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Power-use in cooperative competition: A power-dependence model and an empirical test of network structure and geographic mobility

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ABSTRACT

Although the social exchange paradigm has produced a vibrant research program, the theoretical tradition is rarely used to model the structure of social networks outside of experiments and simulations. To address this limitation, we derive power-dependence predictions about network structure and geographic mobility—the outcomes of power-use—and test these predictions using complete data on competition networks and travel schedules among amateur sports teams. Poisson regression and exponential random graph models provide strong support for our predictions. The findings illustrate exchange dynamics in which status resources desired by teams, coupled with the availability of geographically proximal alternatives, create power and dependence that dictate where and with whom teams compete. Although evidence supports Georg Simmel's classic proposition that networks form on the basis of values and propinquity, we show that this complex dynamic is conditional on power and dependence. We conclude by discussing implications and directions for future research.

> "Sociation. . .is the form (realized in innumerable, different ways) in which individuals grow together into units that satisfy their interests. These interests, whether they are sensuous or ideal, momentary or lasting, conscious or unconscious, causal or teleological, form the basis of human societies."
>
> –Georg Simmel (1950: 41)

1. Introduction

The proposition that networks form on the basis of values and propinquity is among Georg Simmel's most influential contributions (Simmel and Wolff, 1950; see also Blau, 1977; Blau and Schwartz, 1984; Bossard, 1932). To secure wants and desires, actors who share a common location will crystallize lasting relationships that, when taken aggregately, unintentionally produce unique network structures. And these structures, once they materialize, simultaneously constrain and enable individual desires that foster network evolution and change. The result is a dynamic relationship between the individual and structure, where the actor and the network are dependent upon each other and the social space in which they are embedded.

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Contemporary efforts to understand how and why this occurs within the broad sociological literature are perhaps most visible in the social exchange tradition (Blau, 1964; Ekeh, 1974; Emerson, 1962; Emerson, 1964, 1972a,b; Homans, 1950, 1974). Over the last half century this tradition has produced numerous theoretical and empirical insights, ranging from how typologies of exchange produce differential levels of trust and power (Cook et al., 1983; Cook and Emerson, 1987; Molm, 2003; Molm et al., 2007, 1999, 2000; Stolte, 1988; Thye et al., 2006) to how exchange networks constrain individual decisions and shape patterns of social interaction (Cook and Emerson, 1978; Lawler et al., 2008; Lawler and Yoon, 1993; Skvoretz and Lovaglia, 1995; Stolte and Emerson, 1977). The paradigm has also been witness to numerous sub-theoretical innovations, such as power-dependence theory (Cook and Emerson, 1978), resource dependence theory (Pfeffer and Salancik, 1978), exchange-resistance theory (Skvoretz and Willer, 1993), graph-analytic theory (Markovsky et al., 1988), core theory (Bienenstock and Bonacich, 1992), expected value theory (Friedkin, 1986, 1992), and affect theory (Lawler, 2001), all of which have contributed to the growth and development of this tradition.

Despite these substantial accomplishments, and the accumulated body of experimental and observational research (e.g., Schaefer, 2012; Van de Rijt and Macy, 2006), few studies in the social exchange literature have attempted to test Georg Simmel's original insight—that networks form on the basis of individual interests and social propinquity—using naturally occurring network data (see Corra and Willer, 2002; Simpson and Willer, 2002 for exceptions).[1] The missing linchpin connecting social exchange theory (SET) to network analysis is undoubtedly related to issues of appropriate data and methods. This is because standard surveys have difficulty recording the structure of sociation without producing missing data (Butts, 2003; Kossinets, 2006); ethnographies of large populations are too costly and prone to measurement error (Wasserman and Faust, 1994); and analyzing social network data with classic generalized linear models or ordinary least squares regression produces biased and inconsistent estimates (Snijders, 2011). Recent advances in digital record keeping, however, are providing new terrain for social research: real world populations leave digital traces of interaction, including the characteristics of actors, the content of action, and the structure of their relations. Furthermore, advances in the statistical analysis of social networks have created the necessary and proper tools for social scientists to analyze such data (Frank and Strauss, 1986; Pattison and Wasserman, 1999; Wasserman and Pattison, 1996). All of these developments are creating avenues for new research that include the possible fusion of SET with real world network analysis.

Benefitting from these new advents, the present study utilizes innovative network methods, exponential random graph models (Frank and Strauss, 1986; Robins et al., 2007a,b; Snijders et al., 2006), as well as a previously unavailable data set: records of a full community of competitive social actors who are free to, and in fact are obligated to, craft the structure of their own interactions. The case is drawn from a unique corner of competitive amateur sports that blends competition with personal responsibility and self-organization, what is often referred to by outsiders as "Ultimate Frisbee" or by those within the community simply as "Ultimate." Despite the desire to win, Ultimate teams establish their competition schedules cooperatively and cooperatively self-referee their established competitions. These cooperative competitions have been taking place for years, but it is only until recently, with the advent of computer mediated communication systems, that Ultimate competitions have been centrally recorded and easily accessible for empirical analysis.

This unique and previously untapped data set, in addition to the innovative network methods, allows us to investigate SET hypotheses about network formation in naturally occurring settings. Inspired by Georg Simmel's original insight, we derive several hypotheses from power-dependence theory and other models of social exchange (Foa and Foa, 1974, 1976; Meeker, 1971) predicting the network structure of Ultimate competitions and the geographic mobility of Ultimate teams, and operationalize these hypotheses with respect to the institutional features of Ultimate. We propose that Ultimate teams pursue and exchange status as a valued resource (see Foa and Foa, 1974, 1976), and define status as a team's relative rank (or standing) within the Ultimate community's competition hierarchy. To increase status, teams choose competitors whose status yields the greatest mutual dependence and lowest power imbalance. Yet, we expect this process to be conditional on propinquity since geographic distance increases the monetary costs of competition and decreases the availability of alternatives. Thus, increasing geographic space between mutually dependent teams results in more local competition among power imbalanced teams and less extra-local competition among mutually dependent teams. We also expect teams to use structural positions of power to gain distributional bargaining advantages, producing nonmonotonic power-outcomes in which geographic mobility increases at a decreasing rate with status.

