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Why does everybody hate me? Balance, status, and homophily: The triumvirate of signed tie formation

Janice Yap[1], Nicholas Harrigan[*,1]

School of Social Sciences, Singapore Management University, 90 Stamford Road, Level 4, Singapore 178903, Singapore

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ABSTRACT

Despite being one of the foundational theories of signed (positive/negative) tie formation, the evidence for balance theory is far from conclusive. A recent promising alternative is status theory, but a theoretical and explanatory gap still remains, with a dearth of theories and evidence. We put forward and test eight separate theories of signed tie formation on two face-to-face networks of friendship and esteem of 282 students. We use dimension reduction (factor analysis) on the results tables comparing the predictions of these eight theories for 50 ERGM parameters with our estimated models. We find three main paradigms explain the majority of signed network formation: balance, status, and homophily.

1. Introduction

Signed ties are ubiquitous in social networks: in the playground friendships (+) and bullying (−); in the nightclub cliques (+) and fights (−); in the office, gossip of a friendly (+) and unfriendly (−) nature; in a network of firms, partnerships (+) and competition (−); in networks of states alliances (+) and disputes (−); and in social media with chat partners (+) and blocked users (−). Despite this ubiquity, there remains only one major theory that is regularly used to explain signed ties – balance theory. While balance theory is neat and simple – it states that positive and negative ties form to avoid cognitive dissonance – the evidence for this theory is mixed, at very best (Newcomb, 1968, 1979; Truzzi, 1973; Mower-White, 1977, 1979; Epstein, 1979; Doreian and Krackhardt, 2001; Hummon and Doreian, 2003; van de Rijit, 2011).

There is one promising exception to the dearth of theoretical advances in the signed tie literature, and that is the recent proposal of status theory by Leskovec et al. (2010). Status theory conceptualises of positive and negative ties as both reflecting and forming the social hierarchy of a social network. Individuals who receive positive ties will be of higher status, and in turn because of this be less likely to receive negative ties. In contrast, individuals who receive negative ties will be of lower status, and in turn because of this less likely to receive positive ties.

Despite the introduction of status theory, the comprehensive testing of a wide range of theoretical approaches to signed tie networks remains an outstanding task which we set out to remedy with this paper. To do this we put forward eight separate theories that might explain signed tie formation (see Table 1). Many of these eight theories have been applied elsewhere in social network analyses, but only in the context of either solely positive or solely negative tie networks. In Table 1, we outline our interpretation of many classical (and several original) theories of social network analysis as applied to signed tie networks.

The rest of the paper is structured thus. First we provide a literature review, which comprehensively overviews the eight theories we have just outlined, as well as the literature on signed ties more generally. Second, we outline our methods and data, explaining how we estimate a 50 parameter multiplex exponential random graph model of both our networks (the friendship and the esteem networks) of 282 students. We also explain how we compare the prediction tables of these eight theories for these two networks and 50 parameters (a total of 800 predictions) to the actual final estimated models for the networks, and generate a results table of correct and incorrect predictions. By conducting a factor analysis (dimension reduction) on this results table, we are able to identify orthogonal factors that are driving signed tie formation in our social networks. Thirdly, our Results, Discussion, and Conclusion sections present the outcome of this analysis, as well as our interpretation of the results in light of previous research, and their implications for future researchers.

* Corresponding author. +65 6828 0842.
E-mail addresses: janice.yap.2009@smu.edu.sg (J. Yap), nharrigan@smu.edu.sg, nickharrigan@gmail.com (N. Harrigan).

[1] These authors contributed equally to this work.

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Table 1
Definitions for the eight theories of signed tie formation.

Theory	Definition
Activity theory	That an individual's likelihood of sending a new positive tie increases with (1) the number of positive ties they have already sent, or (2) the possession (or level) of an attribute. The same applies to negative ties
Balance theory	That an individual's likelihood of forming a new tie increases when that tie increases cognitive consistency, and decreases when that tie creates cognitive dissonance. The major situations where dissonance occurs is where two friends are in conflict, and the three ties in the triad are not in 'balance'
Homophily theory	That an individual's likelihood of forming a new positive tie increases if the person they are considering forming a tie with shares a similar attribute, such as similar age, gender, or race. In the case of negative ties, it seems likely that the opposite would occur: the likelihood of forming a negative tie increases with dissimilarity of individuals
Karma theory	That an individual's likelihood of sending a negative tie is proportional to the number of negative ties they receive, and their likelihood of receiving negative ties is proportional to the number of negative ties they have sent. The same applies to positive ties
Popularity theory	That an individual's likelihood of receiving a new positive tie increases with (1) the number of positive ties they have already received, or (2) the possession (or level) of an attribute. The same applies to negative ties
Solidarity theory	That an individual's likelihood of receiving a positive tie will increase if both the sender and receiver are both senders or both receivers of negative ties. This configuration involves positive ties between structurally equivalent individuals in the negative tie network
Status theory	That an individual's likelihood of receiving positive ties increases with higher status, and likelihood of receiving negative ties increases with lower status. Ties themselves are indicators of status, with positive ties flowing from low status individuals to high status individuals, and negative ties flowing in the opposite direction
Visibility theory	That an individual's likelihood of receiving positive or negative ties will be proportional to their total number of positive and negative in-ties. (Note that higher numbers of negative in-ties will increase the probability of receiving positive in-ties and vice versa)

2. Literature review

This literature review has three parts, first is an introduction to balance theory, second is an introduction to status theory, and third is a review of the last 5 years of negative tie literature, with an organisation of this third part of the review around the remaining six theories we are testing in this paper.

2.1. Balance theory

Balance theory is the most established and oldest theory of signed tie formation, dating back to 1946 when Heider came up with structural balance theory to explain sentiment relations in dyadic and triadic relationships. A sentiment relation maybe expressed as either positive (like) or negative (dislike). In a dyadic relationship 'balance' occurs when two people reciprocally like or dislike each other. In a triadic relationship, if the multiplication of the signs of these relations is positive then a balanced state is achieved. In other words, balance is achieved when all three ties between nodes are positive or if two ties are negative and one is positive.

Heider's main proposition was that entities (not necessarily individuals or people) tend to either form signed ties (i.e. like/dislike ties) or change the signs of their ties so as to achieve a 'balanced' state. Such a tendency is driven by a person's desire to avoid cognitive dissonance arising from imbalance (Hummon and Doreian, 2003; Taylor, 1967; Zajonc, 1960). If change is not possible, then such a state of imbalance will produce tension (Cartwright and Harary, 1956; Heider, 1946).

Much of Heider's work on balance theory initially focused on dyads and triads by examining undirected ties. Directed networks were commonly dealt with thereafter by simply removing the direction of the ties (Wasserman and Faust, 1994).

Cartwright and Harary (1956) were the first to formalise Heider's ideas of balance as structural balance in social networks – i.e. the application of balance to triads of people. To them, sentiment relations among individuals can be thought of as a social interpersonal network (Kadushin, 2004). Cartwright and Harary also adapted Heider's balance theory of micro-structures (dyads and triads) to macro-structures (entire networks). This became the 'structure theorem' which broadly states that all balanced networks can be divided into two subgroups where only positive ties exist within each subgroup, and only negative ties exist between subgroups. Subsequently, this generalisation has been reformulated to include cases where networks can be divided into two or more subgroups (Davis, 1967).

Support for structure theorem has been found in theoretical models and simulated networks. Wang and Thorngate (2003) developed two Monte Carlo simulations to investigate the effect of balancing in triads on the larger group structure and found that groups eventually moved towards a state of balance containing no more than two subgroups. Similarly, Maulana (2008) in simulating voting behaviour constrained by structure theorem found macro-level polarisation of political preferences. However, these studies are theoretical simulations, not based on empirical data, which calls into question the real world applicability of structure theorem.

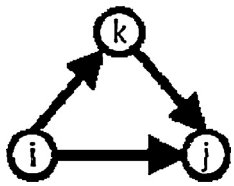
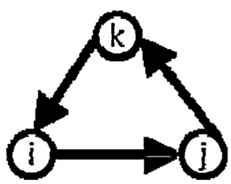
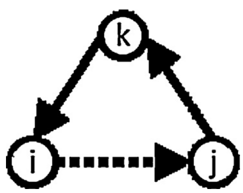
Meanwhile, other studies searching for balance in real world networks find mixed evidence at best (Kalish, 2013). Epstein (1979), in a longitudinal study of friendship choices among secondary school students, found that friendship was not explained by "a single theory of balance". Mower-White (1977, 1979) experimentally tested for balance theory in triads but found that although balance was present, there were other biases (e.g. agreement, observer positivity, social context influence) at play. Truzzi (1973) tested for balance theory in subgraphs of higher orders than dyads and triads through experiments. He found that when participants had a positive orientation to others, balance theory made more successful predictions. However, this result did not hold when participants had a negative orientation to others. Newcomb (1968), Doreian and Krackhardt (2001) found similar results where balance theory did not appear to operate when participants have to direct a negative tie in order to achieve balance. van de Rijit (2011) also discovered 'jammed situations' where changing the sign of any one tie in a network will not reduce the total number of instances of imbalance in that network. In contrast to the conflicting evidence in human networks, some of the strongest evidence for structural balance in the real world has been found recently in non-human mammalian social networks of rock hyraxes (a cat-sized rodent) (Ilany et al., 2013).

This suggests that because of the complexity of human networks, balance theory alone may not be sufficient. So not only may balance not apply consistently on the individual level (as proposed by Heider), but it may also not aggregate consistently into balance at the macro-level either (as theorised by Cartwright and Harary).

2.2. Status theory

Recently a major alternative to balance theory has appeared in the academic literature: Status theory. Status theory was first

Table 2
Examples of predictions by Balance theory and Status theory.

Subgraphs	Graph	Predictions	
		Balance theory	Status theory
Reciprocity AB		–	+
AKT-TA		+	+
AKT-CA		+	–
CAAB		–	+

Notes:
1. A solid arrow represents a positive tie while a dotted arrow represents a negative tie.
2. '+' means the theory predicts a positive parameter value (i.e. a tendency for that subgraph) while '–' means a the theory predicts a negative parameter value (i.e. a disinclination for that subgraph).

applied to signed tie formation by Leskovec et al. (2010) as an alternative to balance theory. The theory stems from the observation that positive/negative ties may have multiple interpretations depending on the intention of the sender (Guha et al., 2004). This suggests that signed tie formation may be driven by other mechanisms than a desire for cognitive consistency.

Leskovec et al. (2010) only provides a cursory description of the mechanism behind Status theory: deference – where positive ties are directed to those of higher status while negative ties are directed to those of lower status (see also Lim and Rubineau, 2013).

The best way to get a clear understanding of status theory is to compare its predictions for dyadic and triadic tie formation on a signed tie network with those of balance theory. Table 2 shows four common subgraphs that might be found in a signed tie network. Looking at the bottom tie in each network (the lowest tie in the dyad/triad), we ask, is this tie more (+) or less (−) likely to form under status theory (or balance theory), given the presence of the other ties in that subgraph (relatively to an empty graph).

So taking the first subgraph, reciprocity AB, the pre-existing tie is a positive tie from *i* to *j*. This makes the likelihood of a negative tie from *j* to *i* less likely (−) because balance theory says that people favour cognitive consistency. However, in the case of status theory, the pre-existing tie acts as a social cue that *j* is of higher status than *i*. Because *j* is of higher status, *j*'s likelihood of sending a negative tie to *i* is actually higher (+), since status theory says that negative ties flow from those of high status to those of low status.

