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Employment Status Driven Interactions in a Bank Wiring Room

A social network analysis of structural similarities between pro-social and anti-social behavior networks

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Introduction

In the following study, we analyzed the Bank Wiring Room data set, an observational study conducted in 1939 by F. Roethlisberger and W. Dickson at the Western Electric plant. This data documented the networks of fourteen employees: two inspectors, three solderers and nine wiremen. For our analysis, we interpreted the roles of each employee type as follows: inspectors regulate and manage the plant's division, solderers join or mend metal materials, and wiremen maintain electrical equipment. The researchers collected data on the network interactions between these individuals for six different behaviors: horseplay, arguments over open windows, antagonistic behavior generally, giving help with work tasks, trading work tasks, and friendship. Additionally, the data was considered in an asymmetric manner, indicating a possible lack of mutuality between two actors.

The data was originally gathered by Roethlisberger and Dickson in order to measure the "Hawthorne Effect," or the way in which individuals alter (most typically by improving) their behavior when they know that they are being watched. At the time, the discipline of social network analysis was not nearly as established as it is now, and they did not have the computer power to conduct the kind of analyses that are now possible. For this reason, we return to this dataset from 1939 to ask new social network analysis questions that are now answerable with current computer power. We propose the following questions:

1. Are the network structures for pro-social behaviors (horseplay, friendship, helping one another with tasks) consistent, and do they significantly diverge from the network structures for anti-social behaviors (arguments over windows and antagonistic behavior generally)?
2. Does employment level influence tie formation within pro-social and anti-social networks?

For our first research question, we predict that the network structures for pro-social behaviors will be consistent with one another and will diverge from the network structures for anti-social behaviors. For our second research question, we predict that actors of higher status will be less involved in the behavioral interactions of the workplace than actors of lower job status. Otherwise stated, job status is inversely related to network centrality and network interaction. This indicates that inspectors will be removed from the behavior networks while employees of a lower status will be central figures within the behavior networks.

Analytical Strategies

Hierarchical Structures

Hierarchical clustering groups actors based on their structural similarity. In our analysis, we specified the Euclidean method for evaluating the actors' structural similarities. The Euclidean method calculates two actors' structural similarity based on their differences in social ties. A large Euclidean distance denotes that two actors have very different social ties from each other, and therefore indicates that the two actors are structurally very different. We employed the *equiv.cluster* function in the R package *sna* to evaluate the Euclidean distance between all actors in the network. Initially, the actors with the smallest Euclidean distance between them were grouped together. The algorithm then recomputed the Euclidean distance between the grouped actors and the other actors in the network, treating the grouped actors as one node. Next, the algorithm clustered the grouped node to the actor with the smallest Euclidean distance from the grouped node. The algorithm continued in this fashion until all of the individual actors in the network were clustered into a group. The results of the hierarchical clustering were then plotted, with height indicating the distance at which the nodes were merged. Smaller height differences between actors indicates more structural similarity between the actors.

Blockmodeling

In order to visualize the most central groups of nodes from the network's hierarchical structure, we reduce the network into a set of blocks using the *blockmodeling* function of the R package *sna*. Here, centrality is based on structural equivalence of nodes. The most central blocks are defined as the groups of nodes having many internal connections, a lot of incoming connections from peripheral blocks, and few outgoing connections to peripheral blocks. Using the *blockmodel* function in the *sna* package, we specify that our block model will be composed of two reduced blocks. The algorithm then randomly assigns the network's nodes into the different reduced blocks. The interaction between two randomly placed nodes is signified with the placement of a block at their intersection. This block will hereafter be referred to as a bi-nodal block because it represents the interaction between two nodes within the larger reduced block. Bi-nodal blocks with a density greater than our threshold of 0.3 are coded as 1 and represented with a black block. Bi-nodal blocks with a density less than our threshold of 0.3 are coded as 0 and represented with a white block. Density is defined as the proportion of all possible ties that are observed in the network. The error in the random block model is calculated by summing the density of the bi-nodal blocks within reduced block zero (B0) and the bi-nodal blocks within reduced block one (B1) by the following formula:

$$Error\ =\ \Sigma_{B1}\,(1-density_{B1})\ +\ \Sigma_{B0}density_{B0}$$

The algorithm creates many more random block models using the method above until settling upon the block model that minimizes the error score. The block model with the minimum error score best captures the centrality of the nodal groups. In this block model, the most central reduced blocks have a high density (represented by a concentration of black unreduced blocks), while the peripheral reduced blocks have a low density (which is represented by white space).

Cliques

In order to identify cliques within the network, we use the *clique.census* function in the R package *sna*. This function identifies groups of people in which all of the people within the group have mutual ties to each other. This indicates that everyone within the group has an outgoing tie to everyone else in the group, and everyone within the group has an incoming tie from everyone else in the group. The function returns every clique of every size that occurs in the network, listing the nodes that are in each clique. It is important to note that the same node can appear in multiple cliques of the same size or of different sizes.

Key players

In the following analysis, we use the R package *sna* and *keyplayer* to evaluate the most influential individuals and groups in the network. We evaluate influence with indegree measure. A higher in-degree signifies more influence because greater in-degree indicates more incoming ties. Using the *sna* package, we found the n individual nodes with the highest indegree. These corresponded to the n most influential individual actors in our network. We then used the *keyplayer* package to calculate the group centrality of the n most influential individual actors. When the n most influential actors form a group, their group centrality is calculated by clustering them as if they constituted one node. The group's in-degree is equal to the maximum number of unique ties coming into the grouped pseudo-node. Uniqueness indicates that ties coming into multiple influential actors from one outside node only counts towards the group's indegree once. Thus, the group of the most influential individual actors is not necessarily the most influential group in the network due to redundancy of ties amongst the influential individuals. We also use the *keyplayer* package to find the most influential group of size n. In this greedy algorithm, a set of n nodes is selected as the initial group. The group's maximum indegree is calculated. Then, the first node in the original group n is replaced with a different node that does not already appear in the group. The maximum indegree of the new group is calculated, and the substitution is kept if the new group has a larger indegree than the original group. This swapping of the first node, and subsequent calculation of new group indegree and possible node replacement, continues for the number iterations specified in the R function. This same process is repeated sequentially for each node in the group of size n. Then the function loops back through the nodes in the same fashion for the number of rounds specified by the R code. The process continues until the change in group centrality score is smaller than the specified threshold or the process has iterated through all the nodes in the group the specified number of times. The most influential group, as calculated by the *keyplayer* algorithm, may not consist of the most influential individual nodes in the network. A group without the most influential individuals may have greater group indegree because the nodes in the group reach the greatest number of unique nodes. This means that the nodes in the keyplayer group have fewer overlapping connections.

ERGM

In an ERGM model, a random graph Y consists of a set of n nodes and m dyads (or edges) $\{Y_{ij} : i = 1, \ldots, n; j=1, \ldots , n\}$ where $Y_{ij}=1$ if the nodes (i, j) are connected and $Y_{ij}=0$ otherwise. The assumption of ERGM models is that the structure of a given observed graph y can be explained by any statistics s(y) depending on the observed network and nodal attributes. We can thereby describe any kind of dependence between the un-dyadic variables:

$$P(Y = y|\theta) = \frac{\exp(\theta^T s(y))}{c(\theta)}$$

Where θ is a vector of model parameters associated with s(y) and c(θ) is a normalizing constant. In this way, these ERGM models provide a probability distribution on each possible network on n nodes. The size of the set of possible networks for an undirected network of size n, by contrast, is 2^(n(n-1)/2). Lastly, due to the fact that the number of possible networks is the set is much larger than the number of parameters which can constrain the model, the ideal probability distribution will be the one that maximizes the Gibbs entropy. (Wasserman, 1994; Newman, 2010).

Methods

To evaluate the similarities in the network structures across pro-social behavior networks (friendship, horseplay, helping others, and trading jobs) and the similarities in network structures across anti-social behavior networks (antagonistic interaction and arguments about open windows), we utilized six different social network analysis techniques: 1. Hierarchical structuring 2. Blockmodeling 3. Plotted network clusters 4. Group Level Analysis a. Cliques b. Keyplayer groups 5. Network measurements: a. Density b. Transitivity d. Reciprocity e. Centralization and lastly 6. ERGM comparing the effect of employee level within different behavioral networks.

