her dependence on her exchange partner. The expected value of an exchange for an agent A depends on the number of resources A expects to obtain from an exchange with B, weighted by the relative frequency of that specific exchange relation. The probability of an exchange depends on the value of the exchange in the previous period. This iterative process, in which the payoffs in one period affect the probability of exchange in the next period, is meant to explain why the most central agent not necessarily receives the largest payoff. The experimental results confirm the model's expectation that the central agent has an initial advantage in exchange which diminishes after some rounds when an exchange equilibrium with small power differences is reached.

### *5.2 The Network Control Bargaining Model*

More recently, Braun and Gautschi (2006) have developed the *Network Control Bargaining Model* (*NCB*) to predict outcomes in exchange networks. The model builds on the generalized Nash bargaining solution and combines it with a specific measure of individual network control. The authors assume that depending on the position in the bargaining network an agent exhibits different degrees of network control. Network control depends crucially on the number of A's exchange partners and the number

8 Other game-theoretic solutions would be the Shapley Value and the Kernel. For a summary, see Bienenstock and Bonacich (1993, pp. 126-128)

of her partners' exchange alternatives. In a negatively connected network, an agent's relative bargaining power and exchange profit will rise with an increase in her network control (or a decrease in the other agent's network control). The relative bargaining power of the agents involved in exchange determines the distribution of exchange profits. For empirical support, Braun and Gautschi (2006) refer to the experimental data of Skvoretz and Willer (1993) and compare the experimental observations with the theoretical predictions of the *NCB-Model* and six alternative approaches.[9] They conclude that the *NCB-Model* performs rather well in predicting profit division in exchange networks and "at least as well as the best fitting published theories" (Braun & Gautschi, 2006, p. 19).

*5.3 Trust and Embeddedness*

Coordination games and their solution are of focal interest to Game Theory. The coordination of behavior can pose a social dilemma in which all agents would value the outcome of shared investments, but nobody actually prefers to invest. The Trust Game (TG)[10] is an example of such a dilemma. The social dilemma inherent to the Trust Game can be solved if a dyadic exchange relation is embedded in a larger network or a repeated setting. Per definition "[e]mbeddedness refers to repeated transactions over time between the same partners and to transactions between partners who share a network with third parties" (Buskens et al., 2010, p. 310). The authors distinguish two mechanisms through which the social dilemma inherent in the TG can be solved: learning and control. Trustors can *learn* either from fellow trustors or from past behavior of the trustee and they can *control*, i.e. sanction, undesirable behavior if the trust game is repeated. Buskens et al. (2010) implement a finitely repeated trust game with two trustors and one trustee in the lab. They find that trustors trust more often in their trustee if information about previous interactions with a fellow trustor is available (network embeddedness) than when no information can be obtained. Trustees are more trustworthy if their behavior is public information (control). As a result trustors experience that their trust is honored more frequently, inducing them to trust with a higher frequency in future interactions. Thus, Buskens et al. (2010) attribute higher trustfulness to learning mechanisms rather than control mechanisms. In a subsequent experiment Van Miltenburg, Buskens, and Raub (2012) test whether more experience leads to network control effects of trustors over trustees and find a weak, but not entirely convincing network control effect for the trustor. The authors suggest that experience in general appears to result in behavior that is closer to the expected equilibrium model.

*5.4 Coordination through Conventions*

Not only embeddedness but also the choice of a *convention*, or norm, to coordinate actions can help to solve a coordination game.[11] Conventions are characterized by the fact that most agents would prefer them to be fulfilled, but are hesitant to comply themselves because of the risk that others do not comply. This translates into a coordination problem with two equilibria, a payoff-dominant and a (lower) risk-dominant equilibrium. An agent can either play cooperate or defect (that is, abide by the convention or not). If all other agents defect (cooperate), the risk-dominant (payoff-dominant) equilibrium is reached. Frey et al. (2012) find, contrary to theoretical expectations, that the payoff-dominant equilibrium is selected overwhelmingly often and early in the game. It is also established faster than the risk-dominant equilibrium. Even if deviations from the payoff-dominant equilibrium occur, the agents within the network manage to re-establish it.

Another form of a coordination game is the Chicken Game. The dilemma inherent in this specific coordination problem is that if the most efficient outcome for the dyad is realized, one agent is always worse off than the other. Experimental results obtained by Tsvetkova and Buskens (2013) show that in a repeated game agents manage to coordinate on the use of specific 'conventions' which may also be interpreted as social norms. The convention to alternate actions independently in each relation, representing direct reciprocity, is preferred to the stationary approach to divide all relations in one or the other relation and stick to it, representing indirect reciprocity. Tsvetkova and Buskens (2013) suggest that

9 The alternative approaches are Lovaglia et al.'s (1995) GPI-RD, Yamaguchi's (1996) Power Model , Skvoretz and Willer's (1993) Exchange Resistance Theory, Friedkin's (1992) Expected Value Theory, Cook and Yamagishi's (1992) Equi-Dependence Theory, and Burke's (1997) Identity Theory.

10 In the classical TG two agents interact. Agent A (the sender or trustor) is endowed with a fixed amount of resources. She can choose to send (a fraction of) the endowment to agent B, thereby placing trust in agent B. The amount sent is multiplied by a factor larger than one. Agent B (the receiver or trustee) can then either keep or send (a fraction of) the received amount back to agent A. By sending back resources he proves to be trustworthy. Exchange in trust games happens sequentially and conditionally.

11 A convention may be traffic rules or dressing formal for official functions (Frey, Corten, & Buskens, 2012).

indirect reciprocity only occurs when direct reciprocity is ruled out.

*5.5 Coalitions in Social Exchange Networks*

A second important application of game theoretical concepts in a network context is coalition formation in asymmetric networks. Under certain conditions, low-power agents are able to reverse the distribution of power in a network through collective action. Emerson (1972b, p. 85) already stated that "when one party has a power advantage based upon alternative relations, this advantage can be reduced if these relations are condensed through coalition."

The general experimental setup is such that one high-power agent is connected to several weak-power agents with whom she can bargain about the division of a pool of resources in a negatively connected network. If weak-power agents manage to coordinate and form a coalition, they can undermine the power of the high-power agent. Agents within a coalition send a collective offer to the high-power agent and split the outcome of the exchange equally among them. With collective action they avoid the usual bidding war. For a coalition to be stable it needs to reach a minimum size in order to rule out being excluded from exchange. But there is a social dilemma inherent in the process of coalition formation, as an agent excluded from the coalition can free-ride on the coalitions' offer if the minimum size is exceeded. Consequently, forming a coalition is beneficial for bidders, but free-riding is an individually dominant strategy. Assuming all agents to be rational payoff maximizers everybody prefers to free-ride on the others' coalition and, therefore, no coalition will be formed, thus preserving the social dilemma.