In the second subgraph, Transitive Triad (T9), all the ties are positive. Balance theory predicts that the tie from *i* to *j* will be more likely to form than chance because *j* is a friend of a friend. Also note that the other method of calculating a balanced triad works: the multiplication of the signs of the ties of the triad is positive, indicating balance. Status theory also predicts that the tie from *i* to *j* will be more likely to form than chance because *j* is of higher status than *i*. This is in turn because *i* directs a tie to *k* (making *k* of higher status), and *k* directs a tie to *j* (making *j* of even higher status).

In the third subgraph, Cyclical Triad (T10), all the ties are positive again. Balance theory, again, predicts that the tie from *i* to *j* will be more likely to form than chance because *j* is a friend of a friend. Note the positive multiplication of signs of sides also works. Status theory, however, makes very different predictions. Status theory predicts that the tie from *i* to *j* is less likely to form than chance because *i* is of higher status than *j*. This is in turn because *j* directs a tie to *k* (making *k* of higher status), and *k* directs a tie to *i* (making *i* of even higher status).

In the fourth subgraph, a mixed cyclical triad (CAAB), balance and status theories again make opposite predictions. Balance theory predicts that the negative tie from *i* to *j* will be less likely (−) to form because *j* is a friend of a friend. Note also, how the multiplication of the signs of the three ties is negative. Status theory, however, predicts that the negative tie from *i* to *j* will be more likely (+) to form because *i* is of higher status than *j*. *i* is of higher status because *j* directs a positive tie to *k*, and *k* directs a positive tie to *i*, thus making *i* the highest status person in the triad.

As can be seen from the above examples, Status theory makes an interesting and useful addition to the theoretical tools available for those wanting to analyse signed tie networks. It provides a large number of predictions which contradict those of balance theory, yet at the same time have a coherent and sound logic of their own. As we will show in our analysis later in this paper, Status theory does seem to have a sound place in the long term cannon of signed tie literature.

2.3. *Other recent negative tie literature*

In this section we review other articles published in the last five years on negative ties, and also the papers presented at the special sessions on negative ties at the Sunbelt Conference in Hamburg Germany in 2013. We organise this section around the theories that are the basis of our later analysis.

2.3.1. *Visibility*

According to our formulation, visibility theory states that an individual will be more likely to receive inties if they are already the recipient of inties, either positive or negative. The existing literature already has at least one example of evidence of this: Carboni (2013) finds that centrality in the positive tie network leads to receiving negative inties.

2.3.2. *Popularity*

Popularity is distinct from visibility in one important way: ties are partitioned from one another in popularity. Positive inties only increase the chance of other positive inties. Negative inties only increase the chance of other negative inties. Much of the existing literature focuses on developing new centrality measures with the aim of better measuring popularity effects (Everett and Borgatti, 2014; Smith et al., 2014). A number of other studies use existing measures of centrality to study the effect of popularity in novel situations (Szell et al., 2010; Ellwardt et al., 2012; Daly and Moolenaar, 2013; Carboni and Casciaro, 2013)

2.3.3. *Activity*

Interestingly, within the existing literature, popularity (indegree) and activity (outdegree) are often addressed within the same papers, and activity receives relatively little distinct attention. As will be shown in our later analysis (see Sections 4 and 5), activity is entirely theoretically distinct from popularity, appearing to load on an entirely different component to popularity. This said, the existing literature which makes reference to signed ties and activity is largely the literature listed under the heading 'Popularity'.

2.3.4. Karma

Our theory of Karma states that an individual's extent of positive indegree will be proportionate to their positive outdegree, their negative indegree will be proportionate to their negative outdegree, and so forth. We were able to find nothing in the existing literature which made reference to any theory or mechanism that approximated this.

2.3.5. Solidarity

This is the theory of the unity of the bullied and the bullies. We were able to find one paper that has found evidence of this: Huitsing et al. (2012) ran an ERG model of networks of like, dislike and bullying and found positive ties between those structurally equivalent in either the dislike and the bullying networks.

2.3.6. Homophily

Homophily is that attraction of like for like. The literature distinguishes between two main types of homophily: inbreeding and baseline homophily. Baseline homophily is the tendency for similar individuals to be attracted to each other, simply because of the population proportions. For example, if 75% of a population is Chinese, then, at random, we would expect 75% of the friends of Chinese people to share their race. Inbreeding homophily is attraction over and above that which would occur at random, and is generally thought to be the product of preference of individuals for people of the same type. For example, if in the case just discussed, 85% of the friends of Chinese people are Chinese, then 10% of these friends are a result of inbreeding homophily (McPherson et al., 2001).

In single time point datasets – such as ours – it is almost impossible to distinguish homophily (a preference for similar others) from either social influence (a tendency to make others like ourselves) and other forms of segregation (such as the tendency to be tied to similar others because of third factors).

We were able to find at least three studies in the last three years that suggested the operation of homophily in signed tie networks. Lusher et al. (2013) found that node attributes (such as racism) help explain negative tie networks ("Do you have a difference of opinion?"). Nieuwenhuis et al. (2013) found that religious diversity, amongst other things, drove conflict between neighbours. Young and Weerman (2013) found that school children tended to adopt the deviant behaviour and beliefs of their friends, and also to select their friends who shared the same deviant behaviour. However, not all studies were as conclusive. Jaspers et al. (2013) found ethnicity and immigrant origin had mixed results on likelihood of school children receiving/sending negative ties across Germany, Netherlands, Sweden, and England.

3. Methods and data

3.1. Dataset

The dataset was collected primarily for use in this paper. This is the first time that this dataset has been published from. The data was collected in January 2013. Our dataset was drawn from the final two years of a medium sized Singaporean business university. The students represented two cohorts of students from a bachelor of social science. All 298 students in the selected cohorts were sent the survey and 282 (94.5%) completed the survey. This is a very high response rate, even for a social network survey.

The final dataset included only the 282 respondents. The 16 non-respondents and any ties to them were removed.

Students were recruited using multiple methods: they were sent emails, and then multiple reminder emails. They were also encouraged to do the survey during class time, and given a $5 incentive to do the survey. The survey was done online to make the survey both easier for respondents to complete, and easier for us as surveyors to enter and clean the data.

The mean age of respondents was 22.7 years. Respondents were approximately evenly split between 3rd and 4th year students. We chose the 3rd and 4th year cohorts because they had had the longest period of continuous contact with one another: The 3rd years had known each other for approximately two and a half years, and the 4th years had known each other for approximately three and half years. The bachelor of social science itself, is very much like a small liberal arts college in Singapore, with small, seminar-style classes, and close student–student, and student–teacher interactions. We felt that this would mean that social network effects would be particularly strong after 2–3 years of their development. From a balance perspective, one would expect that 2–3 years should give time for the effects of balance to be able to 'sort themselves' and become apparent.

Alongside a range of demographic questions (gender (Binary), age (Continuous), race (Categorical), first major (Categorical), membership of executive committee of student society (Binary), family income (Continuous)), students were asked four social network questions. It should be noted, that we originally asked much more abstract questions about friendship and esteem. However, when we did ethnographic pretesting of our surveys, we found that these questions produced very poor responses from interviewees. The problem was that interviewees had trouble knowing exactly what we meant by these abstract terms like 'friendship' or 'esteem'. We workshopped the questions with multiple focus groups, and found that 'proxies' – concrete hypothetical situations – were felt by the majority of participants to be much easier to understand, and also best captured the dimensions of friendship and esteem we were targeting. We also found that students were both more likely to answer, and answered the questionnaire more quickly (response time was reduced threefold), when they were given concrete hypothetical situations. Our final questions were[1]:

1. Who would you invite for lunch?
2. Who would you avoid having lunch with?
3. Who would you nominate to lead the students' council?
4. Who would you avoid nominating to lead the students' council?

These four questions are asked as proxies for (1) like/positive affect, (2) dislike/negative affect, (3) esteem/admiration, and (4) disesteem/disdain.

For each question, the students were asked to nominate between one and five other students in their year/cohort (i.e. 3rd years could only nominate 3rd years, and 4th years only other 4th years). A minimum of one nomination was included to try to overcome the negative and potentially costly action of nominating other

[2] The exact questions for 4th years were: (1) You are going for lunch after class, please list at least one [social science] student admitted in 2009 you would invite for lunch. (2) You are going for lunch after class, please list at least one [social science] student admitted in 2009 you would avoid having lunch with. (You may repeat nominations from previous questions.) (3) There is a new student council at [university] that can potentially change your life in [university] and your prospects after graduation significantly. Please list at least 1 [social science] student admitted in 2009 you would nominate to lead this new student council. (You may repeat nominations from previous questions.) (4) There is a new student council at [university] that can potentially change your life in [university] and your prospects after graduation significantly. Please list at least 1 [social science] student admitted in 2009 you would avoid nominating to lead this new student council. (You may repeat nominations from previous questions.) 3rd year were asked the same questions except they were requested to nominate students admitted in 2010.

students for the negative ties (questions two and four). The literature on force response questions (Russell, 1993; Stieger et al., 2007) says that there are two main potential problems with forced responses: (1) it decreases response rate, and (2) if respondents are expressing an opinion about something they have no knowledge of their answers would reduce the accuracy of the survey. In our case, the first problem did not occur: we had a 94.5% response rate. The second problem, we felt, was not an issue as the students had known each other, and had taken numerous classes together, for at least two and a half years. Informal post-survey interviews with students suggested that the vast majority had no problem with the forced response, with a small minority (15 people) making either one self-nomination or nominating the first person (like a donkey vote) on the survey. This amounted to 19 ties (nominations), and we removed these ties (not the individuals, just the ties) from the dataset and coded them as empty ties.

What makes lunch an operationalisation of friendship and dislike? Through our qualitative interviews, we found that lunch was seen as a good proxy for friendship simply because eat a meal is a necessity, and it is a social situation that can be shared with people whose company you like. What makes nomination to lead/not lead students' council a measure for esteem/disesteem? Through our qualitative interviews we found that nomination to lead students' council was a good proxy for esteem because nominating someone for student council is an act of indicating that you hold them in high respect, for a public office with limited number of positions.

We further tested our operationalisation of friendship and esteem by undertaking a short survey of 448 students from the same university.[2] We asked four questions:

1. List 4 adjectives that describe your feelings towards someone you would go to lunch with. (open-ended)
2. List 4 adjectives that describe your feelings towards someone you would nominate for students' council. (open-ended)
3. Thinking about the people you would go to lunch with, would you best describe them as:
   a. People you have friendship with
   b. People you hold in esteem, respect, or feel have high status
4. Thinking about the people you would nominate for students' council, would you best describe them as:
   c. People you have friendship with
   d. People you hold in esteem, respect, or feel have high status

The results of this survey are collated in Fig. 1a–c. Notice that the most common adjective used to describe a person you would go to lunch with is 'Friendly', while the most common adjective used to describe a person you would nominate for student election is 'Respect'. Note also that when students were presented with a forced choice question as to how to categorise people they would go to lunch with, or nominate for elections, 90%+ chose to associate lunch with friendship, and elections with esteem.