Hierarchical Structuring of the Five Different Networks

For this analysis, we plotted the hierarchical structures of each of the five networks in order to examine whether the pro-social behavior networks (horseplay, helping others with work, and friendship) correlated with one another and if there were significant differences in these networks as compared to the anti-social behavior networks (arguing over open windows and participating in antagonistic behavior generally).

Block Modeling

We then evaluated whether our results from our hierarchical structures for the five different networks corresponded with our block models for these networks. Specifically, we were interested in evaluating which nodes appeared to be more central and more connected to other nodes. We utilized the package *sna* in R in order to first create a directed network graph for each network. We then created an individual two-block model for each network: friendship, horseplay, helping other, trading jobs, antagonistic interaction, and arguments about open windows. With the results, we created reduced matrices with 0-1 entries indicating the number of ties within the network. We used 0.30 as our density cut off to indicate the presence or absence of a tie in our networks. Additionally, we created plots for each network in order to visualize which individual actors belonged to which block. The visualization allowed us to view the interconnectedness of the employees in both pro and anti-social networks.

Network Plots

We utilized the R package *sna* to construct a directed network graph of each behavioral network. This indicates that network ties are not always mutual, meaning two actors can have different perspectives on their relationship with each other. These asymmetric ties are indicated with a directed line which originates from the actor whose perspective is being captured. Additionally, nodes are color coded according to the employee type of the actor they represent. Inspectors are coded with black nodes, wiremen are coded with red nodes, and solderers are coded with green nodes. This color coding allows us to better visualize which types of employees are clustered together. We created network plots for each of the six behavior networks: friendship, horseplay, helping other, trading jobs, antagonistic interaction, and arguments about open windows. Specifically, we used the network graphs to evaluate the similarity in network structure across pro-social behavior networks and the similarity in network structure across anti-social behavior networks.

Group Formation- Cliques and Keyplayer Groups

In order to gain an even more explicit understanding of the way in which the nodes clustered together for each of the different behavior networks, we utilized the R package *sna* to gather information on clique formation in each network ranging. We isolated cliques of different sizes across all six networks, from sizes of one node to five nodes. We evaluated indegree centrality of all actors in each network, then determined whether the actors with the highest in-degree measures associated with each other in cliques. This analysis indicated whether the network's most influential actors form mutual ties with each other.

We then utilized the *keyplayer* package to determine whether cliques of influential individuals were also the most influential groups in the network. We employed group indegree as a measure of group influence similar to the way we employed individual indegree as a measure of individual influence.

We used these analyses to evaluate our two research questions. We first compared clique and keyplayer group formation across pro-social networks and across anti-social networks to better analyze the structural differences between the networks belonging to the two behavioral categories. We then investigated the positions of different employee levels within the network, comparing the influence of inspectors, wiremen and solderers within groups across the different networks. We compared the influence of these different employee types across pro-social behavior networks and across anti-social behavior networks to extrapolate information as to which employee levels were most influential in each category of behavioral network.

Measures of Network Structure

We utilized the R package *sna* to calculate measures of network structure for each of the six networks. We first calculated two measures of network cohesion, density and transitivity. Density confers how densely connected the nodes in the network are. A higher density measure indicate a larger proportion of all possible ties for the network are actually observed in the network, and the maximum possible density is 1. Transitivity confers the probability that two actors will form a transitive triad, otherwise stated that they have a friend in common. A higher transitivity measure indicates a higher proportion of the actors in the network form a transitive triad when connected by a tie. We then calculated two measures of network hierarchy, reciprocity and centralization. Reciprocity measures mutuality in the network. A higher reciprocity score indicates that a higher proportion of ties within the network are mutual ties. Centralization evaluates the concentration of ties at one node or a small group of nodes. A high centralization score indicates that all of the ties in the network are concentrated on one node, while a low centralization score indicates that the ties are evenly dispersed throughout the network and no one node has a concentration of ties. We used these measures to quantitatively compare the network structures across pro-social behavioral networks and to compare the network structures across anti-social behavioral networks.

Exponential Random Graph Model (ERGM)

Lastly, we evaluated the effect of employee type on tie formation in each of the six networks using an Exponential Random Graph Model. Our model followed the formula below:

$$logit[P(w_{ij} = 1 | w_{ij}^{L})] = \theta_1 + \theta_2 Wiremen + \theta_3 Solderer + \theta_4 Same\ Employee\ Type$$

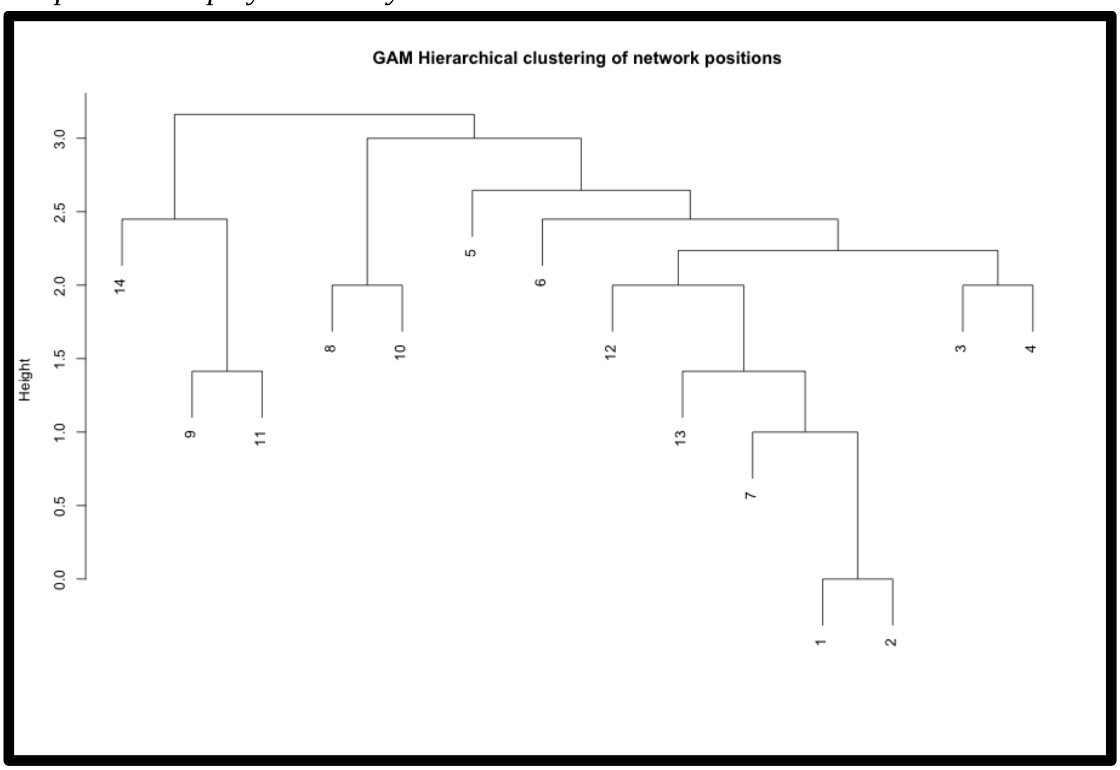
We utilized the aforementioned formula to evaluate the influence of job title on tie formation. Specifically, we evaluated the following effects on tie formation in each of the six networks: the effect of being a wireman as compared to an inspector, the effect of being a solderer as compared to an inspector, and the effect of being the same employee type. We compared the aforementioned effects across pro-social networks and across anti-social networks to quantitatively evaluate our second research question which explores the influence of job title on pro-social network formation and on anti-social network formation.