The first experiment studying how collective action affects power distribution in exchange networks has been conducted by Cook and Emerson (1984), building on the assumptions of *Power-Dependence Theory*. The experimental results show that power-imbalances indeed lead to the formation of coalitions of the weak against the strong and result in an almost equal distribution of profits between the powerful agent and the coalition of weak-power agents. The frequency of coalition formation is highest when power is severely imbalanced and lowest when power is balanced. Simpson and Macy (2001) replicate these findings by including the option to free-ride on the coalition's offer. Their experimental results do not confirm the predicted instability of coalitions which are larger than the minimum size. One explanation for this surprising result may be that each agent expects the other agents to defect in the next round, making cooperation the best strategy.

The social dilemma of the bidding-war between weak-power agents can also take the form of a Prisoner's Dilemma. Cooperation stands for offering exactly half of the points and defection for offering less and free-riding on the other agents' higher offers. If all weak-power agents offer exactly half of the points, the dilemma is solved by collective action, as the high-power agent is now indifferent between the offers. Defection is individually beneficial, but collective cooperation is the best strategy. Contrary to the weak-power agents, the high-power agent plays a Privileged Game where individual and collective preferences are the same and no dilemma emerges, as she cannot be excluded from exchange through her beneficial position in the network. Borch and Willer (2006) find that through the formation of coalitions, low-power agents can countervail power and play the Privileged Game instead of the Social Dilemma Game.

Also following a game-theoretic tradition, Simpson and Willer (2005) suggest that there are collective goods embedded in certain network structures. A collective good is gained if low-power agents act collectively by forming a coalition. As a result everyone is better off compared to acting individually. The authors introduce a sanctioning system which eliminates potential incentives to free ride. The experimental results show that in positively connected networks, coalition formation has no effect on outcomes. In negatively connected networks, average earnings of low-power agents increase substantially when coalitions are formed. The distribution of power is even reversed with the high-power agent receiving less than half of the pie.

The process of coalition formation can also be influenced by non-structural factors such as social identity (Simpson & Macy, 2004) or the endorsement of the coalition by other agents (Walker & Willer, 2014). The endorsement of a coalition by others is expected to influence an agent's vote for (or against) the formation of a coalition. In the experiment of Walker and Willer (2014) weak-power agents are informed about the preferences of the other low-power agents regarding the formation of a coalition before casting their vote.[12] The authors find that legitimacy enhances coalition building. However, coalitions are more likely to be formed in small networks than in larger networks. While coalitions in large networks countervail power, the effect is reversed

12 Note that the preferences communicated to the agents are not the real preferences elicited from the other group members but preferences generated by the experimenter.

in small networks. Simpson and Macy (2004, p. 1400) conclude that "[e]xchange network theories must move away from the traditional conception of social structures as fixed and unyielding."

*5.6 New Perspective and Outlook*

The fact that the structure of a network affects the behavior of its agents has been well established. However, the assumption that network structures are static has already been questioned by researchers considering the formation of coalitions (Buskens, Corten, & Raub, 2014) and the endogenous formation of networks is attracting more and more interest.[13] Because the endogenously emerging structure still influences the agents' behavior, the complexity of models of social exchange is increasing substantially. Every change in the structure of the network can shuffle and reshuffle opportunities, dependencies and power. Therefore, experimental tests may be much more challenging and problematic. One way forward is to use computational simulations to tackle the complexity of new models, a tool which is also increasingly used in social network analysis, as simulations allow for the examination of large structures.

Not only the endogenous emergence of a network's structure is of great interest, but also the behavior leading to the formation of certain network structures and, furthermore, how network formation can be used to solve coordination problems (Raub et al., 2013). Van Dolder and Buskens (2014) examine experimentally whether agents deviate from their preference for profit maximization in a setting of dynamic network formation but find no evidence supporting their hypothesis. Corten and Buskens (2010) study whether and how agents solve a coordination problem in a network by changing the network structure. They find that agents form ties with other agents playing the same strategy (cooperate or defect) and cut ties with those agents playing the other strategy. Agents manage to coordinate on the payoff-dominant equilibrium with higher frequency than expected, thereby suggesting that agents are not as myopic as assumed.

Further experimental studies dealing with social network exchange in general and endogenous network formation in particular are expected to be published rather soon, since several new theoretical models have been published recently (e.g. Frey, Buskens, & Raub, 2015; Raub et al., 2013; Raub, Frey, & Buskens, 2014).

**6. Concluding Remarks**

In this article, we summarize the rich variety of experimental studies conducted in the field of social exchange research. In the early stages, social exchange research evolved relatively close to social network analysis in its research interests. The structure of a network and its implications for exchange outcomes was of focal interest. Over time, the level of analysis expanded from the meta-level of the network, to the micro-level of individuals, relations, and the value of relations for individual agents. By equipping agents with preferences and emotions, the horizon of social exchange theories expanded, but also moved this strand of research further away from a purely structural perspective. Recent developments, especially by scholars using game theory as a tool for analysis, show a shift back to research questions examined by classical social exchange theorists, such as the endogenous emergence of network structures or the study of larger networks.

Several streams of research have evolved in parallel academic worlds without taking much notice of each other's research. However, a more positive reading of the history of social exchange research would suggest that this high degree of self-referential closure may have helped the research programs mature until their findings have become sufficiently robust to fruitfully and confidently confront other perspective and contributing to cumulative knowledge. Recent contributions integrating elements of different research traditions show that the patience of the cumulative work on social exchange networks pays off by generating well-scrutinized propositions and solidly founded theories.

One shortcoming of social exchange theory may be that it has, for a long time, limited itself to very simple network structures of little interest to scholars in network analysis. But the complexity of larger networks mandates substantial departures from the standard theories and methods. Models become analytically intractable and numerical approaches are needed to derive testable predictions. Moreover, simple network experiments are limited in their capacity to reconstruct the theoretical network structures in the laboratory. Social media and other web-based networks may constitute a certain potential for studying and testing these new research questions. Nevertheless, modern social exchange research has much to offer to network analysis with respect to the

13 In economics, the research on network formation has been expanding over the past years. See for example Berninghaus, Ehrhart, and Ott (2006); Callander and Plott (2005); Carrillo and Gaduh (2012); Falk and Kosfeld (2012); Goeree, Riedl, and Ule (2009); Hauk and Nagel (2001); Kirchsteiger, Mantovani, Mauleon, and Vannetelbosch (2013). For an earlier review, see Kosfeld (2004).

analysis of the social consequences of network structures. More than half a century after the founding fathers of social exchange research published their first ideas, the research area is still an expanding area of research. But beyond that, it was exactly the stepwise, cumulative and, in particular, patient approach taken by the researchers in this field, which now places the next generation into a position to engage in even broader and interdisciplinary discourse, which may eventually lead to an even better understanding of human interaction in social contexts.