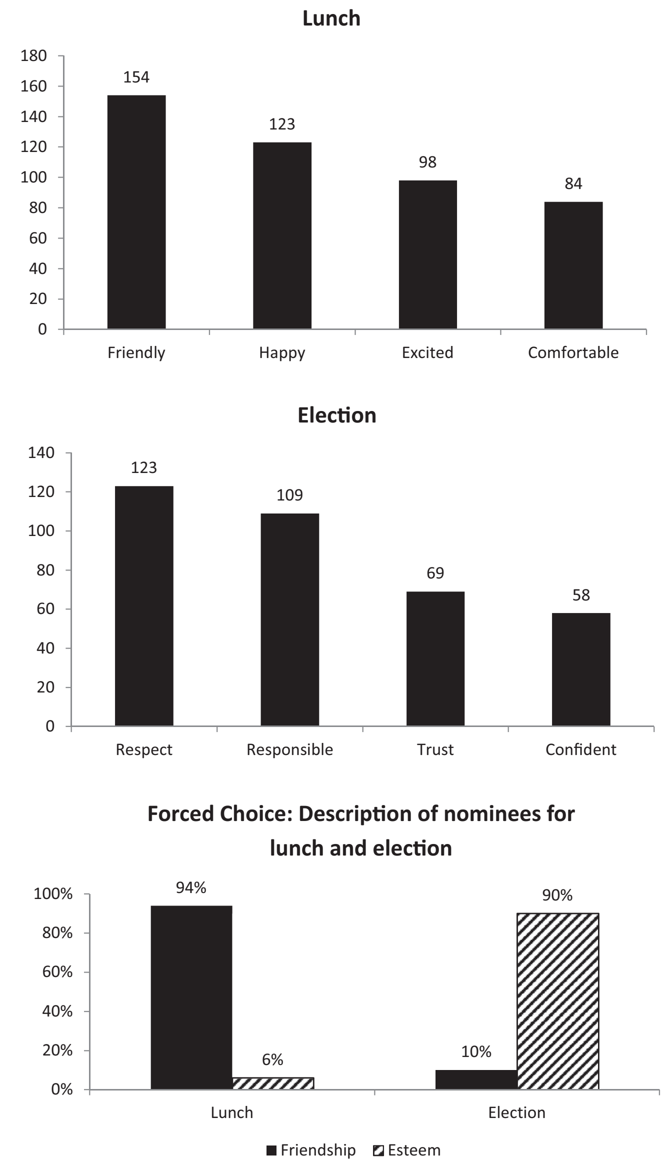


Fig. 1. (a) Four most common adjectives used to describe someone you would go to lunch with. (b) Four most common adjectives used to describe someone you would nominate for students' council. (c) Forced choice description of nominees for lunch and elections: Are they 'friends' or people held in 'esteem'?.

3.2. Exponential random graph modelling

We compare the dynamics of positive and negative tie formation in two different types of networks: an affect (going to lunch) network, and an esteem (nominating for students' council) network. We are interested in both what are known as endogenous network effects – those produced purely by the structural effects of ties on each other – and exogenous network effects – those produced by the effects of attributes of actors on tie formation.

Most prior studies of balance theory have tended to look for over or under representation of triadic configurations associated with balance. They have done this by comparing the prevalence of triads in observed graphs with their prevalence in random graphs (controlling for density, or perhaps degree distribution). However, there is the danger that the prevalence of various balanced triads found in these studies are actually epiphenomena driven by lower order subgraphs, such as stars or paths.

We control for lower order subgraphs using exponential random graph models. In these models, the dependent (outcome) variable is the formation of a new network tie. The independent variables – for structural effects in the model – are various subgraphs that represent network dependencies. These subgraphs include: reciprocity, in- and out-stars, triads, and two-paths (Wasserman and Pattison, 1996; Snijders, 2002; Snijders et al., 2006; Robins et al., 2009).

To model the interplay between positive and negative ties we use a special multiplex version (called XPNet) of the exponential

[3] This survey was done 18 months after the original survey. We believe that the fact that these 770 students are of the same age and drawn from the same cultural context as our first dataset, means that their understanding of the concepts approximates that of our sample population.

Table 3
Key parameters in XPNet.

Parameter	Diagram	Parameter	Diagram	Parameter	Diagram
Arc A*		Arc B*		Arc AB#	
Sink A		Source A		Isolates A	
Sink B		Source B		Isolates B	
Reciprocity A		Reciprocity B		Reciprocity AB	
K-In-StarA		K-In-StarB		In2StarAB	
K-OutStarA		K-OutStarB		Out2StarAB	
A2P-TA		A2P-DA		A2P-UA	
A2P-TB		A2P-DB		A2P-UB	
Mix2StarAB		Mix2StarBA			
AKT-TA		AKT-DA		AKT-UA	
AKT-CA		AKT-TB		AKT-CB	
AKT-DB		AKT-UB			
TABA		TAAB		TBAA	
TABB		TBBA		TBAB	
CAAB		CBBA			

Notes:
1. A solid arrow represents a positive tie while a dotted arrow represents a negative tie.
2. Two strokes on a tie represents the absence of that tie.
3. For a complete list of parameters and more detailed explanations on each parameter refer to the "PNet User Manual" available here: http://sna.unimelb.edu.au/__data/assets/pdf_file/0006/662865/PNetManual.pdf (Wang et al., 2006a,b).
* This parameter was not included in the model because graph density as fixed.
# This parameter was not included in the model because it was prohibited by the nature of the data.

random graph modelling software PNet (Wang et al., 2006a,b; Wang, 2013; see also its use in Robins et al., 2011). PNet estimates ERG models using a MCMCMLE[3] (Snijders, 2002). XPNet allows the modelling of two networks, in our case a positive and a negative network. Because two networks are present, a vast array of new network subgraphs (independent variables) are introduced to the model. In Table 3 we present diagrams and labels for the key parameters used in our models.

Note that in the parameter list in Table 3 the parameter Arc-AB – which is entrainment of the A and B tie – is both excluded from the model, and prohibited (meaning that it cannot form). This prohibition of Arc-AB ties comes from the fact that it is impossible and/or meaningless to both want to and not want to go to lunch with

4 Monte Carlo Markov Chain Maximum Likelihood Estimation.

someone (and similarly to nominate and avoid nominating for students' council). In the cases (48 ties in total: ~3% of all ties) where our survey participants did nominate people for both positive and negative ties of the same type (affect/esteem), then we assumed that their negative tie nominations was a mistake and removed it, since this question was asked after the positive tie question, suggesting that the individual misunderstood the question or was avoiding answering the negative tie question.

The esteem (elections) and the affect (lunch) networks were modelled separately as XPNet only allows for the modelling of the interaction of two networks at one time.

XPNet (and ERGMs more generally) estimate a model of the form (Koskinen and Daraganova, 2013):

$$P(x_i = 1|\boldsymbol{A}, \boldsymbol{B}) = \frac{1}{1 + e^{-1}(\beta_1 s_1 + \beta_2 s_2 + \cdots + c)} \quad (1)$$

Our XPNet/ERG models were estimated on a dataset which combined both the 3rd and 4th year networks. Because actors in these two networks were unable to nominate each other as tie partners, it was necessary to account for this in our model. We did so using structural zeros – basically we fed the computer programme a matrix which specified which ties could form and not – forcing ties to only be formed within each cohort.

To facilitate fitting of the model, graph density was fixed, and hence Arc A and Arc B parameters were not included in the model.

3.3. Factor analysis

Factor analysis is a technique for helping to explain the structure of a set of variables in terms of higher or simpler 'explanatory constructs' knows as factors (or latent variables). These are, generally, a smaller number of variables than the initial set of variables, thus giving name to the concept of 'dimension reduction'.

In our analysis we use SPSS to run a Factor Analysis with a Varimax Rotation on two valued matrices (one for affect, one for status). The columns were the eight theories of signed tie formation, and the rows were the approximately 50 parameters in our converged model. We assigned each cell a score from −2 (if the ERGM results were directly contradicting the theories predictions) to 2 (if the ERGM results were directly in support of the theories predictions). The predictions table is laid out in Table 4, and the detailed scoring system is laid out in Table 5.

4. Results

We present the results in four sections: (1) first, descriptive statistics, where we compare our observed networks (of affect and esteem) to a sample of random graphs; (2) second, ERG models, where we model the effects of various subgraphs on the formation of network ties; (3) third, goodness of fit (GOF) statistics, where we present assessments of the fit of our ERG models; and (4) fourth, factor analysis, where we apply dimension reduction to the range of subgraphs in the ERG models, and attempt to identify the major latent factors driving signed tie formation in our networks.

4.1. Descriptive statistics

Table 6 shows various descriptive statistics for our dataset. Overall there were 298 students who could have potentially participated in our study, of whom 282 did. These 282 students sent 987 like ties to each other, 499 dislike ties to each other, 540 esteem ties to each other, and 394 disesteem ties to each other. Our sample was divided into 181 females and 101 males (reflecting the demographics of the school), with 225 Chinese, and small percentages of Indians, Malays, and other races. Eighteen of the students had served on the executive of the Social Science Society: the representative body of social science students at the university, which is responsible for organising both student social and welfare events.

Tables 7 and 8 show extracts of comparisons of the graph statistics (such as counts of key parameters) for the observed affect (Table 7) and esteem (Table 8) networks, with the graphs statistics of 1000 sample graphs drawn from a distribution of (unbiased) random graphs, with the same density. If the observed count is higher than the sample mean, then this is evidence that there is a statistical tendency towards forming that particular subgraph in the observed network. If, on the other hand, the observed count is lower than the sample mean, then this is evidence that there is a statistical tendency against the formation of that particular subgraph in the observed network.

In these models, A ties are positive ties (i.e. Affect/would like to go to lunch with) and B ties are negative ties (i.e. Dislike/would avoid going to lunch with).

The most important thing to look for when reading these tables is the *t*-statistics (or '*t*-stat'), and in particular, if the absolute value of this is larger than 2. The *t*-statistic is the difference between the observed count and the sample mean count for a statistic, divided by the standard deviation of the sample mean for that statistic. A *t*-stat of larger than 2 signifies that the chance of the observed graph's count on this statistic happened at random is quite small. While we can not necessarily assume a normal probability distribution of the graph, we can use the *t*-stat of 2 (which equates to the *p*-value of 0.05 for a normal distribution) as a rule of thumb for assessing statistical significance.

A brief review of the affect model reveals that the most prominent outlying parameters are: reciprocity A; transitive triad A, cyclical triad A, AKT-TA, AKT-DA, AKT-UA, same category A reciprocity race, same category A first SOSS major, different category A reciprocity race, different category A first SOSS major, 2-In-Star B, 3-In-Star B, K-In-Star B, TABB, and UKT-BAB

A brief review of the status model reveals that the most prominent outlying parameters are: 2-In-Star A, 3-In-Star A, K-In-Star A, A2P-UA, 2-In-Star B, 3-In-Star B, and A2P-UB.

4.2. ERG models

Tables 9 and 10 show the final converged (and fitted) multiplex exponential random graph models for both our affect and esteem networks.

The parameters and standard error can be read as per a standard logistic regression. The star in the last column of our table indicates that the (parameter)/std. err. ≥ 2, using the convention of a *z*-score of 2, and *p*-value (assuming a normal distribution) of 0.05.

Note that it is the values in the second column (under 'parameter') that are used for comparing to our predictions table (Table 4) in our factor analysis.

The third column is the 'convergence statistic'. This is a statistic which is used to check whether the model itself is a good fit for the observed dataset. 1000 sample graphs are generated using the estimated parameters, and the mean graph statistics of these sample graphs are compared to the observed graph statistics of the collected networks. This difference is then divided by the standard deviation of the mean of the sample graphs. The number which results is our convergence statistic. It is very similar to the *t*-stat in the baseline random graph models discussed in the previous section. For parameters in the model, we want this convergence statistic to be ideally below 0.1, and definitely below 0.2 (by convention).

The substance of these tables will be interpreted in the next section, but note that we find homophily (1) in the positive affect network along the dimensions of gender, executive membership, income, and first major; (2) in the negative affect network along

Table 4
Summary of key predictions made by the eight theories of signed tie formation.