Results

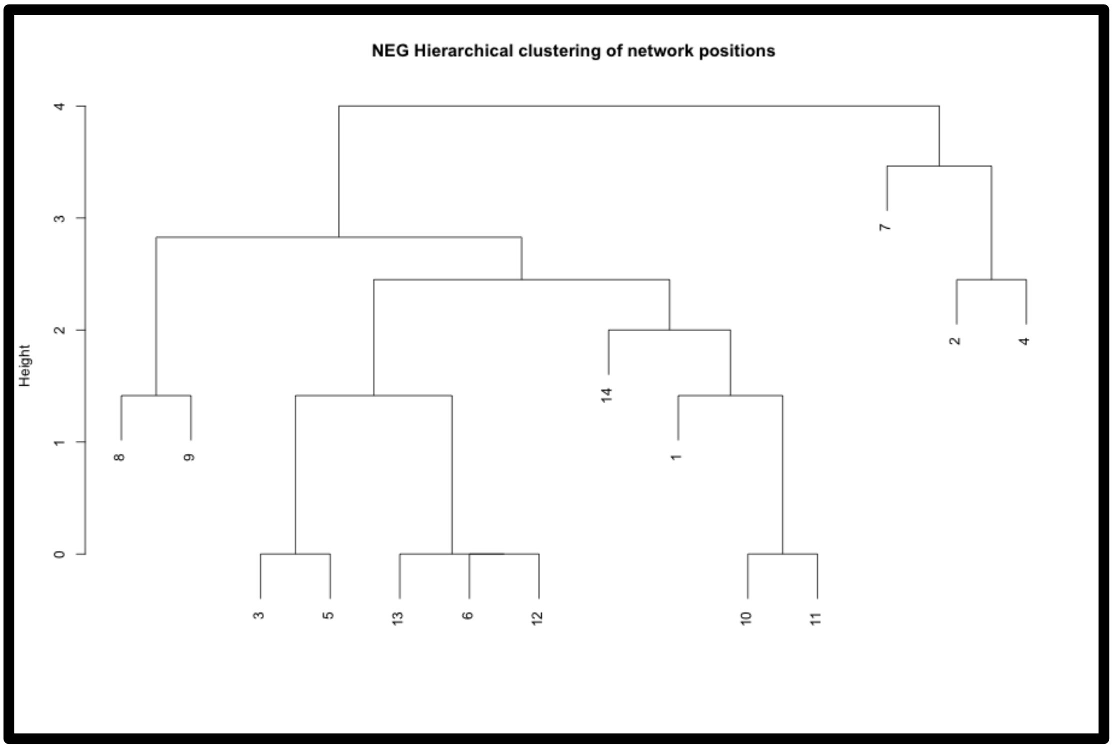
Hierarchical Structure

For our first research question, "Are the networks of network hierarchy structures for pro-social behaviors (horseplay, friendship, helping one another with tasks) consistent with one another and do they significantly diverge from the network hierarchy structures for anti-social behaviors (arguments over windows and antagonistic behavior generally)?" we began by exploring the hierarchical structures of each behavioral network. We found that the hierarchies for helping others and for horseplay were in fact identical to one another, even though the network information for these two networks was distinct. In this way, we can interpret that the behaviors of horseplay and helping others facilitate very similar network structures among individuals. In this way, the behaviors of jocularity and playfulness with others and the inclination to help others seem to go hand in hand, and the individuals who greatly participated in these activities were generally the same, often wiremen and occasionally solderers, whereas the individuals who rarely engaged in horseplay often rarely engaged in helping others, primarily one wireman, W5, and the two inspectors. Interestingly, the two inspectors, who were at the bottom of the hierarchies for horseplay and helping, were very close to the top of the hierarchy for antagonistic behavior. This may indicate that, due to their title, they did not feel they could engage in horseplay or helping their subordinates whom they were intended to be inspecting. However, due to the supervisory role, they were more likely to engage in more antagonistic interactions with the other workers.

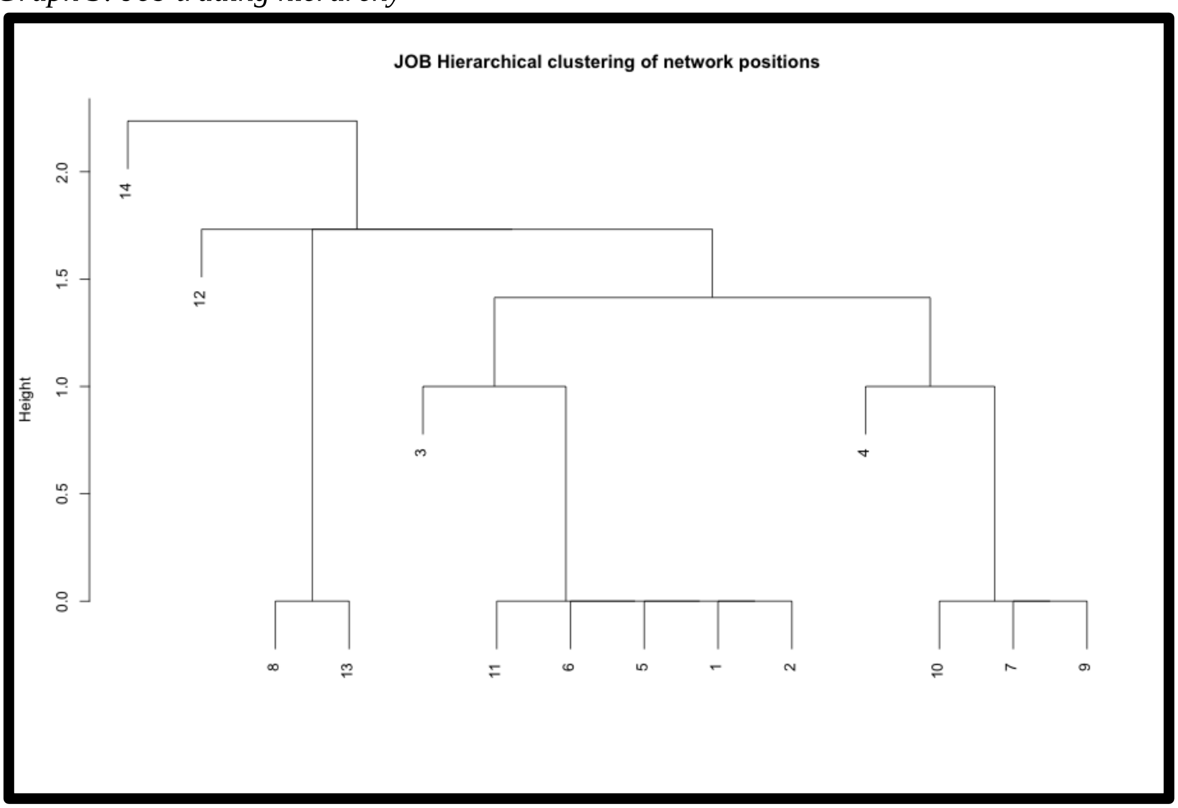
Graph 1: Horseplay Hierarchy



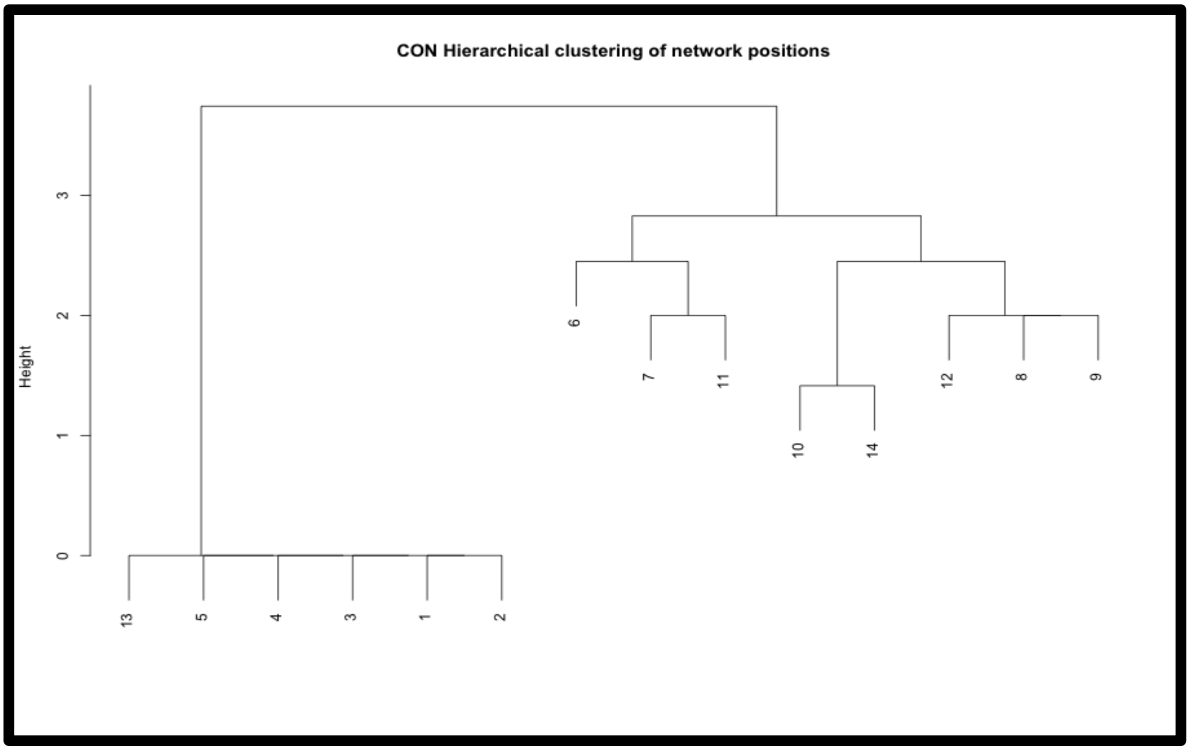
Graph 2: Antagonistic Interaction Hierarchy