Using exponential random graph models and Poisson regression to test these predictions, we demonstrate support for our hypotheses and produce three key findings. First, we show that the desire to increase status in the Ultimate community generates a network of mutually dependent *and* power balanced competitions where the status of two competing teams is equivalent and comparable. High-status teams compete against teams predominantly within and immediately below their status, while low-status teams compete against teams predominantly within and immediately above their status, which allows middle-status teams to bridge the status divide and compete against teams above, below, and within their status. Second, we show that this effect is conditional on propinquity: when geographic distance is great among mutually dependent teams and small among power imbalanced teams, teams will compete against lower status teams from their own region rather than teams of equal or higher status from nonadjacent regions. Third, we show that geographic mobility increases nonmonotonically with status to form an inverted U-shaped relationship where low-status teams and elite-high-status teams travel less

[1] For research exploring similar processes outside of the social exchange tradition see Casciaro and Piskorski (2005), Gulati (1995), Hedstrom (1994), and Zhu et al. (2013).

than their middle- and high-status counterparts. Taken together, our findings suggest that ties of propinquity in the face of social scarcity strengthen local status hierarchies and exaggerate extra-local status hierarchies. The unintended outcome is a classic core-periphery network structure where a densely connected core of high- and middle-status teams are linked across geographic space and a sparsely connected periphery of middle- and low-status teams are confined to ties of propinquity.

The remaining paper is organized as follows. First, we introduce relevant theoretical assumptions and concepts from power-dependence theory and the social exchange tradition; second, we outline our case—the sport of Ultimate—and derive hypotheses about network structure and geographic mobility; third, we describe our data, outline exponential random graph modeling procedures, and present our results; fourth, we explore the theoretical and substantive implications of our findings in relation to social network analysis, stratification and inequality, and organizational studies; and, fifth, we identify directions for future research.

1.1. Power-dependence theory: theoretical background

Emerson (1962, 1964, 1972a,b) originally developed power-dependence theory to show how relative dependencies of actors on one another for resources of value they obtain through exchange can impact the likelihood, the frequency, and the outcome of exchange. Emerson argued that power differentials—the inverse function of relative dependencies—are central to the dynamics of, and consequently any theoretical model of, social exchange. The nuts-and-bolts of Emerson's power-dependence theory are as follows: the power (P) of an actor, A, over another actor, B, in an exchange relation ($A_x - B_y$, where x and y represent resources of value) is equal to the dependence (D) of B on A ($P_{AB} = D_{BA}$), where B's dependence is a positive function of the extent to which B values x, and a negative function of the availability of alternative actors who provide x. These two factors—resource value and resource alternatives—determine the level of B's dependence on A and thus A's power over B. The implication is that actors who control highly valued resources and have access to multiple exchange partners are expected to be more powerful in their exchange relations, yielding distributional bargaining advantages and, ultimately, exchange outcomes in their favor.

Building on the concepts of power and dependence, the theory asserts that all exchange relations vary in terms of mutual dependence and power balance. An exchange relation is mutually independent when $D_{BA} + D_{AB} = 0$ (that is, when neither A nor B depend on each other for y and x, respectively), and becomes more mutually dependent as $D_{BA} + D_{AB}$ increases. Conversely, power in an exchange relation is balanced when $P_{BA} = P_{AB}$ (i.e., when $D_{BA} = D_{AB}$), and imbalanced otherwise (i.e., when $P_{BA} \neq P_{AB}$); thus, the greater the difference between P_{BA} and P_{AB}, the greater the power imbalance in the $A_x - B_y$ exchange relation.

Resources, or x and y in the A_x–B_y exchange relation, are possessions or behavioral capabilities of an actor that are valued by other actors, which, along with monetary and consummatory value, can have status value (Berger and Fisek, 2006; Lovaglia, 1994, 1995; Thye, 2000; Thye et al., 2006). For instance, comments on a working paper from an expert in your field (i.e., high status value) are much more valuable than comments from a high-school student (i.e., low status value). Likewise, a baseball card signed by the player (i.e., high status value) is more valuable than the same baseball card signed by your neighbor's child (i.e., low status value). The present study, on the other hand, treats status not as a dimension of a resource's value (i.e., expert comments or player signature), but as a resource much like money, information, goods, services, or love—as a valued goal in itself (for similar treatments of status see Foa and Foa, 1974, 1976; Frank, 1988; Huberman et al., 2004). In other words, power (and dependence) in our model is a means to an end: actors use mutually dependent and power balanced exchange relationships as a means to maximize status gains and minimize monetary costs of travel, where we conceptualize status as any item, *concrete* or *symbolic*, that conveys prestige, regard, or esteem (see Foa and Foa, 1974, 1976).

These concepts, in conjunction with the following assumptions, form the basis of power-dependence theory (Molm, 1997; Molm and Cook, 1995): (1) actors behave in ways that increase outcomes they positively value and decrease outcomes they negatively value (*actor assumption*); (2) every class of valued outcomes obeys a principle of satiation (in psychological terms) or diminishing marginal utility (in economic terms) (*resources assumption*); (3) exchange relations develop within structures of mutual dependence (*structure of exchange assumption*); (4) benefits obtained from other actors are contingent on benefits given in exchange (*exchange transactions assumption*); and, (5) actors engage in recurring, interdependent exchanges with specific partners over time (*exchange relations assumption*).