	Activity Th.	Balance Th.	Homophily Th.	Karma Th.	Popularity Th.	Solidarity Th.	Status Th.	Visibility Th.
ReciprocityA	0	+	0	+	0	0	–	0
SinkA	0	0	0	0	0	0	0	0
SourceA	0	0	0	0	0	0	0	0
IsolatesA	0	0	0	0	0	0	0	0
In-K-StarA(2.00)	0	0	0	0	+	0	+	+
Out-K-StarA(2.00)	+	0	0	0	0	0	0	0
AKT-TA(2.00)	+	+	0	0	+	0	+	+
AKT-CA(2.00)	0	+	0	+	0	0	–	0
AKT-DA(2.00)	0	+	0	+	+	0	0	+
AKT-UA(2.00)	+	+	0	0	0	0	0	0
A2P-TA(2.00)	0	+	0	+	+	0	+	+
rbA for Attribute_Gender	0	0	+	0	0	0	0	0
rbA for Attribute_Exec	0	0	+	0	0	0	–	0
rsA for Attribute_Gender	0	0	0	0	0	0	0	0
rsA for Attribute_Exec	0	0	0	0	0	0	–	0
rrA for Attribute_Gender	0	0	0	0	0	0	0	0
rrA for Attribute_Exec	0	0	0	0	0	0	+	0
receiverA of Continuous Attribute_Age	0	0	0	0	0	0	0	0
rbDiffA of Continuous Attribute_Income	0	0	–	0	0	0	0	0
Same Category ArcA for Attribute_Race	0	0	+	0	0	0	0	0
Same Category ArcA for Attribute_First_SOSS_Major	0	0	+	0	0	0	0	0
ReciprocityB	0	+	0	+	0	0	–	0
SinkB	0	0	0	0	0	0	0	0
SourceB	0	0	0	0	0	0	0	0
IsolatesB	0	0	0	0	0	0	0	0
In-K-StarB(2.00)	0	0	0	0	+	0	+	+
Out-K-StarB(2.00)	+	0	0	0	0	0	0	0
AKT-TB(2.00)	+	–	0	0	+	–	+	+
AKT-CB(2.00)	0	–	0	+	0	–	–	0
AKT-DB(2.00)	0	–	0	+	+	–	0	+
AKT-UB(2.00)	+	–	0	0	0	–	0	0
A2P-TB(2.00)	0	+	0	+	+	0	+	+
rbB for Attribute_Gender	0	0	–	0	0	0	0	0
rbB for Attribute_Exec	0	0	–	0	0	0	–	0
rsB for Attribute_Gender	0	0	0	0	0	0	0	0
rsB for Attribute_Exec	0	0	0	0	0	0	+	0
rrB for Attribute_Gender	0	0	0	0	0	0	0	0
rrB for Attribute_Exec	0	0	0	0	0	0	–	+
rbDiffB of Continuous Attribute_Age	0	0	+	0	0	0	0	0
ReciprocityAB	0	–	0	–	0	0	+	0
In2StarAB	0	0	0	0	0	0	–	+
TKT-ABA(2.00)	0	–	0	0	0	0	–	+
CKT-ABA(2.00)	0	–	0	–	0	0	+	0
DKT-ABA(2.00)	0	–	0	–	0	0	0	+
UKT-ABA(2.00)	0	–	0	0	0	0	0	0
TKT-BAB(2.00)	0	+	0	0	0	+	–	+
CKT-BAB(2.00)	0	+	0	–	0	+	+	0
DKT-BAB(2.00)	0	+	0	–	0	+	0	+
M-rbm for Attribute_Gender	0	0	–	0	0	0	0	0
M-diffm for Attribute_Age	0	0	+	0	0	0	0	0

Notes:
1. '+' means the theory predicts a positive parameter value (i.e. a tendency for that subgraph) while '–' means a the theory predicts a negative parameter value (i.e. a disinclination for that subgraph).
2. '0' means no prediction is made by that theory.

Table 5
Scoring system for factor analysis on comparison of predictions table with ERG models.

		Result		
		+	–	0
Prediction	+	2	–2	–1
	–	–2	2	–1
	0	–1	–1	1

Notes:
1. '+' means the theory predicts a positive parameter value (i.e. a tendency for that subgraph) while '–' means a the theory predicts a negative parameter value (i.e. a disinclination for that subgraph).
2. '0' means no prediction is made by that theory.

the dimensions of gender (similar genders dislike each other) and age (different ages dislike each other); (3) in the positive esteem network along the dimensions of executive membership, income, first major, and race (negative homophily–heterophily); and (4) in the negative esteem network along zero dimensions.

4.3. GOF statistics

A standard test of the adequacy of an ERG model is a goodness of fit test. This involves running simulations of the model using the estimated parameters, and not only comparing the fit of the model for the estimated parameters, but also for subgraphs which are not in the model.

The rule of thumb which is used in these goodness of fit (GOF) tests is this: parameters that are in the model should have a 'convergence statistic' of below 0.1 ideally, and definitely below

Table 6
Descriptive statistics for the observed networks.

	Year 4	Year 3	Total
No. of students	159	139	298
No. of participants	150	132	282
No. of positive affect ties	501	486	987
No. of negative affect ties	262	237	499
No. of positive esteem ties	270	270	540
No. of negative esteem ties	210	184	394
Female	110	71	181
Males	40	61	101
Chinese	126	99	225
Indian	11	14	25
Malay	5	8	13
Eurasian	3	1	4
Others	5	10	15
Held positions in Student Welfare Exco Committee	8	10	18

0.2; and parameters that are not in the model should ideally have a 'convergence statistic' of below 2.

The GOF statistics for our two models are presented in Tables 11 and 12.

You can see in the affect network (Table 11) that all of the parameters *in the model* are fitted. All but five of the parameters *not in the model* are fitted. Of the 5 parameter that do not fit, two (Out2StarAB and UKT-BAB) have *t*-statistics (convergence statistics) that are greater than three, but both are below four. Given the large number of fitted statistics both in the model (43) and not in the model (131, not including the 43 in the model), we think that having 5 parameters is within an adequate margin of error.

You can see in the esteem network (Table 12) that all of the parameters *in the model* are fitted. All but seven of the parameters *not in the model* are fitted. Of the remaining parameters two (Out2StarAB and Skew Indegree Distribution B) have *t*-statistics (convergence statistics) greater than three, but below five. Given the large number of statistics fitted in the model (47) and not in the model (124) we think that seven parameters slightly outside the margins of good fit is acceptable.

Another thing to note is that much of our problems with fit are related to our original study design, with our initial decision to force both a minimum and maximum outdegree of participants. This subsequently has made modelling outdegree with ERGMs quite difficult, and hence convergence of outdegree parameters in the these models quite fraught.

4.4. Factor analysis

Tables 13 and 14 show the results of the factor analysis of the parameters of the affect and esteem models. The models are

Table 7
Comparison of key parameters in the affect network to a baseline random graph model.

Parameters	Observation	Sample mean	Std. Dev.	*t*-Statistic[a]
ReciprocityA	232	12.518	3.385	64.843
2-In-StarA	2255	1723.231	40.158	13.242
2-Out-StarA	1567	1723.877	42.085	−3.728
3-In-StarA	4309	1999.369	146.09	15.81
3-Out-StarA	1369	2003.431	152.704	−4.155
030TA	743	85.82	9.409	69.844
030CA	173	28.526	5.45	26.509
K-In-StarA(2.00)	1112.375	1041.584	8.407	8.42
AKT-TA(2.00)	601.125	83.961	9.017	57.354
AKT-CA(2.00)	424.125	83.726	15.703	21.677
AKT-DA(2.00)	556.023	84.028	9.041	52.205
AKT-UA(2.00)	610	84.02	9.056	58.081
RbA_Exec	29	3.696	1.885	13.424
Same Category A Reciprocity_Race	134	7.124	2.611	48.592
Same Category A Reciprocity_First_SOSS_Major	94	4.297	2.109	42.527
Different Category A Reciprocity_Race	98	5.394	2.206	41.983
Different Category A Reciprocity_First_SOSS_Major	138	8.221	2.705	47.969
ReciprocityB	7	2.655	1.584	2.743
2-In-StarB	1208	383.526	19.969	41.288
2-Out-StarB	437	381.328	19.133	2.91
3-In-StarB	3574	210.535	35.713	94.18
3-Out-StarB	350	207.92	33.915	4.189
030TB	49	8.954	3.105	12.898
030CB	3	3.034	1.712	−0.02
K-In-StarB(2.00)	485.769	296.781	9.284	20.357
K-Out-StarB(2.00)	296.375	295.523	9.149	0.093
AKT-TB(2.00)	47.5	8.913	3.079	12.532
AKT-CB(2.00)	8.5	9.057	5.089	−0.11
AKT-DB(2.00)	42	8.914	3.082	10.734
AKT-UB(2.00)	47.5	8.908	3.08	12.528
RbB_Exec	4	1.651	1.284	1.829
TABA	40	40.224	6.438	−0.035
TABB	135	18.94	4.515	25.707
TBBA	66	19.302	4.453	10.486
TBAB	39	19.375	4.411	4.449
TAAB	47	40.624	6.355	1.003
TBAA	52	40.511	6.341	1.812
CAAB	55	40.242	6.161	2.395
CBBA	35	18.738	4.384	3.709

Note:
1. This table only shows the key parameters with a high *t*-statistic.
2. For a full comparison, please contact the authors of this paper.
[a] $t\text{-Statistics} = \frac{\text{observation}-\text{sample mean}}{\text{standard deviation}}$.

Table 8
Comparison of key parameters in the esteem network to a baseline random graph model.

Parameters	Observation	Sample mean	Std. Dev.	t-Statistic[a]
ReciprocityA	14	3.708	1.952	5.274
2-In-StarA	1559	512.95	22.942	45.596
2-Out-StarA	495	513.174	21.94	−0.828
3-In-StarA	4665	322.159	47.333	91.752
3-Out-StarA	348	322.695	45.085	0.561
030TA	81	13.864	3.961	16.948
030CA	4	4.638	2.228	−0.286
K-In-StarA(2.00)	604.235	383.463	9.581	23.042
AKT-TA(2.00)	74.75	13.78	3.911	15.59
AKT-CA(2.00)	11.5	13.828	6.611	−0.352
AKT-DA(2.00)	74.75	13.789	3.931	15.51
AKT-UA(2.00)	79	13.775	3.919	16.643
RbA_Exec	21	2.02	1.367	13.889
Same Category A Reciprocity_Race	6	2.1	1.446	2.696
Same Category A Reciprocity_First_SOSS_Major	6	1.343	1.192	3.907
Different Category A Reciprocity_Race	8	1.608	1.246	5.131
Different Category A Reciprocity_First_SOSS_Major	8	2.365	1.56	3.612
ReciprocityB	7	1.847	1.329	3.876
2-In-StarB	776	254.046	16.28	32.06
2-Out-StarB	244	253.555	15.822	−0.604
3-In-StarB	1880	112.788	24.063	73.44
3-Out-StarB	165	111.821	23.262	2.286
030TB	17	4.754	2.153	5.687
030CB	1	1.652	1.323	−0.493
K-In-StarB(2.00)	351.848	205.942	8.84	16.504
K-Out-StarB(2.00)	176	205.687	8.659	−3.428
AKT-TB(2.00)	16.5	4.744	2.147	5.476
AKT-CB(2.00)	3	4.94	3.944	−0.492
AKT-DB(2.00)	16.5	4.738	2.139	5.498
AKT-UB(2.00)	17	4.736	2.142	5.726
RbB_Exec	5	1.384	1.191	3.037
TABA	24	9.893	2.998	4.706
TABB	43	6.999	2.654	13.566
TBBA	21	7.013	2.678	5.223
TBAB	14	6.871	2.659	2.681
TAAB	20	9.848	3.277	3.098
TBAA	43	10.023	3.136	10.515
CAAB	9	9.761	3.226	−0.236
CBBA	12	6.954	2.655	1.9

Note:
1. This table only shows the key parameters with a high *t*-statistic.
2. For a full comparison, please contact the authors of this paper.
[a] $t\text{-Statistics} = \frac{\text{observation}-\text{sample mean}}{\text{standard deviation}}$.

relatively parsimonious – eight theories have relatively neatly loaded across three main components in both models. The models also have strong explanatory value – these three components explaining between 69 and 73% of variance in the observed data.