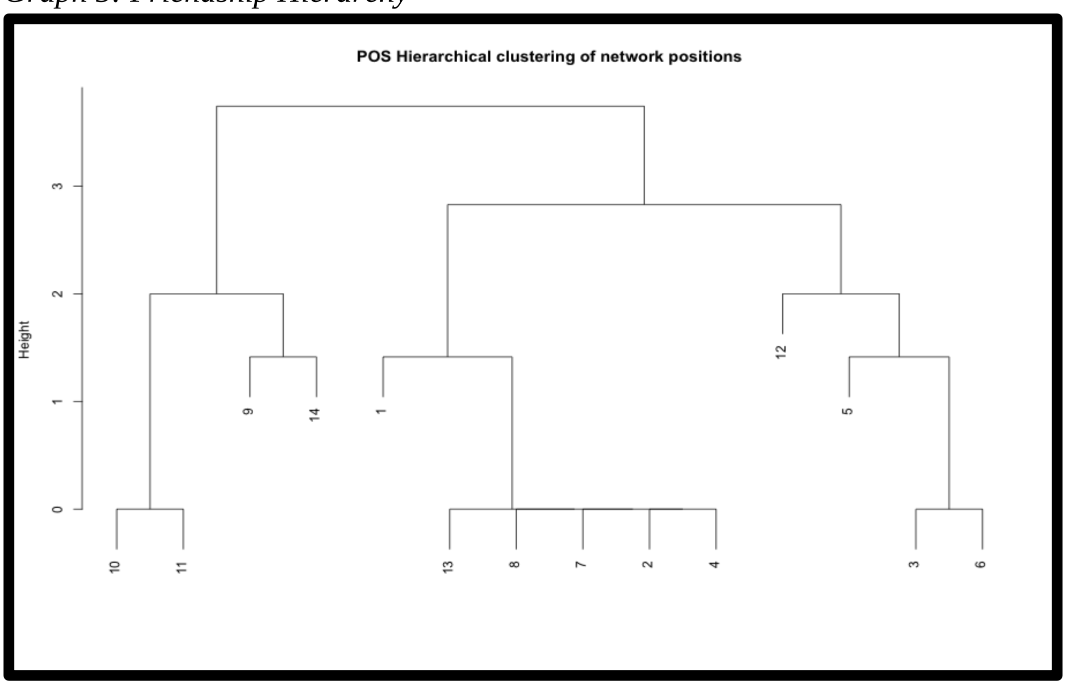
Graph 3: Job trading hierarchy



Graph 4: Conflict over open windows hierarchy



Graph 5: Friendship Hierarchy



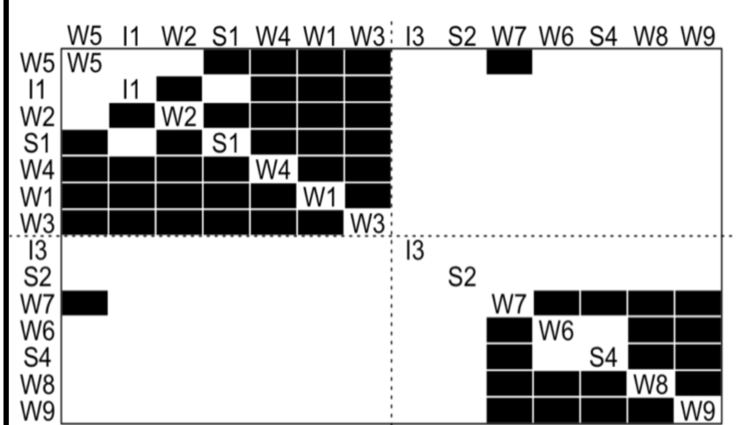
Blockmodeling

We ran block models for each network. We found that horseplay had the number of ties with two densely concentrated blocks. We found that there was one highly tied group, with a mean density of 0.85 consisting of wiremen 1, 2, 3, 4 and 5 as well as Solderer 1 and inspector 1. The second group consisted of wiremen 6, 8, 9 and Solderer 2 and 4 and inspector 3. This group was less correlated with an average mean density of 0.42. Wireman 7 was not a part of either major horseplay group. The friendship network did not reveal any tie formation within any block as the mean density of each block was below our cut off criterion. All of the actors are in block one, but the mean density is 0.23 indicating that there are no significant, observable ties within the network. In the network, helping others with work, observable ties were found in the bottom right quadrant. The block consists of wiremen 6, 8, 3, 4, 5 ,1 2 and solderers 1 and 2 as well as inspectors 1 and 3. Although the block consists of many actors, the concentration of helping others is between wiremen 1,2, 3, 5, 6 and 8. This block contained a density of 0.33. Both the horseplay network and the helping others with work network saw a concentration of similar actors across both networks which belonged to the central group.

The anti-social networks illustrated more concentrated results with blocks forming, more densely observations. In the network concerning arguments about open windows, all of the ties were concentrated within one block. This block consisted of actors wiremen 4, 5, 6, 7, 8, 9 and solderers 1 and 4. Solderers 1 and 4, as well as wiremen 6 and 8 participated in the most arguments about windows. All of the actors which contributed to arguments about windows are concentrated in this block. In the network about antagonistic, or negative behavior, there were three blocks which contained significant ties but the blocks were all made up of the same actors displaying antagonistic behavior towards others. The actors were Wireman 2, Wireman 5, and Inspector 3. The majority of the antagonistic behavior observed belonged to this group of actors. Wiremen 6 and 7 also displayed some antagonistic behavior but not enough for it to be significant.