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# Network Influences on Behavior: A Summary of Tom Valente's Keynote Address at Sunbelt XXXV: The Annual Meeting of the International Network for Social Network Analysis

**Stephanie R. Dyal**
*University of Southern California*
*Los Angeles, CA, USA*

**Author**
**Stephanie R. Dyal, B.S.,** *is a doctoral candidate in the Department of Preventive Medicine, University of Southern California/Keck School of Medicine, Los Angeles, California, USA.*

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*Correspondence concerning this work should be addressed to Stephanie Dyal, Department of Preventive Medicine, University of Southern California, 2001 N. Soto St, MC 9239 Los Angeles, CA 90033 USA. Email: stepharp@usc.edu.*

Tom Valente's 2015 keynote address overviewed his career focused on network models of the diffusion of innovations and behavior change, where he made his mark as a skilled theoretician. He is well known in the academic community as a willing collaborator and networker. He has made singular contributions to network models of the diffusion of innovations, including the role of opinion leaders, and network interventions to promote behavior change. Tom's keynote featured empirical findings from applying his theoretical models to classic diffusion datasets and current work focused on the diffusion of global tobacco policy. He concluded his talk with a summary of network interventions, which may be used to guide intervention development, evaluation, and dissemination (Valente, 2012; Valente, Palinkas, Czaja, Chu, & Brown, 2015). His keynote address emphasized not only his scientific contributions but also how his career was guided and influenced by colleagues, friends, and mentors.

Tom's work highlights the need to examine personal network exposure and thresholds in addition to exposure from the whole network when assessing behavior, behavior change, and intervention effects. Diffusion of innovation theory explains how ideas, behaviors, and products spread throughout a network (Valente & Rogers, 1995). Tom expanded upon diffusion theory for his dissertation by providing theory and techniques for integrating threshold and critical mass models with the diffusion process (Valente, 1995). Tom's network threshold model differed from Granovetter's (1983) threshold model in that Granovetter's model was predicated on people's innovativeness relative to the whole system, whereas Tom calculated thresholds relative to an individual's personal network. The novelty of Tom's dissertation was that some people are innovative relative to the whole community, but late adopters relative to their personal network and vice versa. A person's position in the network determines their exposure and people can be late adopters because their network position is such that they learn about the innovation late.

In order to complete a dissertation on network diffusion, Tom needed data. He realized that he needed to acquire secondary data to analyze as diffusion data can take years to collect since diffusion takes a long time. At this point in time (1989), few network diffusion studies had been conducted and of these some were lost. Of the studies he identified, data from three of them could be obtained and these became the three classic diffusion network datasets: Medical Innovation (Coleman, Katz, & Menzel, 1966), Brazilian Farmers (Rogers, Ascroft, & Röling, 1970), and Korean Family Planning (Rogers & Kincaid, 1981). These three datasets have been

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submitted to Connection's data exchange network and will also be made available for use in UCINET as well as in netdiffuseR, a new R package Tom is developing with George G. Vega Yon. To appreciate the challenges of obtaining these data in a pre-internet era, Tom shared some stories about how he got them. One story related to obtaining the Korean Family Planning data, which Rogers had given to Mark Granovetter, the Sunbelt X keynote speaker. Tom wrote to Granovetter who replied with a letter from Mark's colleague Dr. Roland Song (Figure 1) along with the only copy of the data which was stored on a Vax 750 tape, a data storage format that was outdated even at this point in time (1990).

Tom outlined the methods for and results from analyzing network exposure effects in the three classic diffusion datasets. The data were transformed to an event history dataset, where each person has multiple rows in the dataset, one row for each year when they did not adopt and one row for the year they did, and a binary variable indicating adoption status for each time point. Then, a discrete hazard model was calculated including effects for time, socioeconomic factors, degree, and network exposure. Using this methodology, Tom began his dissertation work assessing if cohesion or structural equivalence exposures were associated with behavioral adoption using two of the three classic diffusion network datasets. He found that the time tendencies were different for the 3 studies, as shown in Table 1. The results suggested that there was no time tendency for the medical innovation data, late adoption for the Korean family planning data, and negative, then positive time effects for the Brazilian farmers data. In Table 2, we see that exposure had a positive, significant effect for adoption for the Brazilian farmers study, but that there was no "contagion" effect for the other two studies. (NB: For Tom's dissertation he only had acquired the Korean Family Planning and Medical Innovation data, neither of which showed network effects.) This was alarming for Tom as diffusion of innovation theory suggests that the diffusion effect, the increasing interpersonal pressure to adopt an innovation as it diffuses, should be significant. This finding led Tom to develop his network threshold model (Valente, 1996).

*Figure 1:* Letter accompanying Korean Family Planning Dataset

Thomas Valente
Annenberg School of Communications
University of Southern California
Los Angeles, CA 90089-0281

December 8, 1990

Dear Thomas:

Per request of Mark Granovetter, I am sending you the tape and the code book for the Korean 1973 survey of 25 villages.

The tape is actually the original tape sent from Everett Rogers in 1978 (see the attached original correspondence). I do not know whether you will be able to get it read in after all this time. Good luck on that !

The code book is somewhat cryptic at places. For example, on the second page of Deck 5, there is a note: "* Attention ! Somewhat wrong - Chung - '. Mark Granovetter had written Chung several times, and has still not received a response to date. Even where the code book seems clear, the data on the file may in fact not be in agreement. I recall having to "clean" the data first, but I no longer have the details now. First of all, you should check for legal values. You may be able to make some corrections (I seem to remember that one field on one record was missing, so that everything else further on was shifted leftwards.). Next, you should check for logical consistency. You may find that someone is married before she was born. Finally, you should note that, according to the original study, the data from Village 12 should be dropped.

Since there are no other copies of the tape nor code book, please make copies and send them back. If you have any questions, you can contact Mark or myself. My telephone number is (212) 254-1550.

Roland Soong
Roland Soong
19 E 21 Street, Apt 2A
New York, NY 10010

cc: M. Granovetter

*Table 1*: Time tendences for likelihoods of adoption for the three classic diffusion datasets.

| Likelihood of Adoption | | | |
|---|---|---|---|
| | Medical Innovation N=868 | Korean Fam. Planning N=6,356 | Brazilian Farmers N=10,085 |
| Time 2 | 1.11 | 1.27 | 0.10* |
| Time 3 | 1.31 | 1.26 | 0.10* |
| Time 4 | 1.61 | 1.14 | 0.59 |
| Time 5 | 2.20 | 1.47 | 3.37** |
| Time 6 | 2.80 | 1.60* | 0.29 |
| Time 7 | 3.71* | 1.66* | 0.29 |
| Time 8 | 2.09 | 1.48 | 1.41 |
| Time 9 | 1.52 | 2.65** | 0.29 |
| Time 10 | 0.53 | 1.96** | 11.4** |
| Time 11 | 3.14 | | 0.70 |
| Time 12 | 2.20 | | 5.65** |
| Time 13 | 1.55 | | 2.26* |
| Time 14 | 3.73 | | 6.01** |
| Time 15 | 4.85* | | 11.54 |
| Time 16 | 1.17 | | 11.67** |
| Time 17 | 1.24 | | 18.1** |
| Time 18 | | | 16.9** |
| Time 19 | | | 22.26** |