In both the affect and the esteem network, the same three latent dimensions (or 'components') were identified and extracted by the factor analysis. We considered a theory to be loaded in a component if its contribution to that theory is greater than 0.6/−0.6.

To further test this, we constructed indexes based on this rule, where for each component, all theories that made a contribution to a component greater than 0.6/less than −0.6 were combined into an index, and the Cronbach Alpha calculated. The results of these Cronbach Alpha calculations are presented in the final row of Tables 13 and 14. As can be seen, in all cases but one (the last), where a Cronbach Alpha can be calculated, it is greater than 0.69, suggesting these theories are measuring a common underlying construct.

Another way to conceptualise the factor analysis contained in Tables 13 and 14 is contained in Fig. 2. This is a Venn diagram of the results of Tables 13 and 14. Theories which are significant in any component for either model (have a loading greater than 0.6/less than −0.6) are grouped together, and this group is named after its most prominent member. We can see that there are three main groupings: Status, Balance, and Homophily. We can see that each dimension (except Homophily) comprises of one or more other theories. We can also seen that, the theories of Solidarity and Activity do not neatly fit into this classification, but seem to lie between the dimensions of Balance and Homophily, or possibly incorporate elements of both into their mechanisms of action.

5. Discussion

The kingdom of signed ties has been ruled by a single theory for many decades: balance. Very recently, a new, and compelling challenge has been posed by status theory. What our study shows, is that in fact, signed ties are ruled by a triumvirate of sociological forces – balance, status, and homophily – which in almost equal measure play their part in contributing to signed tie formation.

In this discussion section we will review our research question and how we came to answer it, including reviewing our evidence. We will then review the implications of our findings for the deeper sociological mechanisms that may be driving signed tie formation. Finally, we will assess the contribution of this study vis-à-vis the existing literature.

Our research question was "What are the fundamental forces driving signed tie formation?" We began by collecting signed tie data on almost 300 university students, and then estimated and fitted two 50 parameter ERGM models for the affect and esteem networks of these students. We then ran a factor analysis (dimension reduction) on the results to see how the eight major theories contributed to explaining the observed models. Factor analysis

Table 9
ERG model of affect network.

	Parameter	Std. Err.	Convergence statistic
ReciprocityA	3.672441	−0.15223	0.018[a]
SourceA	−0.70641	−0.4426	0.033
In-K-StarA (2.00)	0.469839	−0.16993	0.019[a]
Out-K-StarA (2.00)	−0.80121	−0.16287	0.018[a]
AKT-TA (2.00)	0.588566	−0.23725	0.033[a]
AKT-CA (2.00)	−0.4194	−0.06701	0.046[a]
AKT-DA (2.00)	0.07447	−0.13263	0.037
AKT-UA (2.00)	0.688826	−0.19299	0.036[a]
A2P-TA (2.00)	−0.14822	−0.01881	0.032[a]
rbA for Attribute_Gender	0.590079	−0.09428	−0.059[a]
rbA for Attribute_Exec	0.735038	−0.07647	−0.057[a]
rsA for Attribute_Gender	−0.46361	−0.09567	−0.134
rrA for Attribute_Gender	−0.28244	−0.07371	−0.104
rbDiffA of Continuous Attribute_Income	−0.09212	−0.02214	−0.015[a]
Same Category ArcA for Attribute_First_SOSS_Major	0.174457	−0.0505	0.032[a]
ReciprocityB	0.782198	−0.43505	0.033
SinkB	−4.62128	−0.46284	−0.023[a]
SourceB	−1.81699	−0.42099	0.054[a]
IsolatesB	−6.312	−0.6268	−0.041[a]
In-K-StarB (2.00)	2.023473	−0.19827	0.025[a]
Out-K-StarB (2.00)	2.037358	−0.20363	−0.019[a]
AKT-TB (2.00)	0.564812	−0.57167	0.025
AKT-CB (2.00)	−0.22132	−0.20553	0.034
AKT-DB (2.00)	−0.62907	−0.30301	0.018[a]
AKT-UB (2.00)	0.372433	−0.53653	0.026
A2P-TB (2.00)	−0.02818	−0.02071	0.029
rbB for Attribute_Gender	0.647457	−0.198	−0.086[a]
rbB for Attribute_Exec	−0.19711	−0.52576	−0.035
rsB for Attribute_Gender	−0.41067	−0.12444	−0.093[a]
rsB for Attribute_Exec	0.125038	−0.17588	0.001
rrB for Attribute_Gender	−0.46279	−0.12749	−0.091[a]
rrB for Attribute_Exec	0.332742	−0.08359	−0.012[a]
rbDiffB of Continuous Attribute_Age	0.064604	−0.02977	−0.001
ReciprocityAB	−0.44969	−0.59946	−0.015
In2StarAB	0.018953	−0.01038	0.036
TKT-ABA (2.00)	−0.08111	−0.21726	0.039
CKT-ABA (2.00)	0.369151	−0.19485	0.044
DKT-ABA (2.00)	0.026459	−0.19203	0.021
UKT-ABA (2.00)	−0.10392	−0.19087	0.064
TKT-BAB (2.00)	0.359217	−0.20565	0.066
CKT-BAB (2.00)	0.127491	−0.20662	0.076
M-rbm for Attribute_Gender	0.267354	−0.63727	−0.05
M-diffm for Attribute_Age	0.402478	−0.16454	−0.025[a]

[a] $t\text{-Statistics} = \frac{\text{Parameter}}{\text{Std. Err.}} \geq 2$.

allows us to cluster related theories, and to explain observed results in terms of a small number of underlying latent variables. We found that both our affect and esteem networks could be largely explained by three underlying variables: balance, status, and homophily (see Tables 13 and 14 and Fig. 2).

The three factors we were able to identify – balance, status, and homophily – were largely orthogonal factors, although, balance, and homophily did have some common elements.

But what do these paradigms mean in terms of sociological mechanisms? Balance paradigm (which includes balance theory and karma theory) can be understood as representing the general principle of cognitive consistency. Balance theory says that individuals seek cognitive consistency in a signed network, essentially avoiding forming negative ties with friends of friends, and vice versa. Karma theory says that individuals seek cognitive consistency by sending more negative ties if they receive more negative ties, and similarly for positive ties. Karma theory may also work at the level of the tie sender, where individuals observe a person sending many negative (or positive) ties, and thus are predisposed to send more negative (or positive) ties to them.

The balance paradigm contributes to the existing literature by extending traditional balance theory underlying premise of cognitive consistency to generate a new theory: Karma theory. Balance theory is traditionally used to explain the formation of positive and negative tie formations amongst triads of friends or acquaintances. It contains the assumption that there is some level of connection, at most at two degrees of separation, between the actors. Karma theory extends the principles of cognitive consistency to strangers – to people with whom one may have no path or chain of intermediaries. Other individuals respond to your positive and negative ties but they do so irrespective of whether you share connections to third parties or not. In summary, karma theory contributes a new theory of cognitive consistency by extending the mechanism to strangers' and their sending of signed ties.

Status paradigm (which includes status theory, visibility theory, and popularity theory) can be understood as representing the general principle of prominence driving tie formation. Status theory says individuals form positive ties with those of higher status, and negative ties with those of lower status. In status theory, positive and negative ties can be used as proxies for status, and thus, for example, being the sender of the positive tie automatically places one in a lower status position. Popularity theory states that individuals are more likely to receive more positive (or negative) ties when they either (1) have more positive (or negative) in-ties, or (2) have some particular attribute or level of an attribute. Examples of this include (1) the 'rich get richer' principle, where those nodes with existing in-ties of one type (say positive ties), attract even more ties of the same type (more positive in-ties); as well as (2) attribute

Table 10
ERG model of esteem network.

	Parameter	Std. Err.	convergence statistic
ReciprocityA	1.382759	−0.33125	−0.03[a]
SinkA	−4.16966	−0.62619	0.007[a]
SourceA	−1.61857	−0.42554	−0.01[a]
IsolatesA	−5.72539	−0.82106	0.039[a]
In-K-StarA (2.00)	1.879187	−0.19788	0.007[a]
Out-K-StarA (2.00)	0.945767	−0.2163	0.066[a]
AKT-TA (2.00)	−0.55502	−0.47229	0.01
AKT-CA (2.00)	−0.26441	−0.14651	−0.007
AKT-DA (2.00)	0.853616	−0.36639	0.02[a]
AKT-UA (2.00)	0.528076	−0.42111	0.02
A2P-TA (2.00)	−0.08345	−0.02359	−0.001[a]
rbA for Attribute_Gender	0.245798	−0.17746	−0.057
rbA for Attribute_Exec	0.998158	−0.31736	−0.006[a]
rsA for Attribute_Gender	−0.09457	−0.1265	0.046
rsA for Attribute_Exec	−0.05635	−0.22344	0.001
rrA for Attribute_Gender	−0.24199	−0.13379	−0.092
rrA for Attribute_Exec	0.311864	−0.092	−0.021[a]
receiverA of Continuous Attribute_Age	0.029492	−0.02577	0.081
rbDiffA of Continuous Attribute_Income	−0.09324	−0.0355	−0.043[a]
Same Category ArcA for Attribute_Race	−0.20879	−0.07257	0.043[a]
Same Category ArcA for Attribute_First_SOSS_Major	0.203088	−0.08725	0.014[a]
ReciprocityB	1.376285	−0.41246	0[a]
SinkB	−4.78545	−0.49046	−0.015[a]
SourceB	−2.23517	−0.43231	0.002[a]
IsolatesB	−6.96438	−0.6375	0.022[a]
In-K-StarB (2.00)	2.205466	−0.21474	0.016[a]
Out-K-StarB (2.00)	2.137748	−0.26377	0.013[a]
AKT-TB (2.00)	−0.67179	−1.47227	0.019
AKT-CB (2.00)	−0.26044	−0.34292	0.017
AKT-DB (2.00)	−0.10575	−1.22178	0.024
AKT-UB (2.00)	0.895373	−1.44748	0.02
A2P-TB (2.00)	−0.01142	−0.02882	0.019
rbB for Attribute_Gender	0.284191	−0.20741	0.012
rbB for Attribute_Exec	0.01126	−0.51195	−0.01
rsB for Attribute_Gender	−0.19727	−0.14539	0.001
rsB for Attribute_Exec	0.127368	−0.20789	0.001
rrB for Attribute_Gender	−0.30814	−0.14505	0.04[a]
rrB for Attribute_Exec	0.28557	−0.10524	0.012[a]
ReciprocityAB	0.878494	−0.35716	−0.019[a]
In2StarAB	−0.01781	−0.013	−0.013
TKT-ABA (2.00)	0.472087	−0.22086	−0.019[a]
CKT-ABA (2.00)	−0.5331	−0.33698	0.031
DKT-ABA (2.00)	0.284673	−0.22723	0.06
UKT-ABA (2.00)	0.306376	−0.15316	0.005[a]
TKT-BAB (2.00)	0.222079	−0.27161	0.013
CKT-BAB (2.00)	0.103095	−0.28134	0.02
DKT-BAB (2.00)	0.49505	−0.19779	0.023[a]
M-rbm for Attribute_Gender	−1.34483	−1.05291	−0.023

[a] $t\text{-Statistics} = \frac{\text{Parameter}}{\text{Std. Err.}} \geq 2$.

based popularity, such a girls having more friends, or older children having more contacts in their mobile phones. Visibility theory, as a variant of popularity theory, says that individuals will preferentially form in-ties (both positive and negative) with highly visible (well known) individuals. An actor may be 'well known' as a result of an actor attribute, or a high indegree, either positive or negative. The key difference between Popularity theory and Visibility theory is that high degrees of one 'type', say a high positive indegree, in Popularity theory will only lead to more positive in-ties, while if Visibility theory is in operation, it will lead to both greater positive AND negative in-ties.