Blockmodel 1: Participation in Horseplay

Relation - Participation in Horseplay

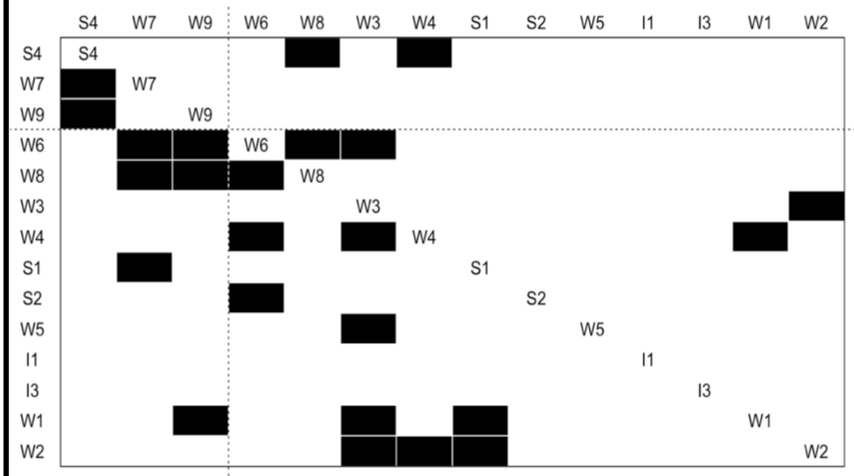


	Block 1	Block 2
Block 1	0.86	0.20
Block 2	0.20	0.43

	Block 1	Block 2
Block 1	1	0
Block 2	0	1

Blockmodel 2: Helping Others

Relation - Helping Others

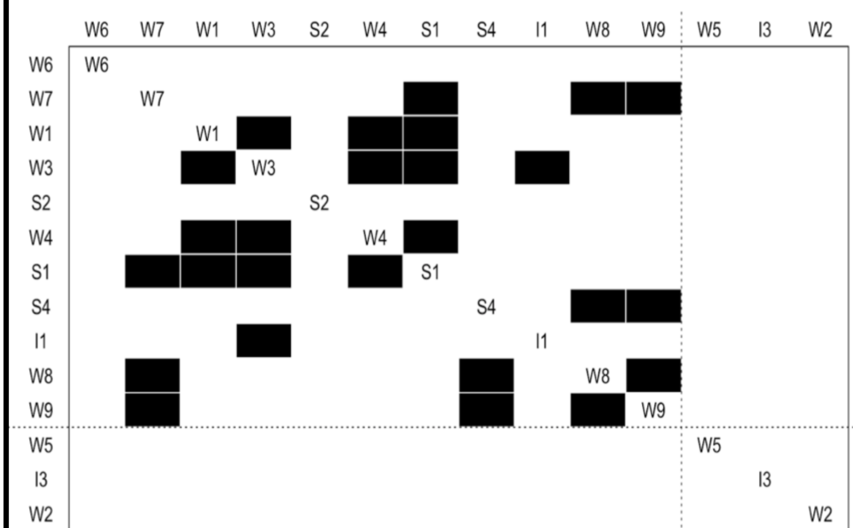


	Block 1	Block 2
Block 1	0.12	0.18
Block 2	0.06	0.33

	Block 1	Block 2
Block 1	0	0
Block 2	0	1

Blockmodel 3: Friendship

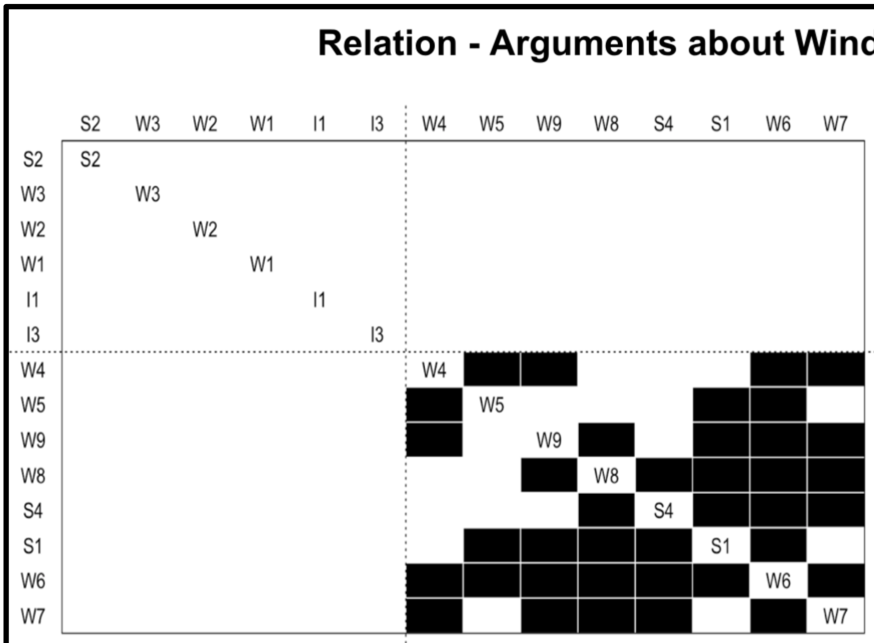
Relation - Friendship



	Block 1	Block 2
Block 1	0.23	0.00
Block 2	0.00	0.00

	Block 1	Block 2
Block 1	0	0
Block 2	0	0

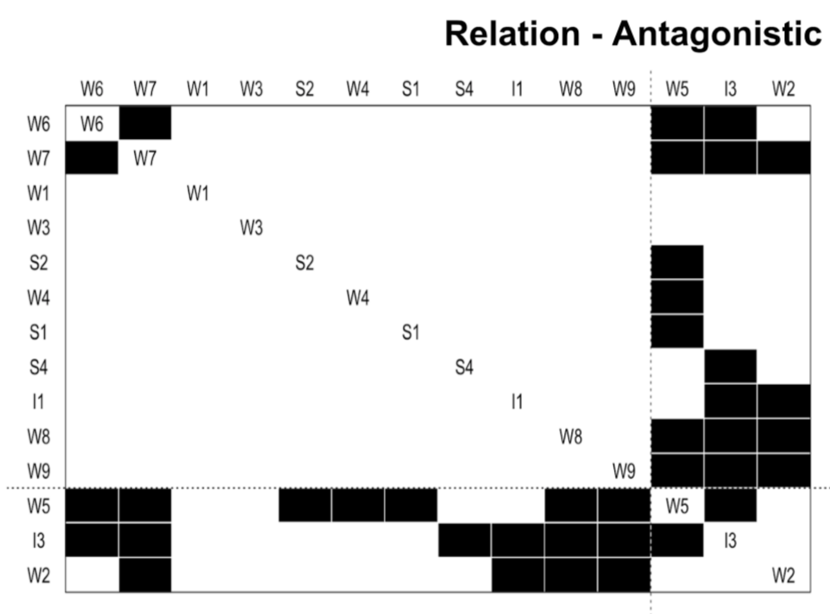
Blockmodel 4: Arguments about Open Windows



	Block 1	Block 2
Block 1	0.00	0.00
Block 2	0.00	0.69

	Block 1	Block 2
Block 1	0	0
Block 2	0	1

Blockmodel 5: Antagonistic Interaction



	Block 1	Block 2
Block 1	0.18	0.52
Block 2	0.52	0.33

	Block 1	Block 2
Block 1	0	1
Block 2	1	1

Group Formation

We then examined the cliques and keyplayer groups within each network. We found that for the anti-social behaviors, two of the same nodes, I3 and W1, arose in both the keyplayer groups (of five nodes total) for antagonism and arguments over open windows. For the pro-social groups, we also found that there were often several nodes that arose in each of the keyplayer groups for these networks of horseplay, friendship, and helping with work. Specifically, inspector 3 and wireman 2 were in both the horseplayer and the friendship keyplayer groups. Additionally, wireman 3 was in both the helping with work and friendship keyplayer groups. Lastly, wireman 7 was in both the helping with work group and the horseplay keyplayer groups. In this way, there appeared to be some continuity between the pro-social groups and the anti-social groups, respectively. However, the keyplayer groups for these networks were certainly not identical.

From the results of clique level analysis, we found that for horseplay, larger cliques of 5 were often comprised of the network's most influential nodes , generally Wiremen 1, 2, 3, or 4. Cliques formed for arguments about open windows also often had the network's most influential individuals, generally Wiremen 6, 7, 8 and 9. For friendship, the cliques of size 4 were comprised of wiremen and solderers, three of whom were the network's most influential individuals (Wiremen 1 and 3, Solderer 1). The cliques for helping others with work were very small, either of sizes one or two. The antagonism cliques were also generally comprised of 2 actors. However, the larger cliques of size 4 had Inspector 3, and Wiremen 5,6, and 7.

In conclusion, we found that larger cliques of 4 or 5 people generally had mostly wiremen in them. In the cliques within pro-social behavior networks, Wiremen 1,2,3, and 4 appeared more frequently, whereas, in the cliques within anti-social networks, Wiremen 5,6,7, 8 and 9 appeared more frequently. It is important to remember that because there are more wiremen in the network, it is more likely that they appear in the cliques. With this in mind, it is not surprising that wiremen are so frequently members of larger cliques. Lastly, different wiremen appear in the pro-social networks (friendship, horseplay, trading work assignments) than those whom appear in the anti-social networks (conflicts over windows and general antagonism). This may suggest that certain individuals, regardless of job title, are more prone to pro-social behavior and therefore have more ties within the pro-social behavior networks. Conversely, others are more prone to anti-social behavior and thus appear prominently across anti-social networks.