Our power-dependence model of tie formation and geographic mobility, however, departs from these assumptions in two important respects. First, our model does not assume that the benefits obtained from other actors are contingent on benefits given in exchange (*exchange transactions assumption*). We assume that social exchange can occur when there is no observable exchange taking place (see Meeker, 1971). For instance, an act of altruism is an exchange even if the altruistic actor receives nothing in return from the beneficiary for their altruism. In our model, status is a valued resource that creates power and dependence between actors. Yet, actors do not explicitly exchange status through a process of negotiation or reciprocity like other goods, services, or monies, where benefits received are contingent on benefits given. Instead, actors determine travel and competition schedules that set the stage for status to be exchanged conditional on the outcome of a match. Status, then, is exchanged as a valued resource, but exchange in our model approximates a contest or a competition rather than a transaction of benefits obtained contingent on benefits given. Second, our model does not rest on the assumption that actors engage in recurring, mutually contingent exchanges with specific partners over time (*exchange relations assumption*). The hypotheses we propose are applicable to actors that engage in sets of independent transactions that occur rarely or only once—a common assumption in classical microeconomic theory—and to actors that repeatedly exchange with the same actors through time.

Next, we describe the sport of Ultimate, integrate the concepts and assumptions of power-dependence theory with Ultimate, and derive hypotheses used to predict power-outcomes—the network structure of competitions and the geographic mobility of teams—in Ultimate.

1.2. The case of Ultimate

Ultimate is a team-based, non-contact field sport where the object of the game is to score goals by throwing and catching a plastic disc into an opponent's end zone. Each team usually consists of 18–27 players, but no more than seven players per team are allowed on the field of competition at any one time. Unlike most sports, foul violations in Ultimate are identified, disputed, and resolved by the players, and not by referees.[2] Because the sport of Ultimate is fairly young (circa 1968), growing rapidly among young adults—especially on college campuses—and maintains a large international network of recreational and competitive-level clubs (Griggs, 2009a,b, 2011; Leonardo and Zagoria, 2005; Robbins, 2004, 2012), it is able to support various levels of competition (i.e., club, college, youth, city league, and local pick-up) and divisions (e.g., masters, open, women's, and mixed). For the present study, the teams we observe—open, club teams in the US—voluntarily coordinate and negotiate pre-series competitions that occur between June and September with little intervention from, or mediation by, the governing body of Ultimate in the United States—*USA Ultimate*.[3]

Because of these characteristics, Ultimate offers a suitable blend of dedicated participation, private-order control, self-organization, and systematic record keeping for testing Georg Simmel's classic proposition.

1.3. Power-dependence theory and Ultimate

The actors in our model—Ultimate teams—can adopt two possible strategies: to exchange or abstain from exchange. If two teams choose to exchange, they engage in a contest over a limited resource and compete for status, which results in either a win or a loss and a shift upwards or downwards in a team's relative rank (or standing) within the Ultimate community. In addition to the assumptions above, we assume that Ultimate teams depend on one another for status and prefer to increase status at a minimal monetary cost.

To determine rank and status, the Ultimate community relies on a standardized algorithm-based system—entitled Rodney's Ranking Index (RRI)—that assigns a rating to each team by factoring (1) the score, (2) each opponent's winning ratio (wins/losses), and (3) each opponent's opponents' winning ratio.[4] With this system, the Ultimate community is able to assess the relative strength of teams that might never compete as a result of geographic divisions. Unlike absolute win–loss ratios, competitions do not always produce zero-sum outcomes for two teams' RRI. For instance, if high-status team *A* competes against low-status team *C* and *A* narrowly defeats *C*, *C*'s RRI can marginally increase along with *A*'s depending on the score, which yields a positive-sum RRI outcome. Yet, if high-status team *A* competes against another high-status team *B*, and *A* narrowly defeats *B*, *A*'s RRI will increase to a greater extent than if *A* narrowly defeated *C*. Thus, teams have an incentive to compete against other teams of comparable or higher status to increase rank (or RRI).

These incentives are further amplified by the fact that competition schedules in Ultimate constitute *negatively connected* exchange relations (Emerson, 1972b). A negative connection is one in which exchange between *A* and *B* necessarily reduces the frequency or amount of exchange in another exchange relation involving either *A* or *B*. For instance, *A*–*B* and *B*–*C* exchange relations are negatively connected if exchange in one of the *A*–*B* or *B*–*C* relations reduces the frequency or amount of exchange in the other. In the sport of Ultimate, then, a competition between team *A* and team *B* constitutes a negative connection that decreases opportunities for *A* and *B* to compete against other teams (or, conversely, *C* to compete against *A* and *B*). The consequence is a scarcity of status resources in Ultimate that motivates teams to compete against opponents of equal or higher status to maximize status gains. In other words, negative connections create disincentives for higher status teams to compete against lower status teams that, ultimately, determine the nature of inter-team relations in Ultimate.

In summary, we assume that Ultimate teams depend on one another for status and prefer to increase status at a minimal monetary cost. Ultimate competitions also fall within the general scope conditions of power-dependence theory: competition is voluntary; the flow of resources is dyadic; and at any point in time teams compete with at most one team. All of which are embedded within sequentially negotiated and negatively connected exchange networks.

Based on the assumptions and concepts of power-dependence theory and the structural conditions found in Ultimate, we propose the following hypotheses.[5]

[2] For a greater understanding of Ultimate and its rules visit www.usaultimate.org.

[3] Team schedules usually constitute a mix of scrimmages and tournaments. Both involve joint decision-making processes where teams negotiate spots in tournaments and teams negotiate travel costs for scrimmages. And although dyadic negotiation is more explicit with scrimmages than with tournaments, power use is present in both: higher status teams use their power to reduce extra-regional travel costs.

[4] The RRI is modeled after the Ratings Percentage Index (RPI) and the KRACH rating system used in NCAA hockey. For more information on the RRI, visit www.usaultimate.org.

[5] In Ultimate, there is little variation in the number of alternatives across teams—every team in the network is an alternative exchange partner; that is, the network itself and every actor in it represents an exchange "opportunity structure" (see Cook et al., 1983). As a result, the sources of power and dependence in our model largely derive from variations in a resource's value between potential exchange partners. Note that geographic propinquity does not impact variation in the absolute number of alternatives across teams. Instead, geographic propinquity impacts the *availability* of these alternatives (see Markovsky et al., 1988).

Hypothesis 1. Greater mutual dependence between two teams increases the likelihood of competition.