There are several things to note about our identification of the larger Status paradigm, as well as its three major subcomponents: the theories of status, popularity, and visibility. First, this is probably the clearest and cleanest loading paradigm of the three in our factor analyses. It is very distinct and separate from the other two dimensions. This suggests it is a strong tendency within the underlying data. Second, the loading across three theories – status, popularity, and visibility – suggests that one theory cannot simply account for all of the variation and theoretical explanation that this paradigm is required to do. In short, status theory is not enough on its own. It needs other theories to explain social networks, even just within the space of its own paradigm it needs popularity and visibility theory. Third, we believe we have made a unique contribution by introducing Visibility theory. The implications of this theory are not just technical. If Visibility theory is of significant explanatory value, then positive ties tend to attract negative ties, and vice versa. This suggests support for the adage "The opposite of love is not hate but indifference." In our dataset, the students who were 'disliked' and 'disesteemed' also were more likely to be 'liked' and 'esteemed', and vice versa. Possibly the most marginalised in our dataset were not the disliked but simply the 'sources' (sending only ties) and 'isolates' (neither send or receive ties). It also suggests a need for future studies to control for a significant proportion of negative ties that will flow to well know individuals, simply as a result of their prominence.

The homophily paradigm is the only one of the three which contains only one main theory – homophily theory itself. Homophily theory, and the larger homophily paradigm, can be understood as an in-group/out-group mechanism, with individuals, in general,

Table 11
Goodness of Fit statistics for affect network.

Parameters	Observation	Sample mean	Std. Dev.	*t*-Statistic[a]
ArcA	987	987	0	NA
ReciprocityA	232	231.893	10.573	0.01
2-In-StarA	2255	2136.673	101.863	1.162
2-Out-StarA	1567	1666.013	52.885	−1.872
3-In-StarA	4309	3561.113	541.368	1.381
3-Out-StarA	1369	1872.968	216.14	−2.332
Mixed-2-StarA	3415	3423.159	129.883	−0.063
030TA	743	759.926	102.132	−0.166
030CA	173	183.087	34.515	−0.292
SinkA	1	2.68	1.631	−1.03
SourceA	21	20.83	4.048	0.042
IsolatesA	1	1.319	1.148	−0.278
K-In-StarA(2.00)	1112.375	1111.977	13.438	0.03
K-Out-StarA(2.00)	1024.5	1024.099	7.971	0.05
K-L-StarA(2.00)	722.711	723.988	13.27	−0.096
K-1-StarA(2.00)	1503.308	1500.488	21.695	0.13
1-L-StarA(2.00)	1657.438	1651.263	13.813	0.447
AKT-TA(2.00)	601.125	598.628	40.898	0.061
AKT-CA(2.00)	424.125	420.843	46.488	0.071
AKT-DA(2.00)	556.023	553.499	36.722	0.069
AKT-UA(2.00)	610	607.389	41.902	0.062
A2P-TA(2.00)	3114.25	3112.294	63.73	0.031
A2P-DA(2.00)	1389.84	1498.896	37.208	−2.931
A2P-UA(2.00)	2052	1952.966	69.116	1.433
RbA_Gender	461	462.792	22.099	−0.081
RbA_Exec	29	26.959	17.728	0.115
RsA_Gender	614	615.99	17.533	−0.114
RsA_Exec	86	80.053	14.049	0.423
RrA_Gender	637	638.581	23.497	−0.067
RrA_Exec	112	91.161	21.004	0.992
T2u11A_Gender	117	111.274	10.266	0.558
T2u11A_Exec	8	11.115	8.407	−0.371
T1u11A_Gender	196	178.214	11.559	1.539
T1u11A_Exec	35	38.582	8.737	−0.41
T1au14A_Gender	1372	1372.464	115.509	−0.004
T1au14A_Exec	402	281.904	139.601	0.86
T1au13A_Gender	2100	2127.391	142.329	−0.192
T1au13A_Exec	501	426.404	195.239	0.382
T1au12A_Gender	940	999.057	65.896	−0.896
T1au12A_Exec	165	180.289	74.69	−0.205
SenderA_Age	22,439	22,448.87	41.702	−0.237
SenderA_Income	2624	2622.606	41.262	0.034
ReceiverA_Age	22,366	22,398	58.677	−0.545
ReceiverA_Income	2595	2609.976	57.117	−0.262
Single SumA_Age	44,805	44,846.87	85.518	−0.49
Single SumA_Income	5219	5232.582	85.257	−0.159
Single DifferenceA_Age	1203	1213.982	52.419	−0.21
Single DifferenceA_Income	1311	1310.484	48.247	0.011
Single ProductA_Age	508,802	509,646.6	1949.158	−0.433
Single ProductA_Income	7093	7169.52	243.359	−0.314
Mutual SumA_Age	10,524	−1,028,042	556,322.8	1.867
Mutual SumA_Income	1225	1,237,132	818,216.9	−1.51
Mutual DifferenceA_Age	280	5,256,833	2,993,025	−1.756
Mutual DifferenceA_Income	277	6,805,048	3,877,515	−1.755
Mutual ProductA_Age	119,403	−3.10E+07	16,830,749	1.845
Mutual ProductA_Income	1712	−5,279,702	2,741,815	1.926
Same Category A Arc_Race	562	568.044	20.385	−0.297
Same Category A Arc_First_SOSS_Major	409	409.94	21.227	−0.044
Different Category A Arc_Race	425	418.955	20.385	0.297
Different Category A Arc_First_SOSS_Major	578	577.061	21.227	0.044
Same Category A Reciprocity_Race	134	133.191	10.331	0.078
Same Category A Reciprocity_First_SOSS_Major	94	102.311	9.75	−0.852
Different Category A Reciprocity_Race	98	98.702	9.834	−0.071
Different Category A Reciprocity_First_SOSS_Major	138	129.583	10.699	0.787
ArcB	465	465	0	NA
ReciprocityB	7	6.838	3.348	0.048
2-In-StarB	1208	1027.614	160.362	1.125
2-Out-StarB	437	488.635	50.916	−1.014
3-In-StarB	3574	2142.467	1198.934	1.194
3-Out-StarB	350	598.493	168.664	−1.473
Mixed-2-StarB	852	845.568	135.861	0.047
030TB	49	51.038	39.285	−0.052
030CB	3	2.961	4.87	0.008
SinkB	14	14.124	3.629	−0.034
SourceB	114	113.732	7.203	0.037
IsolatesB	14	14.114	4.091	−0.028

Table 11 (*Continued*)

Parameters	Observation	Sample mean	Std. Dev.	*t*-Statistic[a]
K-In-StarB(2.00)	485.769	485.38	19.126	0.02
K-Out-StarB(2.00)	296.375	296.787	13.248	−0.031
K-L-StarB(2.00)	256.246	253.999	13.32	0.169
K-1-StarB(2.00)	390.194	382.418	23.319	0.333
1-L-StarB(2.00)	535.75	540.001	24.974	−0.17
AKT-TB(2.00)	47.5	46.887	27.44	0.022
AKT-CB(2.00)	8.5	8.154	10.82	0.032
AKT-DB(2.00)	42	41.625	16.166	0.023
AKT-UB(2.00)	47.5	46.782	27.189	0.026
A2P-TB(2.00)	827.875	824.12	109.452	0.034
A2P-DB(2.00)	411.75	461.347	36.957	−1.342
A2P-UB(2.00)	1181.25	997.621	125.242	1.466
RbB_Gender	187	188.735	23.144	−0.075
RbB_Exec	4	4.018	2.269	−0.008
RsB_Gender	295	296.719	19.172	−0.09
RsB_Exec	34	33.884	7.376	0.016
RrB_Gender	268	270.029	25.803	−0.079
RrB_Exec	81	80.817	16.938	0.011
T2u11B_Gender	6	2.365	1.647	2.207
T2u11B_Exec	1	0.184	0.472	1.727
T1u11B_Gender	6	4.797	2.206	0.545
T1u11B_Exec	3	2.805	2.656	0.074
T1au14B_Gender	694	539.188	98.374	1.574
T1au14B_Exec	278	290.147	117.195	−0.104
T1au13B_Gender	515	474.551	85.135	0.475
T1au13B_Exec	212	169.452	80.067	0.531
T1au12B_Gender	269	307.358	59.785	−0.642
T1au12B_Exec	36	43.634	26.249	−0.291
SenderB_Age	10,574	10,594.19	35.535	−0.568
SenderB_Income	1220	1241.771	34.199	−0.637
ReceiverB_Age	10,625	10,670.44	60.614	−0.75
ReceiverB_Income	1219	1244.507	52.976	−0.481
Single SumB_Age	21,199	21,264.63	73.773	−0.89
Single SumB_Income	2439	2486.278	64.568	−0.732
Single DifferenceB_Age	675	672.184	51.542	0.055
Single DifferenceB_Income	673	708.389	28.584	−1.238
Single ProductB_Age	241,631	243,110.4	1680.683	−0.88
Single ProductB_Income	3198	3312.916	176.698	−0.65
Mutual SumB_Age	318	−1.10E+07	5,996,732	1.833
Mutual SumB_Income	35	59,857.83	158,121.8	−0.378
Mutual DifferenceB_Age	6	−2,311,655	1,203,503	1.921
Mutual DifferenceB_Income	5	8671.946	33,760.14	−0.257
Mutual ProductB_Age	3614	−2.50E+08	1.38E+08	1.834
Mutual ProductB_Income	49	440,562	482,283.3	−0.913
Same Category B Arc_Race	252	269.925	20.026	−0.895
Same Category B Arc_First_SOSS_Major	165	165.26	11.694	−0.022
Different Category B Arc_Race	213	195.075	20.026	0.895
Different Category B Arc_First_SOSS_Major	300	299.741	11.694	0.022
Same Category B Reciprocity_Race	6	3.851	1.992	1.079
Same Category B Reciprocity_First_SOSS_Major	2	2.413	1.647	−0.251
Different Category B Reciprocity_Race	1	2.987	2.53	−0.785
Different Category B Reciprocity_First_SOSS_Major	5	4.425	2.651	0.217
ArcAB	0	0	0	NA
ReciprocityAB	10	9.889	3.238	0.034
ReciprocityAAB	0	0	0	NA
ReciprocityABB	0	0	0	NA
ReciprocityAABB	0	0	0	NA
In2StarAB	1920	1911.994	205.172	0.039
Out2StarAB	1848	1647.48	61.795	3.245
Mix2StarAB	1732	1697.705	89.071	0.385
Mix2StarBA	1738	1787.674	142.6	−0.348
TABA	40	40.372	15.334	−0.024
TABB	135	58.673	27.648	2.761
TBBA	66	39.09	31.554	0.853
TBAB	39	39.218	22.142	−0.01
TAAB	47	46.301	15.419	0.045
TBAA	52	52.566	16.963	−0.033
CAAB	55	55.327	15.963	−0.02
CBBA	35	35.124	21.024	−0.006
IsolatesAB	0	0.09	0.302	−0.298
TKT-ABA(2.00)	37.25	36.425	9.928	0.083
CKT-ABA(2.00)	50.75	49.869	10.443	0.084
DKT-ABA(2.00)	42.75	42.124	10.247	0.061
UKT-ABA(2.00)	48.375	47.331	10.955	0.095
TKT-BAB(2.00)	38.5	37.444	17.744	0.059
CKT-BAB(2.00)	34.5	33.475	16.711	0.061
DKT-BAB(2.00)	59.5	34.574	19.169	1.3