*Note: *indicates p < .05, ** indicates p < .01*

*Table 2:* Predictors of likelihood of adoption for the three classic diffusion studies (controlling for time dummies (Table 1)).

| | Likelihood of Adoption | | |
|---|---|---|---|
| | Medical Innovation N=868 | Korean Fam. Planning N=6,356 | Brazilian Farmers N=10,085 |
| Detail Agents | 1.27 | | |
| Science Orientation | 0.60** | | |
| Journals Subs. | 1.63* | | |
| # Sons | | 1.43** | |
| Media Camp. Exp. | | 1.10** | |
| Income | | | 1.18** |
| Visits to City | | | 1.00 |
| Out Degree | 0.96 | 1.05 | 0.98 |
| In Degree | 1.04 | 1.06** | 1.02* |
| Exposure (Cohesion) | 0.94 | 1.16 | 2.16** |

*Note: * indicates p < .05, ** indicates p < .01*

While working on an evaluation of a media campaign to promote family planning in Bolivia, Tom found that the campaign did not increase contraceptive use. He had hypothesized that the combined effect of mass media and interpersonal communication exposures would be associated with contraceptive use, but the data did not support this. At this point, Tom was at his first job working in a staff evaluation position at the Center for Communication Programs at Johns Hopkins University. Not wanting to report back to the program developers that their program was not effective, Tom applied the threshold model from his dissertation. Table 3 presents the results of the Bolivian campaign analysis when the data are stratified by personal network threshold level. The Bolivia data showed that women with low thresholds to adoption reported higher exposures to the media campaign. The campaign was effective primarily for the women with low thresholds, in both panel and cross-sectional analyses. The threshold model provides a way to measure the two-step flow hypothesis of media effects (Valente & Saba, 1998). More than just modeling a theory, this research suggests that intervention effects may be missed if network thresholds to adoption are ignored. Tom's analysis found that health media campaigns are effective, but mostly worked by increasing contraceptive use for those people lacking contraceptive users in their network (Valente & Saba, 1998). This study suggested that media interventions may interact with social network characteristics: Exposure, position, embeddedness, and so on. Many media interventions may be effective through peer communication and assessing media effects using the threshold model may prove useful when conducting such studies.

Tom pointed out that the problem with network diffusion studies conducted to date is that they have used static measures of networks and adoption data are often retrospective recall or from incomplete records. One of his recent projects is attempting to correct this shortcoming by analyzing diffusion with complete adoption data and multiple, dynamic networks. This project was instigated when Tom heard about GLOBALink, an electronic forum which was developed to facilitate communication on global tobacco control issues. One of the outcomes of tobacco control advocates' work has been the creation, ratification, and implementation of the Framework Convention on Tobacco Control (FCTC) Treaty. GLOBALink consisted of about 7,000 members over its 20-year history, providing a large dataset with multiple networks for diffusion network analysis.

The advantages of the FCTC diffusion data are that the adoption data are accurate, there is no missing data, and there are multiple, dynamic networks. The influences of country attributes and exposures to treaty ratifications of other countries were analyzed using international trade and GLOBALink networks using similar methodology to that used on the classic diffusion datasets. Results of this study indicate that exposure to treaty ratification is predictive of future treaty ratification for some networks.

Tom wanted to do something more interesting with this dataset than just test prior theories. This inspired him to develop a dynamic model of diffusion effects (Figure 2) which includes peer influence, selection, external influence, and the role of opinion leaders, aggregating research findings from the past 60 years of

*Table 3:* Campaign exposure as a predictor of likelihood of adoption for Bolivian contraception study, stratified by threshold (from Valente & Saba, 1998).

| | Cross-Sectional | | Panel | |
|---|---|---|---|---|
| | Low Threshold | High Threshold | Low Threshold | High Threshold |
| Education | 1.35** | 1.75** | 1.31 | 1.4 |
| Income | 1.35** | 1.17 | 1.13 | 0.97 |
| Age | 0.92** | 0.92** | 0.98 | 0.98 |
| # Children | 1.15 | 1.2 | 1.05 | 1.21 |
| Campaign Exposure | 2.36** | 1.92 | 1.71* | 1.26 |

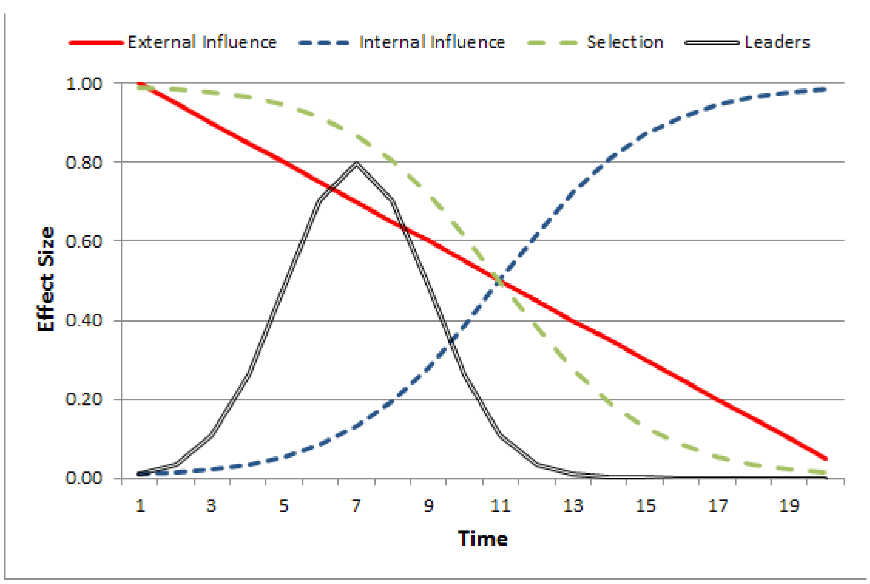
*Note: * indicates p < .05, ** indicates p < .01* diffusion research. The model proposes that external influence decays over time, selection is important early and decays over time, peer influence increases, and the role of opinion leaders varies. We have tested the model on the FCTC diffusion data and found partial support for its components. This work is currently being expanded upon in the Global Diffusion of Tobacco Control study (Valente, Dyal, Chu, Wipfli, & Fujimoto, 2015).

Tom has translated his empirical and theoretical work from network diffusion research to provide a framework for the use of social network data to design, adopt, implement and sustain behavior change interventions (Valente, 2012; Valente, Palinkas, et al., 2015). Research documenting the association between networks and behavior spurred researchers in the 1990's to pose this question: "If networks are so important how can they be used to accelerate change?" Many interventions have used the opinion leader model where opinion leaders are identified through social network analysis and recruited to be change agents who give talks and promote a new practice during informal conversations. Tom and his wife, Dr. Rebecca Davis expanded on the opinion leader model with their observation that leaders aren't necessarily leaders for everyone. They published a paper proposing the optimal Leader/Learner model in which leaders are identified and then matched to the members who nominated them (Valente & Davis, 1999). This model was tested in a randomized control trial and found to be more effective than when leaders are chosen via network nominations but groups constructed randomly (Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003; Valente, Unger, Ritt-Olson, Cen, & Johnson, 2006). Tom proposed that many research avenues remain unexplored in network interventions, such as whether it is better to identify groups first then choose leaders within them or identify leaders first and build groups around them, comparing different network approaches, and how contextual factors affect network interventions.