Hypothesis 2. Greater power imbalance between two teams decreases the likelihood of competition.

To illustrate how hypotheses 1 and 2 operate, suppose that status in Ultimate consists of high (3), middle (2) and low (1) values. Based on the parameters and hypotheses specified above, we expect two high-status teams (A_3–B_3) to have the highest probability of competition: A_3's and B_3's generate the highest mutual dependence *and* lowest power imbalance. We expect the opposite pattern for high- and low-status teams (A_3–B_1) since B_1's greatly depend on A_3's to increase rank and A_3's have little rank to gain and much rank to lose as a result of power imbalances. We also expect a greater likelihood of competition among high- and middle-status teams (A_3–B_2) than low-status teams (A_1–B_1). To explain, A_1's depend very little on B_1's to increase rank. For A_1's (and B_1's) to increase rank they must compete against higher status teams (e.g., B_2's). Yet, B_2's have little rank to gain and more rank to lose if they compete against A_1's. And although the A_1–B_1 exchange relation is power balanced, these two teams are less likely to compete than A_2's and B_3's since A_2's and B_3's are more dependent on each other to either secure rank (in the case of B_3's) or improve rank (in the case of A_2's) than the A_1–B_1 exchange relation. In short, hypothesis 1, in conjunction with hypothesis 2, produces the following inequalities in tie formation for high-, middle-, and low-status teams: $A_3–B_3 > A_3–B_2 = A_2–B_2 > A_1–B_1 = A_2–B_1 = A_3–B_1$.[6]

Hypothesis 3. Greater monetary costs of competition between two teams decrease the likelihood of competition.

An increase in geographic distance between Ultimate teams increases the costs of competition. As a consequence, hypothesis 3 predicts that the likelihood of competition between two teams decreases as travel costs increase. For instance, team A_3 from region δ is less likely to compete against team B_3 from region γ than a similar team (e.g., C_3) from region δ. This constraint applies to both mutually dependent and power imbalanced exchange relations.

Hypothesis 4. The likelihood of competition between two power imbalanced teams increases as the monetary costs of competition between mutually dependent alternatives increases.

Hypothesis 4 expands hypothesis 3 and predicts that power-imbalanced teams from the same region are more likely to compete than mutually dependent teams from different regions. In other words, long-distance travel costs shift the availability of status-improving alternatives that create a situation where high- and middle-status teams become more dependent on lower status teams to increase status. Thus, hypothesis 4 builds from the assumption that teams prefer to increase status at a minimal monetary cost.

Hypothesis 5. Greater power imbalance between two teams from different regions increases the likelihood of travel for the less powerful team at a decreasing rate.

Unlike the four previous hypotheses, hypothesis 5 concerns geographic mobility and suggests that, as the relative power differences between two teams from different regions increase, the likelihood of travel for the less powerful team increases. Powerful teams, in other words, use their structural positions of power to gain distributional bargaining advantages, producing power outcomes in which the less powerful travel to compete. This effect, however, weakens as status decreases since power imbalances and geographic divisions undermine competition options for low-status teams, thereby limiting their geographic mobility: middle- and high-status teams have little status to gain and much status to lose by competing against low-status teams and low-status teams have little status to gain and monetary resources to lose by competing against other extra-regional low-status teams. All of which yields a nonmonotonic relationship between power imbalances and travel.

2. Data and method

For the present paper we used data abstracted from the *Ultimate Score Reporter*, which is a public, web-based archive of competitions that stores information on team names, rosters, regional affiliations, and competition histories (see www.usa-ultimate.org). The latter of which is organized by level of competition and division, and includes results, scores, dates, and locations. The primary function of the score reporter is to annually rank and index teams using the RRI. Below we consider year 2005 open, club Ultimate pre-series competitions that occurred from early June (i.e., after team formation) to early September (i.e., prior to the *USA Ultimate* series). We analyze the structure of competitions for one entire pre-series (June to September) and not multiple pre-series through time. Data on teams are complemented by detailed results from the 2004 season.

2.1. Dependent variables

The first dependent variable, *competition*, is a contest between two 2005 open, club pre-series teams and signifies an edge (or tie) in our exponential random graph models. We use the competition variable exclusively in our analysis of network formation (hypotheses 1–4). The second dependent variable, *travel*, is the number of 2005 pre-series tournaments,

[6] Mutual dependence inequalities in tie formation (hypothesis 1): $A_3–B_3 > A_3–B_2 > A_2–B_2 = A_3–B_1 > A_2–B_1 > A_1–B_1$. Power imbalance inequalities in tie formation (hypothesis 2): $A_3–B_3 = A_2–B_2 = A_1–B_1 > A_3–B_2 = A_2–B_1 > A_3–B_1$.

scrimmages, and non-tournament competitions a team attended outside of their region. We use the travel variable only in the analysis of geographic mobility (hypothesis 5).

2.2. Independent variables

We employ two measures of status to test our hypotheses. First, we use an ordinal *status* variable derived from the *Ultimate Score Reporter*. Teams from 2005 were given three different hierarchical attributes. A "1", or "low status", indicates a team from 2004 that met one of the following criteria: (a) did not participate in the 2004 *USA Ultimate* series, (b) was a new team that formed in 2005, or (c) participated in the *USA Ultimate* series (i.e., sectionals) in 2004 but failed to advance to the second round (i.e., regionals). Likewise, those teams in 2004 that advanced to the second round but failed to advance to the final round (i.e., nationals) were ascribed a "2", or "middle status". Finally, a "3", or "high status", indicates a team from 2004 that advanced to nationals. Thus, greater values denote higher status (3 > 2 > 1). Note that for our analysis of network formation, "high status" encapsulates "elite-high status", which refers to high-status teams that did not travel outside of their region to compete during the 2005 pre-series. We only make the distinction between "high status" and "elite-high status" in our analysis of geographic mobility (see Section 3.3 for a greater discussion of this). Second, we use the 2004 RRI ranking to construct a continuous *rank* variable ranging from 1 (highest ranking) to 123 (lowest ranking), with the value of 123 representing new teams or teams without a 2004 RRI ranking.[7] These values were then divided by 10.