Table 11 (*Continued*)

Parameters	Observation	Sample mean	Std. Dev.	t-Statistic[a]
UKT-BAB(2.00)	128.5	56.158	21.677	3.337
mrs_Gender	0	0	0	NA
mrs_Exec	0	0	0	NA
mrr_Gender	0	0	0	NA
mrr_Exec	0	0	0	NA
exab_Gender	7	5.526	2.444	0.603
exab_Exec	2	1.452	1.289	0.426
exba_Gender	4	−321.935	185.338	1.759
exba_Exec	0	−281.995	192.203	1.467
mrb_Gender	0	0	0	NA
mrb_Exec	0	0	0	NA
mrbm_Gender	4	3.986	2.037	0.007
mrbm_Exec	0	0.226	0.514	−0.439
msum_Age	465	465	0	NA
msum_Income	58	58	0	NA
mdiff_Age	23	23	0	NA
mdiff_Income	22	22	0	NA
msumm for Missing Attribute_Age	0	−8.359	150.551	0.056
msumm for Missing Attribute_Income	0	−5.822	18.341	0.317
mdiffm for Missing Attribute_Age	0	−0.269	10.809	0.025
mdiffm for Missing Attribute_Income	0	−8.582	5.601	1.532
Same Category ArcAB_Race	0	0	0	NA
Same Category ArcAB_First_SOSS_Major	0	0	0	NA
Different Category ArcAB_Race	0	0	0	NA
Different Category ArcAB_First_SOSS_Major	0	0	0	NA
Same Category ReciprocityAB_Race	3	5.284	2.338	−0.977
Same Category ReciprocityAB_First_SOSS_Major	4	3.678	1.942	0.166
Different Category ReciprocityAB_Race	7	4.604	2.298	1.043
Different Category ReciprocityAB_First_SOSS_Major	6	6.211	2.59	−0.081
# Std. Dev. In-degree dist A	2.691	2.527	0.14	1.175
# Skew In-degree dist A	1.243	0.869	0.226	1.659
# Std. Dev. Out-degree dist A	1.537	1.748	0.104	−2.014
# Skew Out-degree dist A	−0.474	0.665	0.216	−5.276
# Global Clustering Cto A	0.237	0.228	0.026	0.368
# Global Clustering Cti A	0.165	0.178	0.019	−0.674
# Global Clustering Ctm A	0.218	0.221	0.023	−0.171
# Global Clustering Ccm A	0.152	0.16	0.025	−0.316
# Std. Dev. In-degree dist B	2.738	2.485	0.202	1.25
# Skew In-degree dist B	3.012	2.049	0.391	2.459
# Std. Dev. Out-degree dist B	1.425	1.544	0.113	−1.055
# Skew Out-degree dist B	1.339	2.217	0.296	−2.962
# Global Clustering Cto B	0.056	0.051	0.029	0.192
# Global Clustering Cti B	0.02	0.024	0.01	−0.327
# Global Clustering Ctm B	0.058	0.057	0.025	0.01
# Global Clustering Ccm B	0.011	0.009	0.01	0.13

[a] t-Statistics $= \frac{\text{observation}-\text{sample mean}}{\text{standard deviation}}$.

Table 12
Goodness of Fit statistics for esteem network.

Parameters	Observation	Sample mean	Std. Dev.	t-Statistic[a]
ArcA	540	540	0	NA
ReciprocityA	14	14.135	4.191	−0.032
2-In-StarA	1559	1392.022	108.699	1.536
2-Out-StarA	495	530.08	50.41	−0.696
3-In-StarA	4665	3357.854	721.964	1.811
3-Out-StarA	348	530.151	288.918	−0.63
Mixed-2-StarA	989	996.798	108.332	−0.072
030TA	81	87.624	36.167	−0.183
030CA	4	4.736	7.187	−0.102
SinkA	4	4.035	1.921	−0.018
SourceA	118	118.081	6.683	−0.012
IsolatesA	3	2.945	1.687	0.033
K-In-StarA(2.00)	604.235	604.409	15.834	−0.011
K-Out-StarA(2.00)	353.875	353.993	7.834	−0.015
K-L-StarA(2.00)	306.734	301.655	11.186	0.454
K-1-StarA(2.00)	471.44	444.296	26.049	1.042
1-L-StarA(2.00)	661.313	677.355	23.259	−0.69
AKT-TA(2.00)	74.75	75.616	19.664	−0.044
AKT-CA(2.00)	11.5	12.37	14.591	−0.06
AKT-DA(2.00)	74.75	75.637	20.988	−0.042
AKT-UA(2.00)	79	80.02	21.615	−0.047
A2P-TA(2.00)	959.75	962.667	83.192	−0.035
A2P-DA(2.00)	464.125	500.634	34.586	−1.056

Table 12 (*Continued*)

Parameters	Observation	Sample mean	Std. Dev.	*t*-Statistic[a]
A2P-UA(2.00)	1525.25	1361.452	99.13	1.652
RbA_Gender	194	194.492	15.645	−0.031
RbA_Exec	21	21.382	8.93	−0.043
RsA_Gender	351	350.397	12.162	0.05
RsA_Exec	44	44.79	11.462	−0.069
RrA_Gender	279	280.147	20.371	−0.056
RrA_Exec	119	119.371	18.499	−0.02
T2u11A_Gender	4	3.999	2.005	0
T2u11A_Exec	1	3.43	2.804	−0.866
T1u11A_Gender	13	9.98	3.404	0.887
T1u11A_Exec	3	6.604	3.572	−1.009
T1au14A_Gender	644	594.297	97.704	0.509
T1au14A_Exec	549	544.893	142.296	0.029
T1au13A_Gender	567	517.59	63.181	0.782
T1au13A_Exec	237	274.281	117.295	−0.318
T1au12A_Gender	314	348.144	41.552	−0.822
T1au12A_Exec	56	70.323	58.598	−0.244
SenderA_Age	12,249	12,250.11	30.417	−0.036
SenderA_Income	1399	1439.44	32.026	−1.263
ReceiverA_Age	12,416	12,413.17	57.102	0.05
ReceiverA_Income	1448	1425.956	52.826	0.417
Single SumA_Age	24,665	24,663.28	65.332	0.026
Single SumA_Income	2847	2865.396	65.325	−0.282
Single DifferenceA_Age	751	753.499	35.257	−0.071
Single DifferenceA_Income	747	746.855	27.921	0.005
Single ProductA_Age	281,733	281,634.1	1485.599	0.067
Single ProductA_Income	3794	3882.776	181.932	−0.488
Mutual SumA_Age	640	−1.20E+07	6,399,381	1.854
Mutual SumA_Income	70	−5,760,140	3,579,987	1.609
Mutual DifferenceA_Age	22	2,320,484	1,344,176	−1.726
Mutual DifferenceA_Income	18	5,277,528	2,906,804	−1.816
Mutual ProductA_Age	7316	−2.80E+08	1.49E+08	1.853
Mutual ProductA_Income	90	−2.40E+07	14,412,406	1.666
Same Category A Arc_Race	273	272.547	16.093	0.028
Same Category A Arc_First_SOSS_Major	209	208.69	12.598	0.025
Different Category A Arc_Race	267	267.453	16.093	−0.028
Different Category A Arc_First_SOSS_Major	331	331.31	12.598	−0.025
Same Category A Reciprocity_Race	6	6.135	2.457	−0.055
Same Category A Reciprocity_First_SOSS_Major	6	5.757	2.436	0.1
Different Category A Reciprocity_Race	8	8	3.298	0
Different Category A Reciprocity_First_SOSS_Major	8	8.378	3.28	−0.115
ArcB	380	380	0	NA
ReciprocityB	7	6.973	2.676	0.01
2-In-StarB	776	689.256	65.992	1.314
2-Out-StarB	244	265.244	33.801	−0.628
3-In-StarB	1880	1203.171	285.382	2.372
3-Out-StarB	165	266.104	103.234	−0.979
Mixed-2-StarB	543	545.835	65.265	−0.043
030TB	17	17.587	9.424	−0.062
030CB	1	1.075	1.428	−0.053
SinkB	17	16.93	3.706	0.019
SourceB	116	116.016	7.015	−0.002
IsolatesB	17	16.893	4.082	0.026
K-In-StarB(2.00)	351.848	351.774	14.859	0.005
K-Out-StarB(2.00)	176	175.77	10.552	0.022
K-L-StarB(2.00)	209.929	213.065	9.912	−0.316
K-1-StarB(2.00)	282.075	283.586	18.589	−0.081
1-L-StarB(2.00)	399.875	400.456	17.95	−0.032
AKT-TB(2.00)	16.5	16.586	7.694	−0.011
AKT-CB(2.00)	3	3.164	4.029	−0.041
AKT-DB(2.00)	16.5	16.574	7.628	−0.01
AKT-UB(2.00)	17	17.095	8.234	−0.011
A2P-TB(2.00)	537.25	539.393	60.361	−0.036
A2P-DB(2.00)	236.375	258.224	30.002	−0.728
A2P-UB(2.00)	768	682.183	62.904	1.364
RbB_Gender	138	137.45	14.374	0.038
RbB_Exec	5	5.154	3.275	−0.047
RsB_Gender	239	238.52	11.53	0.042
RsB_Exec	30	30.14	6.909	−0.02
RrB_Gender	205	204.497	17.588	0.029
RrB_Exec	63	63.608	16.135	−0.038
T2u11B_Gender	6	2.115	1.468	2.647
T2u11B_Exec	0	0.261	0.608	−0.428
T1u11B_Gender	7	4.995	2.206	0.909
T1u11B_Exec	3	2.575	1.934	0.22
T1au14B_Gender	403	312.044	62.133	1.464

Table 12 (*Continued*)