Tom's approach to his work focuses on examining the whole by looking at the parts. That is, in order to understand the behavior of a network, he considers how each individual node views its network and that each node can have a unique response to its network's influence. Calculating thresholds from nodes' personal networks, modeling effects of public health campaigns stratified on threshold, and acknowledging that leaders are only leaders for some nodes in a network all suggest attention paid to heterogeneity in nodes' perceptions of their network and nodes' susceptibility and influence. Without considering individual variation within networks, Tom would not have seen the influence of interpersonal communication on innovation adoption in the classic diffusion studies, or in his later research.

Tom proves that his theories are applicable to the real world with his work in network interventions and evaluations of health campaigns. Many interventions are evaluated without considering thresholds. Some interventions may have been deemed ineffective when they actually made a difference for people with low thresholds and low exposure. If we know that media interventions may not affect those people with high thresholds, what is the best intervention design to reach these people? Similarly, how do we identify those people likely to have low thresholds prior to diffusion occurring

*Figure 2*: Hypothesized dynamic model of diffusion effects (from Valente et al., 2015).



in order to design campaign advertising to reach these people?

Tom's research has spanned from studying societies where interpersonal communication occurs in person to studying communication enabled by the internet. Understanding how technology affects communication may prove important in future diffusion research. Work by Tom and his former graduate student Dr. Grace Huang suggests that exposure through social networking sites to photos of friends participating in risky activities may influence an adolescent's own risk behaviors (Huang et al., 2014). It is unclear how technology affects explicit and implicit endorsement, how people interpret information received through social media in comparison to in person, and how exposure and thresholds may be affected by technology.

In sum, Tom has provided theoretical models, empirical research, and practical intervention applications for diffusion of innovation theory. He stated that we know networks influence behaviors in profound and diverse ways, and diffusion theory provides a way to compare network influences on behavior and behavioral influences on networks. His research exemplifies the need to guide network research with theories and frameworks. However, his speech highlighted more than just his research contributions. Tom detailed how his career was influenced by his own social network filled with mentors, colleagues, and collaborators. His mentor, Dr. Everett Rogers, encouraged him to connect with other scholars and made sure he realized there were people behind the authors. Tom and Everett even conducted oral history interviews with about a dozen diffusion scholars from which Tom learned more about diffusion research than he ever did reading about it. Tom summarized his career so far by saying that networks matter, finding good mentors and colleagues is critically important, and that it takes time to build a career. Tom has certainly demonstrated these ideals as a researcher.

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# The South Carolina Network Exchange Datasets

**John Skvoretz**
*University of South Florida*
*Tampa, FL, USA*

**Abstract**
The article describes datasets from network exchange experiments collected at the University of South Carolina Laboratory for Sociological Research during 1989-1998. These datasets record time stamped negotiations between subjects as they seek to complete exchanges with one another.

*Keywords*: *Exchange networks, negotiation, structural advantage*

**Authors**
***John Skvoretz**,* is a Professor of Sociology at the University of South Florida and Carolina Distinguished Professor Emeritus from the University of South Carolina. He is a Fellow of the American Association for the Advancement of Science and past President of INSNA.

*Correspondence concerning this work should be addressed to John Skvoretz, Department of Sociology, University of South Florida, 4202 E. Fowler Ave CPR 107, Tampa FL 33620 USA. Email: jskvoretz@usf.edu*

## 1. Overview

The South Carolina Network Exchange datasets were collected at the University of South Carolina Laboratory for Sociological Research during 1989-1998 using ExNet, a computer program written by J. Skvoretz that implemented experiments on networks of exchange relations using a local area network of workstations, managing subject-to-subject interaction and experimenter monitoring of interaction. In these experiments, subjects connected by an exchange relation typically bargain in rounds of three to five minutes in length over the division of a pool of 24 resource points. In most cases, if they agree to a division before time runs out in a round and neither of them has exhausted the number of deals each is allowed in a round, an exchange is concluded and the agreed upon points are credited to the respective accounts. Each point earned has monetary value and the total points earned in an experiment determine the overall earnings of a subject. Experiments consist of multiple rounds and the main outcomes of interest are the points earned by a position in exchange with other positions and the frequency of exchange agreements in specific relations.

## 2. Data Collection

Data collection was supported by the following grants from the National Science Foundation:

- *Collaborative Research On: Fundamental Processes of Network Exchange*. September 1996 - November 1997, SES 9515434.
- *Action in Social Structures: New Research on Social Exchange Networks*. June 1993 - July 1994, SES 9223799.
- *Inclusion as a Basis for Power in Exchange Networks*. June 1991 - July 1993, SES 9109528.
- *Acquisition of Instrumentation for an Advanced Experimental Network*. June 1991 - July 1993, DBI 9016125.
- *Power, Exclusion and Network Exchange Dynamics* September 1990 - October 1991, SES 9010888.

All experiments followed the same basic protocol. Subjects unknown to each other were seated at terminals in individual rooms after completing a consent form. Communication between rooms was only possible through the workstation in the room. Subjects read instructions presented on the monitor and then engaged in a practice session in a simple network against actors

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simulated by an unsophisticated computer algorithm. A lab assistant monitored this training and practice stage to answer any questions. (In some later experimental runs a short quiz was part of the training session). After this stage, the experiment began and usually consisted of a known number of periods divided into a known number of rounds with the understanding that subjects would change positions in the network between periods. In full information conditions, a chart of the network was prominently displayed next to the monitor so that subjects could locate their current position and the positions occupied by partners and third parties. All "moves" in all negotiations were recorded and time stamped. A round ended when the 3 or 5 minutes allocated to a round ran out or a configuration of agreements, that is, exchanges, was completed that meant that no more exchanges could be made in that round. At the conclusion of the experiment subjects were paid based on the total number of points they earned. Subjects were instructed to try to earn as many points as possible.

**3. Data Files and Formats**

Individual data files are text files with a DAT extension and have the following organization. Each record begins with one of five identifiers: IA, IB, IC, ID, or D. The first four refer to records with initialization information. The fifth signifies a data record. The record identified by IA lists the network name, the id of the run, and the number of ties in the network. The record identified by IB list s the number of subjects and the number of periods. The record identified by IC is a list of elements, each element a list of five items: two positions that are connected to each other in alphabetical order, a number indicating the structural contrast holding between the two positions, a number indicating the presumptive advantage of the first position over the second position (+1 if advantaged, 0 if no advantage, -1 if disadvantaged), and a number indicating the advantage of the second position over the first position (again +1 if advantaged, 0 if no advantage, -1 if disadvantaged). The record identified by ID stipulates the rotation of subjects through positions by periods so if there are k periods, the first k entries are the positions occupied by the first subject in period 1 through period k, the next k entries are the positions occupied by the second subject in period 1 through period k and so on. Records IC and ID end with $$.