To indirectly measure monetary value we employ a *region* variable that captures travel costs expressed as team location. This categorization by *USA Ultimate* produces six distinct team attributes: Northwest (NW), Southwest (SW), Central (CN), South (SO), Northeast (NE), and Mid-Atlantic (MA).

Finally, for our analysis of geographic mobility we include a continuous variable, *matches*, to measure the total number of 2005 open, club pre-series competitions per team. This was done to control for team activity since overzealous teams that frequently compete throughout the pre-series exhibit, on average, higher status *and* greater rates of travel than less active teams.

2.3. Modeling approach for the analysis of network structure

We investigate our hypotheses about network formation using exponential random graph (ERGMs) or p^* models, which permit the researcher to estimate the probability that a relation exists between two nodes (or teams) as a logistic linear function of covariates (Frank and Strauss, 1986; Robins et al., 2007a,b; Snijders, 2011; Snijders et al., 2006). We employ ERGMs instead of alternative statistical models for single networks, such as Conditionally Uniform Models (CUMs) (Holland and Leinhardt, 1976) or Latent Space Models (LSMs) (Hoff et al., 2002; Lazarsfeld and Henry, 1968), for a number of reasons. First, CUMs "...become very complicated...when richer sets of conditioning statistics are considered (Snijders, 2011, p. 135)" and a rejection of the null hypothesis in CUMs does not facilitate model construction for the phenomenon being observed. Second, LSMs do not represent network dependencies between ties directly and are limited in the kinds of network dependencies they can model because of assumptions about space. ERGMs, on the other hand, are more flexible in that they can specify a large number of dependence structures between ties in a network (e.g., reciprocity, homophily, transitivity, degree differentials, higher-order processes, etc.); they can capture the social regularities giving rise to network ties; they permit inferences about which social processes in a network are expected by chance and which are not; and, finally, they can evaluate competing hypotheses about the sources of network structure (e.g., structural balance versus uniform homophily).

To familiarize the reader, we will provide a brief introduction to ERGMs. Every ERGM consists of an observed network that a researcher has collected and is interested in modeling. ERGMs assume that possible ties among nodes in an observed network are an outcome of an unknown stochastic process where the observed network is regarded as one particular pattern of ties out of a large set of possible patterns. Since the stochastic process that generated the pattern of observed ties is unknown, the goal of the researcher is to formulate a theoretically-driven model for this process. For any given model, the range of possible networks, and their probability of occurrence under the model, is represented by a probability distribution on the set of all possible networks of fixed size. In the distribution of graphs, some network configurations—such as balanced triads or 2-stars—are more likely to occur than others, with the exact probabilities depending on the value of the specified parameter. Using a maximum likelihood approach, the goal is to select a model specification that maximizes the probability of generating the observed network from a distribution of possible networks associated with various specifications of the model. If we estimate a model with a parameter for balanced triads, we may infer that there are more balanced triads in the observed network than expected by chance if the parameter is positive and statistically significant (e.g., see Goodreau, 2007).

Strictly speaking, ERGMs allow us to test whether hypotheses derived from power-dependence theory can explain the network structure of competing Ultimate teams. To do this, we consider disassortative mixing for specific nodal attributes—a team's status and regional location—and absolute difference in rank, while controlling for overall density of the network as well as k-triangles, k-twopaths, and k-stars expressed as geometrically weighted edge-wise shared partner (GWESP),

[7] We only consider competitions among North American teams, since teams from outside of North American are prohibited from participating in any *USA Ultimate* series. Based on this criterion, one non-North American team was excluded from the analysis.

dyad-wise shared partner (GWDSP), and degree (GWD) distribution parameters, respectively. All network analysis procedures were executed with the *statnet* package in R (http://www.statnetproject.org) (Handcock et al., 2003). Refer to Hunter (2007), Lusher et al. (2012), and Robins et al. (2007a,b) for detailed discussions of ERGMs. For a formal expression of the ERGM equations, see Appendix A.

2.3.1. Edges

We include a network configuration—*edges*—that adds one parameter to the model, denoting the number of edges (or competitions) in the network. In the absence of covariates, this parameter represents the overall rate of tie formation in a network and, when transformed, equals the density of the observed network. In the presence of covariates, this parameter acts as an intercept and represents the conditional log-odds of tie formation for any referent category (in the current study, we have referent categories for status, A_3–B_3, and region, A_{NE}–B_{NE}).

2.3.2. Nodal attribute mixing

We use one mixing pattern which tests for disassortative mixing, called *nodal attribute mixing*. This network configuration adds one parameter to the model for each possible pairing of team attribute values. For instance, there are six possible combinations for status: A_1–B_1, A_2–B_1, A_2–B_2, A_3–B_1, A_3–B_2, and A_3–B_3; thus, a parameter is added to the model for each unique combination (save one referent category). We parameterize nodal attribute mixing as dummy variables and include terms for status and region (see Section 2.2). If a specific mixing coefficient is positive, the effect suggests that the probability of tie formation between the two team attributes is greater than the referent category and vice-versa if negative.

Note how nodal attribute mixing is used to assess hypotheses 1–4. Based on hypotheses 1 and 2 (mutual dependence and power imbalance hypotheses, respectively), we expect the log-odds of tie formation to be greatest to smallest in the following order: A_3–B_3 > A_3–B_2 = A_2–B_2 > A_1–B_1 = A_2–B_1 = A_3–B_1. Based on hypothesis 3 (monetary cost hypothesis), we expect the log-odds of tie formation to be greatest to smallest as follows: teams from the same region (e.g., A_{NE}–B_{NE}) > teams from adjacent regions (e.g., A_{NE}–B_{MA}) > teams from nonadjacent regions (e.g., A_{NE}–B_{NW}). And based on hypothesis 4 (power imbalance and monetary cost hypothesis), we expect the log-odds of tie formation to be greater among status incongruent teams from the same region (e.g., $A_{3,NE}$–$B_{2,NE}$) than status congruent teams from different regions (e.g., $A_{3,NE}$–$B_{3,NW}$).