Parameters	Observation	Sample mean	Std. Dev.	t-Statistic[a]
T1au14B_Exec	191	196.548	83.307	−0.067
T1au13B_Gender	320	279.322	43.694	0.931
T1au13B_Exec	125	115.343	59.298	0.163
T1au12B_Gender	143	155.203	32.977	−0.37
T1au12B_Exec	22	33.36	24.682	−0.46
SenderB_Age	8665	8644.812	26.618	0.758
SenderB_Income	973	1018.954	26.429	−1.739
ReceiverB_Age	8726	8704.229	44.744	0.487
ReceiverB_Income	1052	1029.081	47.767	0.48
Single SumB_Age	17,391	17,349.04	55.08	0.762
Single SumB_Income	2025	2048.034	55.432	−0.416
Single DifferenceB_Age	539	514.382	27.391	0.899
Single DifferenceB_Income	601	583.125	25.718	0.695
Single ProductB_Age	198,984	198,047.1	1254.641	0.747
Single ProductB_Income	2671	2754.95	152.767	−0.55
Mutual SumB_Age	318	−8.68E+06	4,900,920	1.772
Mutual SumB_Income	34	−1,705,139	1,145,003	1.489
Mutual DifferenceB_Age	10	1,346,352	756,037.8	−1.781
Mutual DifferenceB_Income	4	−690,642	397,073.2	1.739
Mutual ProductB_Age	3605	−2.00E+08	1.13E+08	1.771
Mutual ProductB_Income	41	−4,368,213	3,001,036	1.456
Same Category B Arc_Race	215	218.141	14.282	−0.22
Same Category B Arc_First_SOSS_Major	142	133.878	10.566	0.769
Different Category B Arc_Race	165	161.86	14.282	0.22
Different Category B Arc_First_SOSS_Major	238	246.122	10.566	−0.769
Same Category B Reciprocity_Race	5	3.992	1.953	0.516
Same Category B Reciprocity_First_SOSS_Major	2	2.45	1.562	−0.288
Different Category B Reciprocity_Race	2	2.981	1.853	−0.529
Different Category B Reciprocity_First_SOSS_Major	5	4.523	2.189	0.218
ArcAB	0	0	0	NA
ReciprocityAB	10	10.102	3.767	−0.027
ReciprocityAAB	0	0	0	NA
ReciprocityABB	0	0	0	NA
ReciprocityAABB	0	0	0	NA
In2StarAB	944	950.345	184.526	−0.034
Out2StarAB	949	751.236	43.439	4.553
Mix2StarAB	791	783.975	86.251	0.081
Mix2StarBA	718	817.512	106.906	−0.931
TABA	24	24.544	15.276	−0.036
TABB	43	22.305	9.539	2.17
TBBA	21	22.337	19.726	−0.068
TBAB	14	14.33	10.215	−0.032
TAAB	20	22.371	18.369	−0.129
TBAA	43	45.84	18.832	−0.151
CAAB	9	10.889	13.044	−0.145
CBBA	12	12.546	11.027	−0.05
IsolatesAB	1	0.218	0.463	1.688
TKT-ABA(2.00)	22	22.868	11.818	−0.073
CKT-ABA(2.00)	9	9.453	7.621	−0.059
DKT-ABA(2.00)	19	19.644	12.081	−0.053
UKT-ABA(2.00)	42.5	43.573	14.06	−0.076
TKT-BAB(2.00)	13.5	13.889	8.876	−0.044
CKT-BAB(2.00)	11.5	12.039	9.092	−0.059
DKT-BAB(2.00)	19.5	20.573	15.322	−0.07
UKT-BAB(2.00)	42.5	21.822	8.172	2.53
mrs_Gender	0	0	0	NA
mrs_Exec	0	0	0	NA
mrr_Gender	0	0	0	NA
mrr_Exec	0	0	0	NA
exab_Gender	5	4.087	2.153	0.424
exab_Exec	2	2.386	2.36	−0.163
exba_Gender	3	−41.054	383.211	0.115
exba_Exec	2	68.763	114.434	−0.583
mrb_Gender	0	0	0	NA
mrb_Exec	0	0	0	NA
mrbm_Gender	1	1.031	1.023	−0.03
mrbm_Exec	0	1.268	1.637	−0.774
msum_Age	465	465	0	NA
msum_Income	62	62	0	NA
mdiff_Age	13	13	0	NA
mdiff_Income	18	18	0	NA
msumm for Missing Attribute_Age	0	3.061	173.685	−0.018
msumm for Missing Attribute_Income	0	−7.019	23.086	0.304
mdiffm for Missing Attribute_Age	0	2.301	6.765	−0.34
mdiffm for Missing Attribute_Income	0	−3.507	6.437	0.545
Same Category ArcAB_Race	0	0	0	NA
Same Category ArcAB_First_SOSS_Major	0	0	0	NA

Table 12 (*Continued*)

Parameters	Observation	Sample mean	Std. Dev.	*t*-Statistic[a]
Different Category ArcAB_Race	0	0	0	NA
Different Category ArcAB_First_SOSS_Major	0	0	0	NA
Same Category ReciprocityAB_Race	6	4.982	2.323	0.438
Same Category ReciprocityAB_First_SOSS_Major	8	3.773	2.045	2.067
Different Category ReciprocityAB_Race	4	5.119	2.813	−0.398
Different Category ReciprocityAB_First_SOSS_Major	2	6.329	2.869	−1.509
# Std. Dev. In-degree dist A	3.05	2.846	0.134	1.517
# Skew In-degree dist A	2.602	2.093	0.291	1.751
# Std. Dev. Out-degree dist A	1.326	1.412	0.113	−0.764
# Skew Out-degree dist A	1.169	1.924	0.51	−1.478
# Global Clustering Cto A	0.082	0.081	0.024	0.02
# Global Clustering Cti A	0.026	0.031	0.011	−0.48
# Global Clustering Ctm A	0.082	0.086	0.023	−0.187
# Global Clustering Ccm A	0.012	0.013	0.016	−0.054
# Std. Dev. In-degree dist B	2.244	2.1	0.11	1.311
# Skew In-degree dist B	3.103	2.253	0.257	3.31
# Std. Dev. Out-degree dist B	1.123	1.185	0.097	−0.632
# Skew Out-degree dist B	1.763	2.57	0.459	−1.759
# Global Clustering Cto B	0.035	0.032	0.013	0.186
# Global Clustering Cti B	0.011	0.013	0.006	−0.29
# Global Clustering Ctm B	0.031	0.032	0.012	−0.017
# Global Clustering Ccm B	0.006	0.006	0.006	−0.007

[a] $t\text{-Statistics} = \frac{\text{observation}-\text{sample mean}}{\text{standard deviation}}$.

Table 13
Factor analysis of affect model.

	Component		
	1	2	3
BalanceTh	0.78	−0.041	−0.459
SolidarityTh	0.744	0.053	0.103
StatusTh	−0.154	0.802	−0.004
VisibilityTh	0.307	0.715	−0.179
KarmaTh	0.65	0.151	0.135
PopularityTh	0.344	0.875	0.15
ActivityTh	0.611	0.378	0.203
HomophilyTh	0.15	−0.038	0.934
% variance explained	28%	26%	15%
Cronbach Alpha	0.69	0.75	NA

Notes:
1. The Cronbach Alpha for Component 1 comprises Balance Theory, Solidarity Theory, Karma Theory, and Activity Theory.
2. The Cronbach Alpha for Component 2 comprises Status Theory, Popularity Theory, and Visibility Theory.
3. There is no Cronbach Alpha for Component 3 as only Homophily Theory has a coefficient above 0.6.

Table 14
Factor analysis of esteem model.

	Component		
	1	2	3
BalanceTh	0.934	0.126	0.033
SolidarityTh	0.444	0.371	0.535
StatusTh	−0.192	0.796	0.13
VisibilityTh	0.304	0.787	−0.044
KarmaTh	0.864	0.064	0.15
PopularityTh	0.332	0.787	0.31
ActivityTh	0.188	0.244	0.713
HomophilyTh	−0.049	−0.053	0.849
% variance explained	26%	26%	21%
Cronbach Alpha	0.84	0.76	0.47

Notes:
1. The Cronbach Alpha for Component 1 comprises Balance Theory, and Karma Theory.
2. The Cronbach Alpha for Component 2 comprises Status Theory, Popularity Theory, and Visibility Theory.
3. The Cronbach Alpha for Component 3 comprises Activity Theory, and Homophily Theory.

likely to form ties with people who are more similar to themselves, and less likely to form ties with those who are different to themselves. Homophily can be the result of both conscious choice, unconscious bias, and environmental and institutional constraints of opportunity.

What is important to note about our identification of homophily as one of the three – and relatively equal – key paradigms of signed tie formation, is that homophily has largely been only applied in the past to positive ties. While the previous two paradigms we addressed – status and balance – are closely associated with signed ties, this is not the case with homophily. Also, it is worth noting that it was not the author's intention to particularly look for homophily

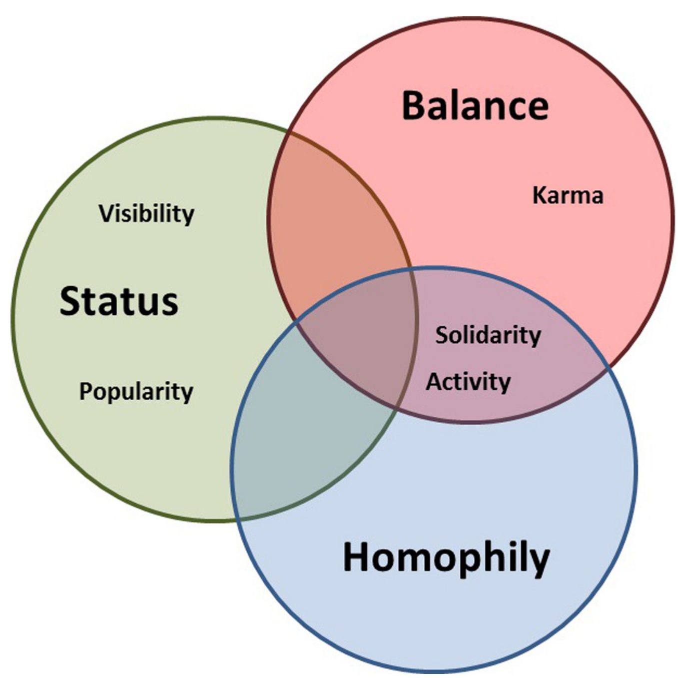


Fig. 2. Venn diagram of factor analyses of the eight theories of signed tie formation. *Note*: While we have named the paradigms after the major theories they encompass (illustrated in larger font), the 'paradigm' and the 'theory' are not synonymous i.e. although balance paradigm is named after Balance theory it also encompasses Karma theory.

as a likely candidate as a third major dimension driving signed tie formation. Nonetheless, the analysis shows that homophily is indeed significant across our networks, and it forms an independent paradigm.

We have identified that there are three orthogonal components to the formation of signed ties: balance, status, and homophily. Like the three primary colours, these three components can often be found in the real world combined in many shades, and also it does not make sense to talk about one or another of the primary colours as the 'dominant' one.

We think the relatively equal variance in explanatory power that we found for each of the three paradigms of balance, status, and homophily, probably explains the mixed evidence for balance and status in the existing literature. We find that balance explains about 25% of the variation in tie formation. This is something, but it is not a huge amount. Similarly, we find about the same amount for status. However, together with homophily, we think that the models move into much more robust territory with much higher levels of explanatory power – with 60–70% of explained variance. We think this is not a small contribution to make to the signed tie literature.

6. Conclusion

In this last section, we are going end with a more modest application of our research to the title question of this paper: "Why does everybody hate me?"

Our study finds there are three main sources of negative ties. The first source of negative ties is our need for 'cognitive consistency', and the balance paradigm. For example, in our study, if someone is disesteemed (disliked for election), that person is likely to return the negative tie (see the Reciprocity B parameter in Table 10).

The second source of negative ties is our attraction to 'prominence', and status paradigm. For example, in our study, if someone is esteemed (liked for election), this person's higher status means that they are actually more likely to reciprocate the tie with a negative tie (see the Reciprocity AB parameter in Table 10).

The third source of negative ties is our dislike for outgroups, and the homophily paradigm. For example, in our study, we found that men and women were much more likely to direct negative ties at the opposite gender than at members of their own gender (see the rrB for Attribute_Gender parameter in Table 10).

As well as identifying these three main paradigms, this paper's contribution has been to develop and legitimise a range of new theories within these paradigms, most particularly Karma theory (within balance paradigm) and Visibility theory (within status paradigm).

One of this paper's main contribution's has been the development of a framework for thinking about signed tie formation that does not rely on a single theory. We hope that this will allow for the complexities and contradictions of real world human networks to be properly modelled and captured.

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