Records identified by D have eight elements following D: period (number), round (number), deal-number (number), sender (position letter), receiver (position letter), sender-share (number), action-type (offer/O, counteroffer/C, offer-acceptance/A, offer-rejection/R, exchange/E) and time-of-action-from-round-beginning (seconds). An action is coded as an offer when it is the first action in a negotiation or it follows an action by the same negotiator in a pair before a response is made by the other negotiator in that pair. An action is coded as a counteroffer if it is an offer made in response to an offer by a partner before the partner takes another action. Acceptances and rejections are actions that respond to a particular offer by a partner without offering new terms. In most runs, exchange occurs when an offer made by one partner is accepted by the other partner and then confirmed by the first partner. However, in runs made after August 1996, the protocol was changed so that all offers were bona fide, that is, acceptance by the receiver completed the exchange. The change in protocol was occasioned in part by the increasing size and complexity of the networks investigated.

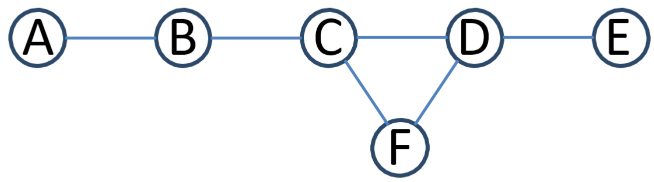
Here is one example.

```
IA L4EIIE   021694B     3
IB  4  1
IC A B 1 -1  1 B C 1    0 0 C D 1 1 -1 $$
ID A B C D $$
```

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| D | 1 | 1 | 1 | D | C | 16 | O | 3.24 |
| D | 1 | 1 | 1 | A | B | 15 | O | 3.35 |
| D | 1 | 1 | 1 | B | A | 22 | C | 5.43 |
| D | 1 | 1 | 1 | B | A | 23 | O | 9.55 |
| D | 1 | 1 | 1 | A | B | 14 | C | 11.09 |

The network name is L4EIIE, and its entry in the "Guide" describes it as a network of four positions connected as depicted below with experienced actors in the A and D positions and inexperienced actors in the B and C positions. The run-id is 021694B which is the date of the run (February 16, 1994) with B signifying that it was the second run of that day. There are three ties in the structure, four actors and only one period. Positions A and B are structurally distinct and A is disadvantaged over B while B is advantaged over A with respect to the first (1) and only structural contrast. Positions B and C are not structurally distinct with respect to the first (or any) structural contrast and so B is coded as having 0 advantage over C and C as having 0 advantage over B. Positions C and D are structurally distinct (in the same way that A and B are) with respect to the first structural contrast with C having advantage over D and D being disadvantaged over C. Since there is only one period there is no rotation so subject 1 occupies position A throughout the run, subject 2 occupies position B, etc. The first data record says that in period 1, round 1, deal-number 1, the subject in position D sent an offer to C in which the share to D was 16 points (and so the share to C was 24-16=8 points) at the 3.25 second mark. The second data record says that in period 1, round 1, deal-number 1, A sent an offer to B for a share of 15 to A (and so 9 to B) at the 3.35 second mark. The third data record says that B sent a counteroffer to A for a share of 22 to B (and so 2 to A) at the 5.43 second mark. The fourth record says that B revised his/her offer upward at the 9.55 second mark to A for a share of 23 to B (and so 1 to A).


The network name is BORG, and its entry in the "Guide" describes it as a network of six positions connected as in the figure below. The run-id is 041994B which is the date of the run (April 19, 1994) with B signifying that it was the second run of that day. There are six ties in the structure, six actors and six periods. All pairs of positions are structurally distinct from one another so there are a total of 6 structural contrasts. Positions A and B are in the first structural contrast and A is disadvantaged over B while B is advantaged over A. Positions B and C are in the second structural contrast with B advantaged over C and C disadvantaged over B. Positions C and D are in the third structural contrast with C advantaged over D and D disadvantaged over C and so on. The ID record stipulates the rotation: subject1 starts in position F in period 1, moves to position C in period 2, then A in period 3, then E in period 4, then B in period 5, and ends in position D in period 6, while subject2 starts in position C, moves to F, then B, then D, then A, and ends in E and so on. The first data record says that in period 1, round 1, deal-number 1, the subject in position B sent an offer to A in which the share to B was 20 points (and so 4 to A) at the 7.36 second mark.




Here is another example.

```
IA BORG      041994B     6
IB 6 6
IC A B 1 -1 1 B C 2 1 -1 C D 3 1 -1 C F 4 1 -1 D E 5 1 -1 D F 6 1 -1 $$
ID F C A E B D C F B D A E A E F C D B B D C F E A E A D B F C D B E A C F $$
```

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| D | 1 | 1 | 1 | B | A | 20 | O | 7.36 |
| D | 1 | 1 | 1 | C | B | 14 | O | 9.72 |
| D | 1 | 1 | 1 | B | C | 21 | C | 10.93 |
| D | 1 | 1 | 1 | E | D | 8 | O | 12.96 |

**4. Data Details**

| | |
|---|---|
| Response Rate | N/A |
| Non-Respondent Bias | N/A |
| Theoretical Grouping | Network Exchange Theory, Core Theory, Expected Value Theory, Power Dependence Theory |
| Publications Using These Data | Lovaglia, M.J., J. Skvoretz, B. Markovsky, and D. Willer. (1996). "Automated Theoretical Analysis of Exchange Networks: Prerequisites and Prospects." Connections 19:38-52.<br>Lovaglia, M., J. Skvoretz, B. Markovsky, and D. Willer. (1995). "Assessing Fundamental Power Differences in Exchange Networks: Iterative GPI." Current Research in *Social Psychology* 1: 8-15.<br>Lovaglia, M., J. Skvoretz, D. Willer, and B. Markovsky. (1995). "Negotiated Exchanges in Social Networks." Social Forces 75: 123-155. (Reprinted in Network Exchange Theory edited by D. Willer. Westport, CT: Praeger, pp. 157-184, 1999.)<br>Markovsky, B., J. Skvoretz, D. Willer, M. Lovaglia and J. Erger. (1993). "The Seeds of Weak Power: An Extension of Network Exchange Theory." *American Sociological Review* 58: 197-209.<br>Skvoretz, J. and T. Burkett. (1994). "Information and the Distribution of Power in Exchange Networks." *Journal of Mathematical Sociology* 19: 263-278.<br>Skvoretz, J. and M. Lovaglia. (1995). "Who Exchanges with Whom: Structural Determinants of Exchange Frequency in Negotiated Exchange Networks." *Social Psychology Quarterly* 58: 163-177.<br>Skvoretz, J. and D. Willer. (1993). "Exclusion and Power: A Test of Four Theories of Power in Exchange Networks." *American Sociological Review* 58: 801-818. (Reprinted in Network Exchange Theory edited by D. Willer. Westport, CT: Praeger, pp. 129- 154, 1999.)<br>Skvoretz, J. and D. Willer. (1991). "Power in Exchange Networks: Setting and Structural Variations." *Social Psychology Quarterly* 54: 224-238.<br>Skvoretz, J., D. Willer and T.J. Fararo. (1993). "Toward Models of Power Development in Exchange Networks." *Sociological Perspectives* 36: 95-115.<br>Skvoretz, J. and P. Zhang. (1997). "Actors' Responses to Outcomes in Exchange Networks: The Process of Power Development." Sociological Perspectives 40: 183-197.<br>Willer, D. 1999. Editor. *Network Exchange Theory*. Westport, CT: Praeger<br>Willer, D. and J. Skvoretz. (1997). "Network Connection and Exchange Ratios: Theory, Predictions, and Experimental Tests." Advances in Group Processes 14: 199-234. (Reprinted in Network Exchange Theory edited by D. Willer. Westport, CT: Praeger, pp. 195-226, 1999.) |
| Data Context | Experimental studies |
| Respondents | Undergraduate students |
| Longitudinal | Networks are fixed but negotiation moves are time stamped |
| Temporality | None |
| Analytical or Pedagogical Utility | Illustrates how structural position impacts behavior and outcome |
| Known Issues | None |