2.3.3. Absolute difference

We infer the effects of our *rank* variable on tie formation (see Section 2.2) from the sum of the absolute differences between the rank of team *A* and the rank of team *B* for all competitions (*A*, *B*) in the network. As such, an absolute difference coefficient in ERGMs represents the log-odds of a tie forming between team *A* and team *B* with respect to every 10-unit difference between *A* and *B* in the rank attribute. If the coefficient is negative, the effect implies that the probability of competition between two teams decreases the more teams differ with respect to the quantitative attribute (i.e., rank) and vice-versa if positive. Following hypotheses 1 and 2, we expect the log-odds of tie formation to decrease as the absolute difference in rank increases.

2.3.4. Shared partner distributions

We also include three newly developed geometrically weighted parameters for edge-wise shared partner distributions (GWESP), dyad-wise shared partner distributions (GWDSP), and degree distributions (GWD) to measure *k*-triangles, *k*-twopaths, and *k*-stars, respectively, and to avoid model degeneracy (Hunter, 2007). For an illustration of the network configurations that GWESP, GWDSP, and GWD parameterize, see Fig. 1. In contrast to the dyadic conceptions of power proposed in the present manuscript, we use geometrically weighted terms to control for graph-theoretic representations of structure, or what Cook et al. (1983) call "structurally similar locations in a network (p. 279)" and "power through point centrality of positions (p. 289)". According to social network analysis scholars (e.g., Wellman, 1983), graph-theoretic representations of structure gauge power distributions in entire networks, and, as a result, offer structural accounts of power in direct competition with the dyadic and relational accounts familiar to power-dependence theory. Although Cook and Yamagishi (1992) have bridged dyadic and structural conceptions of power with the equi-dependence principle of network vulnerability, we argue that geometrically weighted terms are superior to the equi-dependence principle in that they capture local *and* global conceptions of power beyond algorithms based on how vulnerable a network is to the removal of central actors.

The GWESP is a function of the edge-wise shared-partner statistics, defined as the number of linked teams, *A* and *B*, that are both connected to exactly γ other teams, where γ is the number of shared teams between *A* and *B*. For instance, a γ of 1 is equivalent to a triangle, while a γ of 2 is equivalent to a 2-triangle (i.e., a higher-order triangle in which *A* and *B* are connected to both *C* and *D*, but *C* and *D* are unconnected) and so on. The GWESP statistic also includes a weighting parameter α, which is used to estimate the rate of declining marginal returns to tie formation as γ increases.

The GWDSP, on the other hand, is a function of the dyad-wise shared-partner statistics, defined as the number of unlinked teams, *A* and *B*, that are both connected to exactly δ other teams, where δ is the number of shared teams between *A* and *B*. For instance, a δ of 1 is equivalent to a 1-twopath, while a δ of 2 is equivalent to a 2-twopath (i.e., a higher-order twopath in which unlinked nodes, *A* and *B*, are connected to both *C* and *D*, but *C* and *D* are unconnected) and so on. Like GWESP, the GWDSP statistic includes a weighting parameter π, which is used to estimate the rate of declining marginal returns to tie formation as δ increases.

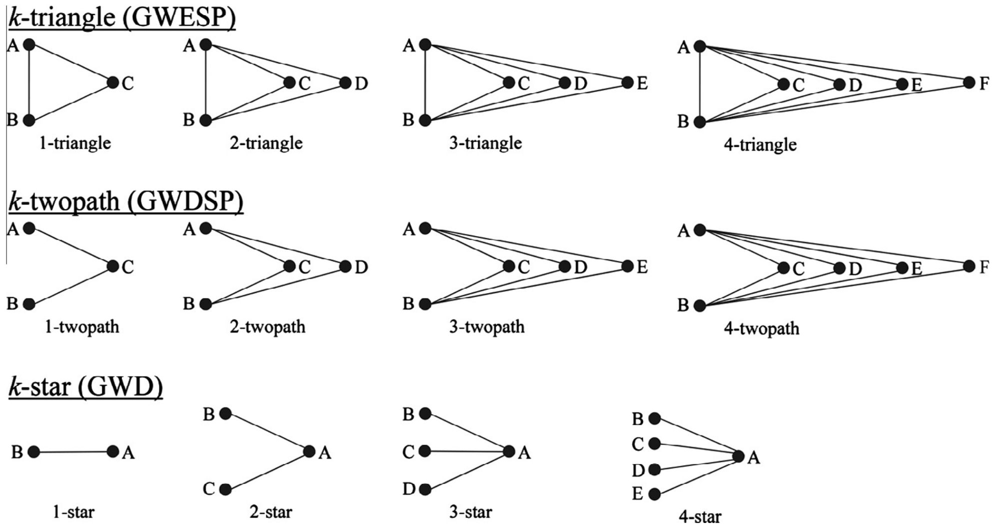

Fig. 1. *k*-Triangle, *k*-twopath, and *k*-star configurations.

The GWD is a function of the degree distribution statistics, defined as the number of teams, *A*, that are connected to exactly τ other teams, where τ is the number of unlinked teams connected to *A*. For instance, a τ of 1 is equivalent to a 1-star, while a τ of 2 is equivalent to a 2-star (i.e., a higher-order star in which node *A* is connected to *B* and *C*, but *B* and *C* are unconnected) and so on. Like the other geometrically weighted terms, the GWD statistic includes a weighting parameter λ, which is used to estimate the rate of declining marginal returns to tie formation as τ increases.[8]

In short, the geometrically weighted terms are important to control for as they capture higher-order groups of triangles, twopaths, and stars in a network that might confound the relationship between power-dependence and network structure.