Table 1: Keyplayer Groups

	Friendship	Trading Jobs	Helping others	Horseplay	Arguments about open windows	Antagonistic Behavior
Groups of four						
Four most central individuals	W3 S1 W1 W4	S4 S1 S2 I1	W3 W6 W7 W9	W1 W3 W4 W2	W6 W7 W8 W9	W5 I3 W2 W7
Group centrality:	**2**	**45**	**7**	**3**	**4**	**8**
Most central group of size four	I1 I3 W4 W8	I1 S1 S2 S4	W3 W6 W7 S4	I3 W2 W7 S2	I1 I3 W1 W6	I3 W1 W5 W7
Group centrality:	**6**	**45**	**8**	**10**	**7**	**9**
Group of five						
Five most central individuals	W3 S1 W1 W4 W7	S4 S1 S2 I1 I3	W3 W6 W7 W9 W4	W1 W3 W4 W2 W5	W6 W7 W8 W9 S1	W5 I3 W2 W7 W6
Group centrality:	**3**	**45**	**7**	**3**	**3**	**7**
Most central group of size five	I3 W2 W3 W5 W8	I1 I3 S1 S2 S4	W3 W4 W6 W7 W9	S4 W2 W5 W7 S2	I1 I3 W1 W9 S1	I3 W1 W3 W5 W7
Group centrality:	**7**	**45**	**7**	**9**	**6**	**9**

Measures of Network Structure

From our quantitative analysis of network structure through network measures, we isolated two interesting findings. First, we found that the density measures for both anti-social behavior networks (Arguments about open windows and Antagonism) were 0.209. This indicates that the density of both anti-social behavior networks is exactly the same, and therefore an aspect of their network structure is the exact same. Both anti-social networks had a density measure greater than all other pro-social networks except for one. This indicates that a larger proportion of the bank room workers participate in anti-social networks than pro-social networks, except for the horseplay network.

Second, we found that the centralization measures of the anti-social networks were far greater than the centralization measures of the pro-social networks. The smallest centralization measure for an anti-social network (Arguments network, 0.385) was two times as large as the greatest centralization measure for the pro-social networks (Friendship network, 0.192). This indicates that the anti-social behavior networks have much higher centralization of ties, meaning a larger proportion of the ties in the anti-social networks are centered around a small group of nodes as compared to the pro-social networks in which ties are more dispersed across nodes. Intuitively, this indicates that there are a few influential nodes in the anti-social networks that are participating in a lot of negative interactions whereas in the pro-social networks, the positive ties in the network are not centered around a small group of people.

Table 1: Network Level Measures within all Six Behavior Networks

Network Level Measures						
	Friendship	Horseplay	Trading Jobs	Helping Others	Arguments about windows	Antagonism
Network Cohesion						
density	0.143	0.308	0.038	0.132	0.209	0.209
transitivity	0.643	0.798	1	0.163	0.671	0.254
Network Hierarchy						
reciprocity	1	1	0.923	0.78	1	1
centralization	0.192	0.179	0.135	0.16	0.385	0.474

Exponential Random Graph Models

From our ERGM analysis on the effect of employee type on tie formation, we isolated three interesting findings regarding the Friendship and Antagonism networks. First, from ERGM analysis on the friendship network we found that solderers are more likely to form friendship ties than inspectors ($P<0.05$). Specifically, solderers are e^1.58= 4.85 times more likely to form a friendship tie than inspectors. From ERGM analysis of the antagonism network, we found two significant results. First, we determined that wiremen are less likely to form antagonistic ties than inspectors ($P<0.05$). Specifically, inspectors are 1/e^-1.246 = 3.5 times more likely to form an antagonistic tie than wiremen. Second, we discovered that solderers were less likely to form antagonistic ties than both wiremen and inspectors ($P<0.01$). Specifically, inspectors are 1/e^-2.146 = 8.55 more likely to form an antagonistic tie than solderers.

These findings indicate two things. First, they indicate that inspectors are more likely than either of the other employee types to form an antagonistic tie. Second, they indicate that solderers are more likely to form a friendship tie than either of the other two professions.

Table 1: ERGM results for the Friendship network

Friendship Network			
	Estimate	Std. Error	Pr(>|z|)
edges	-18.889	1003.878	0.985
Wiremen	16.055	1003.878	0.987
Solderers	1.58	0.798	0.048
Same Employee Type	-14.832	1003.878	0.988

Table 2: ERGM results for the Antagonistic Behavior network

Antagonistic Behavior Network			
	Estimate	Std. Error	Pr(>|z|)
edges	0.631	0.730	0.387
Wiremen	-1.246	0.612	0.042
Solderers	-2.146	0.590	0.000
Same Employee Type	0.769	0.677	0.256

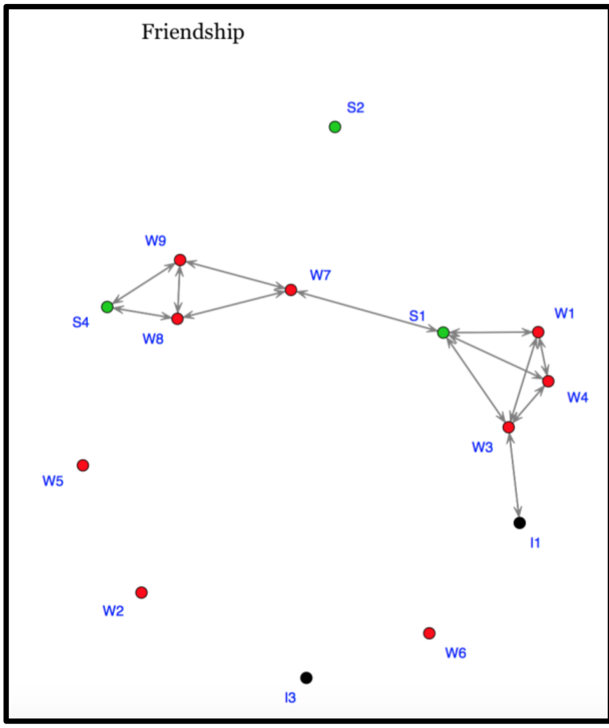
Network Plots

Pro-social Interactions

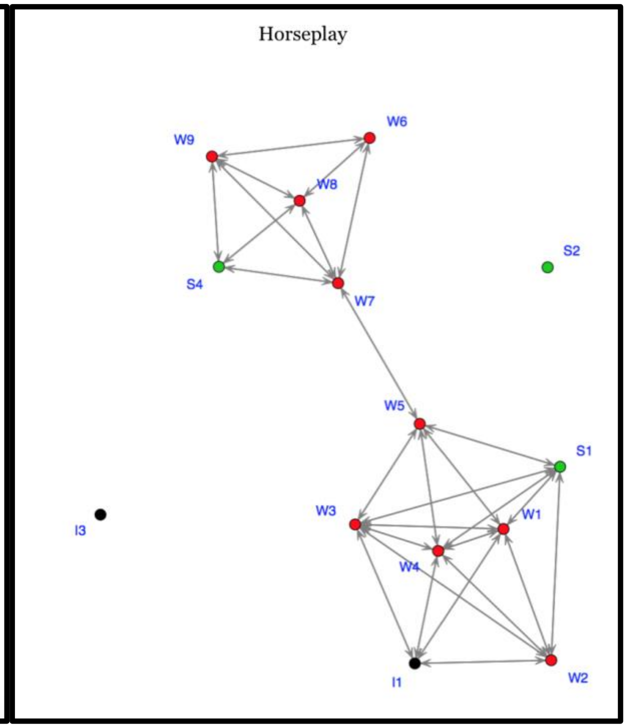
Within our comparison of pro-social network structures, we decided to group our analysis into two separate comparisons. First, we compared the network structures of the friendship and horseplay networks. We chose to group these two networks for comparison due to the similar nature of their interactions. Friends usually participate in friendly banter and horseplay. Thus, we hypothesized that the structure of interactions would be similar between the two networks. Second, we compared the network structures between the helping network and job trading network. We again conducted this comparison due to the similar nature of their interactions. We hypothesized that nodes who often help each other would likely trade jobs since it is a form of helping. The results from the aforementioned comparisons are as follows.