# The “Madre Sana” Data Set

**Sabina B. Gesell**
*Wake Forest School of Medicine*
*Winston-Salem, NC, USA*

**Eric A. Tesdahl**
*Vanderbilt University*
*Nashville, TN, USA*

**Abstract**
The Madre Sana data set was compiled as a part of a community-engaged health promotion research study. The data set includes 150 actor variables plus multiplex edges between study participants (N=116 pregnant women) at two time points.

*Keywords*: *Social networks, Hispanic*

**Authors**
***Sabina B. Gesell, PhD,*** *Department of Social Sciences & Health Policy, Wake Forest School of Medicine, Winston-Salem, North Carolina, USA.*
***Eric A. Tesdahl, PhD,*** *Department of Human and Organizational Development, Vanderbilt University, Nashville Tennessee, USA.*

**Notes**
Data collection was supported by the State of Tennessee Department of Health (Contract # GR-11-34418, Gesell). Data management and analysis was supported by Award Number K23HD064700 (Gesell) from the Eunice Kennedy Shriver National Institute of Child Health and Development; and Award Number UL1TR000445 at the National Center for Advancing Translational Sciences supported the REDCap database. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding agencies.

*Correspondence concerning this work should be addressed to Sabina B. Gesell, Department of Social Sciences & Heakth Policy, One Medical Center Blvd, Winston-Salem, NC 27157. Email: sgesell@wakehealth.edu*

## 1. Overview

The Madre Sana data set was collected as a part of a community-engaged health promotion research project entitled Madre Sana (Healthy Mother). The project was conducted in 2011 in a mid-sized city in the southeastern United States, in conjunction with that city’s department of parks and recreation. Participants in the Madre Sana program were expecting mothers, the majority of whom were Latina. This research study was designed with two aims: (1) To assess the feasibility and initial efficacy of a skills-based cognitive-behavioral intervention to prevent excessive gestational weight gain in a hard-to-reach, high-risk population; and (2) To intentionally monitor whether new supportive social relations developed among treatment group members, and to assess the potential effectiveness of such relations in further reducing excessive gestational weight gain. Participants were randomized to one of two groups: All participants received the control intervention; the treatment group also received the healthy lifestyle intervention. The intervention met weekly for 12 weeks in small, consistent groups of 8-10 women to learn to achieve healthy weight gain during pregnancy, and, were also engaged through a number of activities designed to build supportive social relations among participants. The control group members were not introduced to other study members. The study details are published elsewhere (Gesell, Katula, Strickland, & Vitolins, 2015). The intervention showed efficacy in preventing excessive weight gain during pregnancy in normal weight women (47.1 % usual care vs. 6.7 % intervention; absolute difference 40.4 %; p = .036) (Gesell, Katula, Strickland, & Vitolins, 2015). We found that the intervention activities had a significant and positive effect on the likelihood of tie formation, however, in this particular timeframe we did not detect any additional effect of such relations on gestational weight gain (Tesdahl & Gesell, In Press). As the sum

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of intervention attendances increased among dyads, the likelihood of their forming a tie increased proportionally with the number of sessions attended (β=0.09, p<.001). For example, a pair of participants in this study who both attended four intervention sessions, had a 71.6% greater likelihood of forming a new supportive tie (OR=1.716, p<.001) relative to pairs where each member attended just one session. The effect for session attendance was linear and the same for high attenders as well as low attenders.

**2. Data Collection**

Data collection occurred between January and April of 2011. Six inclusion criteria were used in recruiting participants to this study. Enrolled participants were: (1) between 10 and 28 weeks pregnant, (2) 16 years of age or older, (3) receiving prenatal care, (4) a fluent speaker of either Spanish or English, (5) expecting to remain in the geographic area of the study for the remainder of their pregnancy, and (6) willing to release medical chart information for the purposes of the study. Participants were randomly assigned to either the control or treatment group, with randomization stratified by pre-pregnancy body mass index categories (under-weight, normal weight, over-weight, obese) as indicated by previous research (IOM 2009). The study was approved by the Institutional Review Boards at Vanderbilt University Medical Center and Wake Forest School of Medicine and registered on ClinicalTrials.gov.

Sociometric data were collected from all participants (both the control and treatment groups) in two waves by bilingual, trained study staff via interview in participants' homes, at Week 6 (Wave 1_edges) and Week 12 (Wave 2_edges). A total of 116 women (57 in the control group, 59 in the treatment group) completed at least one wave of data collection. Among all 116 participants, the mean number of ties was 1.72 (sd = 2.27), yielding an overall network density of 0.7%. Among treatment group participants, the mean number of ties during the study was 3.56 (sd = 2.11), yielding an overall network density of 2.1%. Respondents were asked to freely recall the names of alters (“other women in the Madre Sana program”) to whom they had ties. Respondents were first asked to list the other women in the program they knew by name: (“We are studying how social relationships affect our health. These next questions will be about relationships you may have with other women in the Madre Sana program. We do not expect you to have made new friendships but if you did, we would like to know. Who do you know in the Madre Sana program? What are their names?”); all respondents were allowed to name alters from both the treatment and control groups. The data collection sheet allowed for up to 15 names to be listed. After respondents named alters, they were shown pictures of the alters to confirm the person she had in mind (to avoid confusion with common names and nicknames). This was not aided recall. This process ensured that we were reliably distinguishing individuals with the same name. Respondents were then asked a series of questions about the names generated: (a) “Of the people you listed, who is/are your closest friend/s?” (b) “Have you spoken with this person about any of these things: your pregnancy weight, eating healthy, getting enough sleep or exercise?” (c) “How often have you spoken to her about these things in the last month?” (d) “Did you know her before the Madre Sana program?” (e) “Are you related?”