2.4. Modeling approach for the analysis of geographic mobility

Frequency of travel in Ultimate appears to be Poisson distributed as the underlying event (number of travels) is highly positively skewed. And although frequency of travel has many zero counts (84 zero observations versus 57 non-zero observations), the Vuong test indicates that the Poisson model is preferred to a zero-inflated Poisson regression model. The Poisson model also does not substantively differ from a negative binomial model with over-dispersion either measured as a function of the expected mean or as a constant. Accordingly, we model geographic mobility and frequency of travel in Ultimate using Poisson regression, with the number of pre-series tournaments, scrimmages, and non-tournament competitions a team attended inside *and* outside of their region as the exposure variable.

To clarify the links between our model of power-dependence theory, the sport of Ultimate, exponential random graph models of tie formation, and Poisson regression models of geographic mobility, see Table 1.

3. Results

3.1. Descriptive network analysis

In this next section, we use descriptive statistics from the analysis of social networks to outline and summarize the network structure of Ultimate competitions. Fig. 2 provides a graphical representation of open, club pre-series competitions that occurred in the year 2005 after the formation of teams in early June and just prior to the start of the *USA Ultimate* series in early September. Fig. 2 shows how the 2005 pre-series exhibits a classic core-periphery network structure, where a sparsely connected periphery of competing teams surrounds a densely connected core. Fig. 3, in contrast, is a graphical representation of the 2005 *USA Ultimate* open, club Nationals series that occurs directly after the 2005 pre-series, which reveals a drastic evolution in the structure of competitions once teams abide by a centrally coordinated schedule. Unlike Fig. 2, Fig. 3 does not support a densely connected core of competing teams. Instead, the centrally coordinated competition schedule imposed by *USA Ultimate* found in Fig. 3 produces a classic star-shaped network. For all of the analyses presented below, we

[8] For the present paper, we use fixed values of 0.75 for α (GWESP) and π (GWDSP), and a fixed value of 0.30 for λ (GWD) (models with freely estimated α, π, and λ failed to converge). These values were determined by exploring model convergence and the log-likelihood of models at multiple values of α, π, and λ starting at 0 and increasing by a value of 0.05. We found that the maximum was generally close to 0.75 for GWESP and GWDSP and 0.30 for GWD.

Table 1
Power-dependence theory, Ultimate, tie formation, and geographic mobility.

Concept	Power-dependence theory	Ultimate	Tie formation (ERGM)	Geographic mobility (Poisson)
Team	Actor	2005 Pre-series team	Node, vertex	Case, *N*
Competition, matches	Outcome of power-use	2005 Pre-series competition	Edge, tie	Independent variable
Status	Valued resource	2004 Series result	Nodal attribute (disassortative) mixing	Independent variable
Rank	Valued resource	2004 RRI	Absolute difference	Independent variable
Region	Monetary cost	Regional team location	Nodal attribute (disassortative) mixing	Cluster robust S.E.
Travel	Outcome of power-use	2005 Extra-regional pre-series travel		Dependent variable
Match outcome	Exchange	Win or loss		

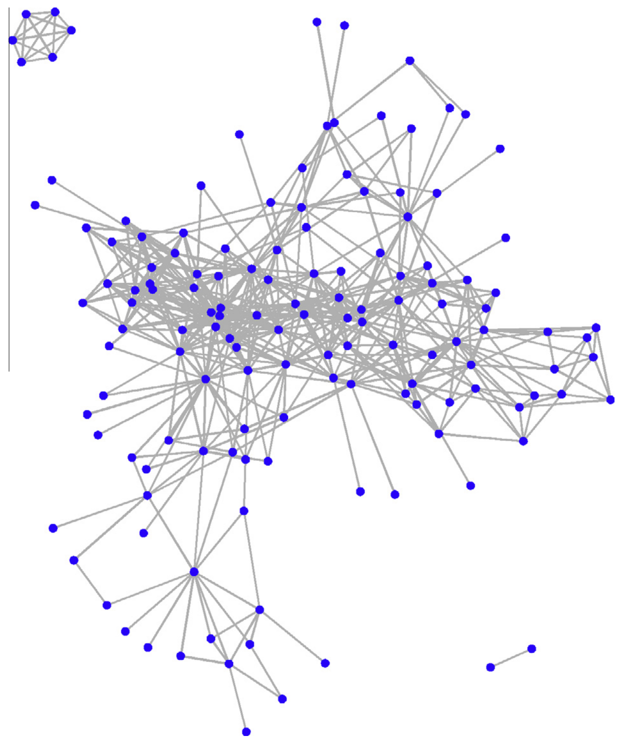

Fig. 2. 2005 Pre-series competitions.

investigate data from Fig. 2. Fig. 3 is used for descriptive purposes only: to illustrate the difference between networks that emerge through decentralized processes (see Fig. 2) versus centralized processes (see Fig. 3).

Table 2 provides descriptive statistics for the 2005 pre-series network (see Fig. 2). We can see that the network has 141 nodes and 565 edges. In other words, in the year 2005, 141 open, club Ultimate teams competed in the pre-series, yielding 565 unique and non-redundant competitions. These two descriptive statistics produce a density of 0.057, which is the proportion of all possible ties (or competitions) within the network. We can also see that teams have a propensity to form triads where *A*, *B*, and *C* are interconnected (i.e., '300') and triads where *A* and *B* are connected but *C* is unconnected to either *A* or *B* (i.e., '102') (see Wasserman and Faust, 1994).

Table 2 also reveals that the median and mean degrees are 6 and 8, respectively, and that the maximum degree is 24. At the bottom of Table 2, we present the total number of teams by status and region. Interestingly, the Northeast region has the most teams and the Southwest has the fewest. Yet, the Southwest has the most high-status teams in relation to their total, while the Northeast has the fewest. Table 3 expands this analysis with disassortative mixing matrices by status and region, producing descriptive data on the total number of edges among disassortatively mixed categories (with densities in parentheses).