For the two pro-social networks of Friendship and Horseplay, we found a strong similarity in their network structures. For both friendship and horseplay, the networks were concentrated around two distinct groups of nodes. Within the friendship network, the first group (shown on the left of the friendship plot below) consisted of Wireman 7, Wireman 9, Wireman 8 and Solderer 4. The second group (shown on the right of the friendship plot below) was comprised of Wireman 1, Wireman 3, Wireman 4, Solderer 1, and Inspector 1. Within this friendship network, there were five actors without connections to any other actor. When examining the horseplay network, we saw that the same two distinct groups from the friendship network appeared in the horseplay network. However, within the horseplay network, the two distinct groups were comprised of more nodes. This indicated that the same friendship groups existed in the horseplay network, but that the friendship groups pulled in some peripheral nodes when forming their horseplay groups. The horseplay network drew in more nodes to interact, thus leaving fewer peripheral actors in the horseplay network than in the friendship network. Interestingly, Inspector 3 and Solderer 2 remained peripheral, unconnected actors in both the friendship and horseplay networks. In summation, there was an observable overlap in the networks of horseplay and friendship among the wiring room employees. This indicated an identical core structure within the two pro-social networks.

Network Plot: Friendship

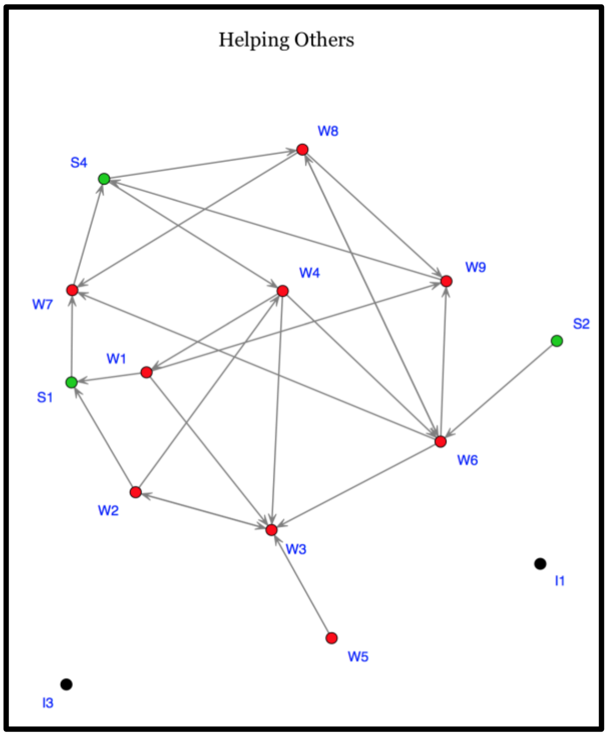


Network Plot: Horseplay

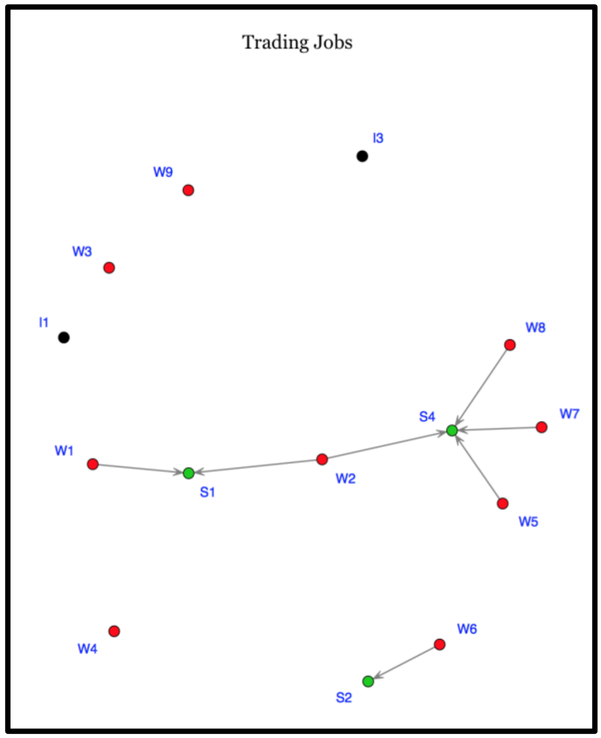


When comparing the help and job trading networks, we saw far less similarity in their structures than we found in our previous comparison. The helping network consisted of one large group of nodes who had frequent interactions with each other and two peripheral nodes with no connections. The trading jobs network consisted of a small string of interactions between nodes with a lot of nodes on the periphery. The only similarity between the two networks was in the identity of their peripheral nodes. In both the help and trading jobs network, the two inspectors were on the periphery. This is likely due to the inspector's elevated position within the group. The inspector is responsible for evaluating the work of the wiremen and solderers, thus he is unlikely to give them help with their work. His position as an evaluator gives him an elevated status, and as such, it is unlikely he would trade positions with a wireman or Solderer of lesser status.

Network Plot: Helping Others



Network Plot: Trading Jobs with others

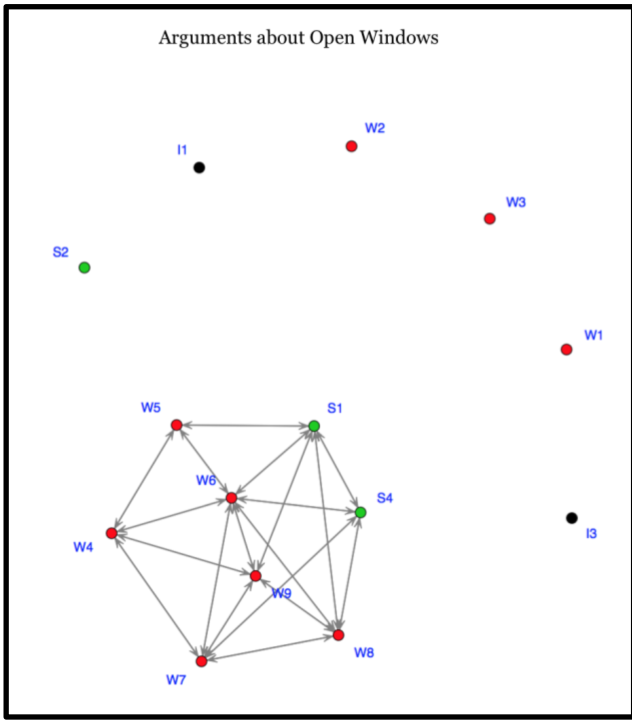


Antisocial Interactions

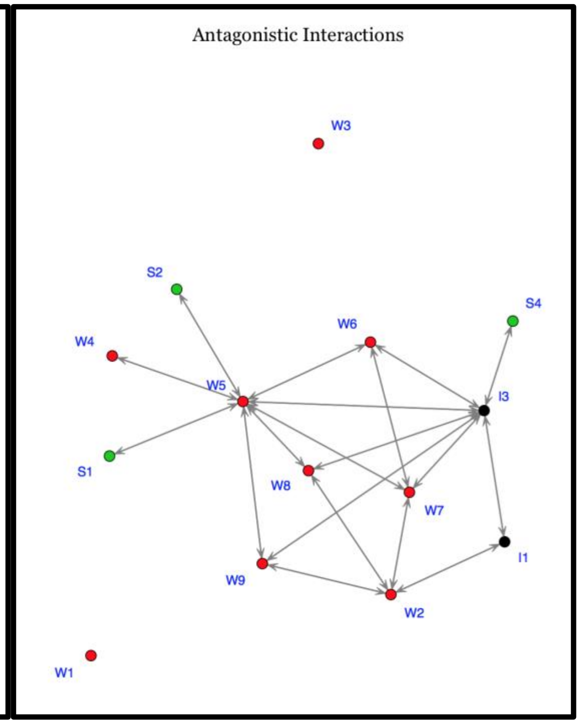
When comparing the network structures of the two anti-social networks, we found similarity in the nodes that appeared as outliers in both networks. In both networks, Wireman 1 and Wireman 3 appeared as outliers. This indicates that no one feels antagonism towards the two wireman and the wireman do not feel antagonism towards anyone else. This is interesting because both wireman 1 and wireman 3 are very connected within the pro-social networks. Both wiremen have a lot of ties within the friendship, horseplay, and helping other networks. This indicates that wireman 1 and wireman 3 are readily engaged in various pro-social interactions but removed from anti-social interactions.