In addition to sociometric data, respondents completed a questionnaire covering a variety of health status and behavior variables at all three waves. Actor-level survey data were collected in three waves by bilingual, trained study staff via interview in participants' homes at baseline (variablename_1), Week 6 (variablename_2), and Week 12 (variablename_3). Included are sets of variables capturing respondents' day to day self-reported sleep, exercise habits, intentions for infant feeding, dietary patterns (fruit and vegetables, sweetened beverages, fat intake), total weight gain during pregnancy, general and pregnancy-specific medical conditions, and demographics (including food insecurity).

At baseline only, the Social Network Index was administered to all participants (both the control and treatment groups), to assess 12 types of relationships (Cohen, 1991; Cohen et al., 1997). These include relationships with a spouse, parents, parents-in-law, children, other close family members, close neighbors, friends, workmates, school mates, fellow volunteers (e.g., charity or community work), members of groups without religious affiliations (e.g., social, recreational, or professional), and members of religious groups. Items were added to capture members of an additional group relevant to the focal population: members of other groups (e.g., home visitors, coordinators of social services, social workers, therapists, friends of your husband/partner, friends you meet regularly at the park or bakery or market). One point was assigned for each type of relationship (possible score of 13) for which respondents indicated that they speak (in person or on the phone) to someone in that relationship at least once every 2 weeks. This tool was used to assess social network diversity. The total number of persons with whom they speak at least once every 2 weeks (number of network members) can also be assessed from these variables.

**3. Data Files and Formats**

The data for this study are stored in one MS Excel workbook, with individual worksheets containing actor-level data, two waves of sociometric data, and the additional relations 'Knew before the study began' and 'Related as kin', respectively. Sociometric data are stored as directed edgelists with the sender and receiver of each tie given in the first two columns, and tie variables denoted by subsequent column headers. Tie variables are binary, with the exception of 'Q4_Spoken_To_Preg_Health_Frequency' which indicates the frequency of the 'Q3_Spoken_to_Pregnancy_Health' relation in each wave. Each worksheet containing edgelist data includes self-loop ties with a value of zero to ensure that all actors in the study (including network isolates) are included within the analysis. These are denoted with gray shading. Study participants are identified by a three-digit numeric variable 'ID'. As an added convenience, those persons included in the treatment group have ID numbers beginning with a 1, and those in the control group have ID number beginning with 2. All potentially identifying information on participants within this study have been removed to safeguard participant confidentiality.

A detailed codebook describing the data collection measures for actor-level and sociometric data has also been included. Data collection forms with the exact item wording (Spanish – English) are also provided.

**4. Data Details**

| | |
|---|---|
| Response Rate | 12-week study retention rate: 81% in treatment group, 82% in control group |
| Non-Respondent Bias | We did not observe differential attrition between study arms. |
| Theoretical Grouping | These data were collected as part of a group-level health behavior change intervention. |
| Publications Using This Data | Tesdahl E & Gesell SB (2015). Assessing the impact of de novo social ties within health intervention settings: New questions for health behavior intervention research. *Clinical and Translational Science*, 8(6):676-81. doi: 10.1111/cts.12345.<br><br>Additional publications using other (not network) data collected in the trial:<br><br>Gesell SB, Katula JA, Strickland C, & Vitolins MZ (2015). Feasibility and initial efficacy evaluation of a community-based cognitive-behavioral lifestyle intervention to prevent excessive weight gain during pregnancy in Latina women. *Maternal and Child Health Journal*, 19(8):1842-52.<br>Arinze NV, Karp SM, & Gesell SB (2016). Evaluating provider advice and women's beliefs on total weight gain during pregnancy. *Journal of Immigrant and Minority Health*, 18(1):282-6. doi: 10.1007/s10903-015-0162-8. |
| Data Context | Small randomized controlled trial |
| Respondents | Pregnant women |
| Longitudinal | Yes, two time points 6 weeks apart |
| Temporality | High. Tesdahl & Gesell paper 2015 (In Press) showed ties were short lived |
| Analytical or Pedagogical Utility | • Analysis of social network and self-reported health behavior data collected at the same time points<br>• Analysis of development of new social ties within the context of a group intervention, including comparison of treatment and control group<br>• Analysis of pre-existing ties between study participants |
| Known Issues | Gesell, Katula, Strickland & Vitolins (2015) describes variable attendance at protocol-specified group sessions, which likely affected formation of new ties (the network is sparse), along with the recruitment and retention strategies used. |

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Tesdahl E & Gesell SB (2015). Assessing the impact of de novo social ties within health intervention settings: New questions for health behavior intervention research. *Clinical and Translational Science*, 8(6):676-81. doi: 10.1111/cts.12345.

# INSNA

## International Network for Social Network Analysis

**International Network for Social Network Analysis**
Connections is the official journal of the International Network for Social Network Analysis (INSNA). INSNA is a scientific organization made up of scholars across the world. Updated information about INSNA's annual conference (Sunbelt Social Network Conferences) can be found on the website at www.insna.org.



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The Sunbelt Conferences bring researchers together from all over the world to share current theoretical, methodological, and empirical findings around social networks. While previous annual conferences for INSNA members have been held in North America and Europe, conference locations will now expand to include other countries such as Austalia and those in East Asia. Information on the annual Sunbelt Social Network Conferences can also be found on the INSNA website.

**Manuscript Submissions**
Submit articles to editorconnections@gmail.com. Full manuscripts should be submitted as an MS Word document, and should not exceed 6000 words including all tables and figures Brief Reports submissions should be under 2500 words. All images, figures, and tables should be sent as seperate files. Rastor (photographic) images and figures should be sent in a high resolution (300ppi min.) graphics format (EPS, TIFF, or JPEG), while line work images and figures should be sent as a vector-based format (EPS or SVG). Format and style of manuscript and references should conform to the conventions specified in the latest edition of the Publication Manual of the American Psychological Association. Further instruction on submission formatting can be found on the INSNA website, http://www.insna.org. Manuscripts that do not follow submissions criteria will be returned for revision. The journal follows a double-blind review process for research articles. Published articles are protected by both the United States Coyright Law and International Treaty provisions. All rights reserved (ISSN: 0226-1766).

**DEN (Data Exchange Network)**
We recently introduced a new section in Connections, which functions as an outlet for publishing datasets. The Data Exchange Network (DEN) has been designed with two goals: first is to build a community resource for network datasets and the second is to provide a format for citable references of datasets and instruments. Submissions should include an electronic version of the network dataset and/or instrument and a short article (not to exceed 2500 words) describing the data being submitted. All materials submitted for the DEN will be peer-reviewed to ensure the utility and usability of the data/instrument. Accepted DEN contributions will appear in the hard copy of Connections, and the data sets will be available on the INSNA website through an indexed, searchable web interface.