We also isolated some differences between the two anti-social networks. First, we found that the general antagonistic network had far fewer peripheral nodes than the network representing arguments about open windows. This indicated that more total nodes engaged in general antagonistic behavior than engaged in arguments about open windows. Consequently, when analyzing the differences in peripheral nodes, we found that neither of the inspectors engaged in conflicts about open windows. This supports our previously mentioned prediction that in their supervisory role, inspectors do not engage in many of the typical behaviors practiced by their subordinates. However, the two inspectors did have general antagonistic interactions with others in the bank wiring room. We hypothesized a reason for this antagonistic interaction due to their role as authority figures. It is possible that subordinates did not agree with their style of leadership, got upset for reprimands brought against them by the inspectors, or disagreed with the way an inspector managed a situation. In this way, the network structures reflect the kind of working relations we would expect to find among the wiremen, solderers, and inspectors. In summation, the anti-social networks do not have very similar network structures, but both do reflect the influence of employee type on social interactions.

Network Plot: Arguments about Open Windows



Network Plot: Antagonistic Interaction



Conclusions

Research Question 1: Similarities in the Network Structures of Pro-social and Anti-social behaviors

Behaviors and attitudes shaped network structures in order to create different network structures. Hierarchical structure for horseplay and helping others, both pro-social behaviors, were identical in structure. This indicates that individuals who engage in pro-social behaviors influence network structures in similar manners. Participation in horseplay was generally divided into two distinct groups, which is represented both in the clustering plot as well as the block model. One block, with a density of 0.82, consisted of actors Wiremen 1,2, 3, 4, Inspector 1, Solderer 1 and on the periphery of the model wireman 5. The second group consisted of wiremen 6, 8, 9 and Solderer 4. The rest of the actors were in the periphery of the block not interacting heavily with other actors. This is similar to the structure illustrated by the clustering plot for horseplay. The network, helping others with work, is less dense, than that of horseplay. In this network only select wiremen and solderers traded jobs with one another, with no inspectors helping others with work. Wiremen 3 and 6 as solderers 1 and 2 had the greatest number of ties in this network. Wiremen, in general tended to trade jobs with one another, with the exception of wireman 5, who did not help others. Inspectors and Solderer 2 refrained from helping other members of the network. In anti-social behavioral networks (negative behavior and arguments about open windows), the networks do not resemble one another as clearly as those in pro-social behavior. However, key actors appear in both anti-social networks that were in the periphery of pro-social networks. Wireman 2 and 5 and Inspector 3 were the most connected in the antagonistic behavior network. In the block model for antagonistic behavior only, these Wiremen 2 and 5 and Inspector 3 formed significant ties in the antagonistic network. In the clustering plot, all actors except for wiremen 1 and 3 were connected within the network. In the pro-social networks Wiremen 1 and 3 were the most central actors indicating that their pro-social behaviors removed them from harboring or others harboring negative behavior toward them. In arguments about open windows, there was a strong cluster of actors that participated in arguments in open windows. This cluster is primarily made up of wiremen 5, 6, 7, 8 and 9 as well as solderers 1 and 4. All other actors did not participate in arguments about open windows. Once again wiremen 1 and 3, the most central actors in pro-social networks refrained from participating in arguments regarding open windows. Only one central actor from the antagonistic network appears in arguments about open windows. From this we can infer that network formation for anti-social behaviors are not similar across networks. From the results of our ERGM, we found that solderers were less likely to form antagonistic ties when compared to wiremen and inspectors. Inspectors are 8.55 times more likely to form antagonistic ties when compared to solderers. Wiremen are 3.48 times more likely than solderers to form antagonistic ties. From our analysis of the network structures we found that density measures for anti-social behaviors, arguments about open windows and antagonism, were identical at 0.209. This was a higher density than any other network, excluding horseplay whose density was 0.308. This indicates that overall a larger proportion of workers participate in anti-social behaviors than in pro-social behaviors. Centralization for anti-social networks was far greater than that of anti-social networks. Antagonism has the highest centralization with 0.47. This is consistent with the block model data which illustrate three main actors carrying the majority of the density in the network. Trading jobs and helping others had the lowest centrality with measures of 0.14 and 0.16, respectively. This indicates that anti-social networks are centered around a small group of nodes as compared to pro-social networks which have a larger distribution of ties. Transitivity between nodes in a network was more likely in pro-social networks. The transitivity for friendship, horseplay and trading jobs was 0.64, 0.80, and 1 respectively. The transitivity in anti-social networks was lower with arguments about open windows measuring 0.67 and antagonism measuring 0.25. This indicates that pro-social networks tended to have more interconnected nodes than anti-social networks. In conclusion, pro-social network formations are similar across pro-social behaviors while anti-social networks are not similar across behaviors. Pro-social actors tended to be key players, while anti-social actors remained on the periphery of the networks.

Research Question 2: Does job title influence network formation?

Social status can affect the manner in which a network is formed. Similar people tend to form social groups based on similarity. Power dynamics can also influence the formation of cliques and network formations as they generally, hold more social capital than those in lower positions but have less ties to other individuals in the network. We sought out to answer how job title influences network formation. We predicted that actors with a higher job status would be more isolated from each network. In keyplayer groups we found that Inspector 1 (I1) and Wireman 1 (W1) appeared in anti-social groups. Wireman 1 is an actor which was central in pro-social networks as well. When we evaluated network clusters I3 received a large portion of ties in the antagonistic, or negative network. However, I3 and W3 were both not involved in arguments about open windows. However, in arguments about open windows only wiremen and solderers participated in this anti-social behavioral network. Wiremen, which constituted the largest job type being observed, at least some wiremen tended to be central key actors in the networks compared to some of the other networks where other job types did not partake in. Wiremen were more central in pro-social behavior networks horseplay, helping others with work and trading job assignments. Wiremen 1 and 3 tended to be key players in pro-social groups and outliers, not participating in anti-social behaviors. The majority of the key players in the friendship, helping others and horseplay networks were wiremen, with wiremen 3 appearing as a key player in each network. In arguments about open windows, the key players tended to be wiremen, specifically wiremen 6, 7, 8 and 9. Three of these wiremen were also individual key players in helping others indicating that they were central in both pro-social and anti-social networks. The central people in the network observing antagonistic behavior was consistent with our other data which placed wiremen 2 and 5, as well as inspector 3 and wiremen 7 as the most central in that group. These individual actors all appeared in the periphery of pro-social networks. Actors in keyplayer groups varied from the individual key players. In the keyplayer group for pro-social networks, horseplay and friendship inspector 3 appears as keyplayer which differs from the previous results. Inspector 3 also still appears in arguments about open windows and antagonistic behavior. This indicates that Inspector 3 has ties across multiple networks, both pro and anti-social. In arguments about open windows, inspectors 1 and 3 appeared in the group keyplayer total but not as the most central individuals. Surprisingly, wireman 1 appeared in the most central group for antagonistic behavior. Given that wiremen 1 did not harbor any negative emotions nor did any other node have negative emotions towards them. Overall, the individual key players were more representative of the clustering and block model data of the networks. In our clique data we found that for horseplay, larger cliques of five had key players generally consisting of wiremen 1,2,3, or 4. Cliques for arguments about open windows included wiremen 6, 7, 8 and 9. These results are consistent with the keyplayer data indicating that central people also created cliques within the social group. Cliques for helping others with work and antagonism tended to be small, generally consisting of one or two actors. However, larger antagonism networks that had larger cliques of 4 included inspector 3, and wiremen 5, 6, and 7. Two of the actors in this larger clique are also key players in the antagonism network, Inspector 3 and wiremen 5 and 7. In conclusion, job title did affect network formation in both pro-social and anti-social networks. Wiremen tended to be central in both pro-social and anti-social networks, while solderers tended to appear in pro-social networks and inspectors appeared in anti-social networks. Job type and the individual behaviors of actors affected the manner in which the networks were formed. Pro-social networks tended to have key players which were wiremen, but the network structure expanding to include solderers. Solderers, the actors with the lowest job title in the bank wiring room, were the least likely to engage in anti-social behaviors, while inspectors, those with the highest position, were more likely to engage in anti-social behaviors. Similarities persisted among the pro-social networks and the most central actors within them as well as those within the anti-social networks.

Discussion and Limitations

Despite our findings, there are limitations to the study. First, our data was collected in the 1930s for purposes other than social network analysis. This limits the amount of information we can extract from the dataset. However, our theories can be applied in other contexts that test for their effects. It is also difficult to study the effects of peer influence on a network, particularly when the data is not collected for the purposes of social network analysis. The method in which the data was collected did not allow us to combine networks in our model thereby limiting the results of our ERGM. In the future, we would like to call for more studies that examine the effects of peer influence on a social network in order to expand upon our findings.

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