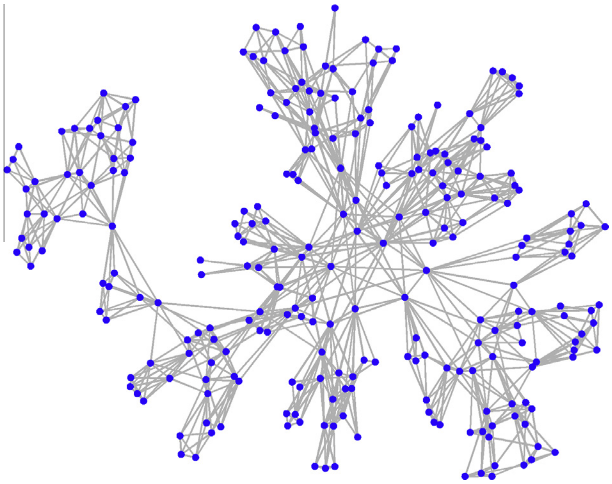

Fig. 3. 2005 Series competitions.

With respect to status, the mixing matrix found in Table 3 reveals the following observed density inequalities: A_3–B_3 > A_3–B_2 > A_2–B_2 > A_1–B_1 = A_2–B_1 > A_3–B_1. In other words, the observed inequalities better align with the predicted additive inequalities of hypotheses 1 and 2 (A_3–B_3 > A_3–B_2 = A_2–B_2 > A_1–B_1 = A_2–B_1 = A_3–B_1) than with either hypothesis 1 or hypothesis 2 alone. And in spite of some incongruence between predicted and observed inequalities, many of the densities predicted to be equal are, in fact, approximately equal. For instance, the densities of A_1–B_1 dyads and A_2–B_1 dyads are 0.04, while the density of A_3–B_1 dyads is 0.02. Taken together, the mixing matrix found in Table 3 offers preliminary support for hypotheses 1 and 2. With respect to region, the mixing matrix shows that densely connected competitions are more common among intra-regional teams than extra-regional teams, providing preliminary support for hypothesis 3.

In short, the descriptive statistics report balance and transitivity in the network as well as disassortative mixing by status and region. Yet, it is unclear whether a team's status, geographic location, or some other higher-order network process such as *k*-triangles and *k*-twopaths account for the 2005 pre-series network structure. To accomplish this task and evaluate our hypotheses, we employ exponential random graph models below.

3.2. ERGM results

We estimate our ERGMs using a Markov chain Monte Carlo (MCMC) maximum likelihood estimation method.[9] Table 4 reports detailed results of our ERGMs, again using 2005 pre-series network data. Convergent estimates were obtained for both models presented in Table 4 (i.e., parameter estimates stabilized and were non-degenerate).[10] Model 1 includes parameter estimates for network density (i.e., edges) and disassortative mixing by status and region where the edges coefficient represents referent categories for disassortative mixing—A_3–B_3 dyads and A_{NE}–B_{NE} dyads. The parameter estimates show that the log-odds of competition produce the following inequalities in tie formation: A_3–B_3 > A_3–B_2 > A_2–B_2 > A_1–B_1 = A_2–B_1 > A_3–B_1.[11] In other words, teams are more likely to compete against those teams that form mutually dependent (hypothesis 1) and power balanced (hypothesis 2) exchange relations, which parallels the mixing matrices found in Table 3. Model 1 also shows that the log-odds of tie formation are greatest for teams from the same region (e.g., A_{NW}–B_{NW} dyads) and smallest for teams from nonadjacent regions (e.g., A_{MA}–B_{NW} dyads), while teams from adjacent regions (e.g., A_{MA}–B_{SO} and A_{NW}–B_{SW} dyads) yield log-odds of tie formation somewhere in-between. Altogether, model 1 supports the proposition that monetary costs of competition decrease the likelihood of tie formation (hypothesis 3).

Model 1 also provides strong support for hypothesis 4, which suggests that the likelihood of competition between local power imbalanced teams is a function of the geographic distance (and resulting monetary costs of competition) between mutually dependent alternatives. To illustrate, consider a competition between two weakly power-imbalanced teams from the same Northwest region: $A_{3,NW}$–$B_{2,NW}$. The log-odds that these two teams form a tie is −0.06 (predicted probability = 0.49), which is greater than the log-odds of tie formation between all other status configurations—including mutually dependent and power balanced status configurations—from nonadjacent regions (e.g., see $A_{3,NW}$–$B_{3,NE}$, $A_{2,NW}$–$B_{2,NE}$, and

[9] We estimate our MCMC chains as follows: a burn-in of 100,000, a MCMC sample size of 50,000, a thinning interval of 50,000, and a Newton–Raphson optimizing steplength of 0.5. Chains started with maximum pseudo-likelihood estimation values obtained through logistic regression. New estimates were obtained, and then re-initiated, from this updated starting point up to 60 times. We use a Metropolis-Hastings algorithm and a lognormal method to approximate the log-likelihood.

[10] A Hotelling's T^2 test for equality of MCMC-simulated network statistics to observed network statistics revealed convergence; MCMC trace and density plots revealed stable chains; Geweke *Z*-scores were below 1.96 for all parameters; and, autocorrelation between MCMC draws was approximately zero for all parameters.

[11] In an alternative model, using A_1–B_1 dyads as a referent category revealed A_1–B_1 and A_2–B_1 parameter estimates to be statistically equivalent.

Table 2
Network descriptive statistics for 2005 pre-series Ultimate competitions.

Descriptive statistics	2005 Pre-series
Nodes	141
Edges	565
Density	0.057
Triadcensus (102)	67,422
Triadcensus (300)	804
Median (mean) degree	6 (8)
Max degree	24

Region	Status			
	Low (1)	Middle (2)	High (3)	Total nodes
Central (CN)	17	6	3	26
Mid-Atlantic (MA)	11	5	3	19
Northeast (NE)	28	11	2	41
Northwest (NW)	10	6	4	20
South (SO)	18	9	2	29
Southwest (SW)	1	3	2	6
Total Nodes	85	40	16	141

Table 3
Disassortative Mixing Matrices by Status and Region.

Status	Disassortative mixing matrices					
	1	2	3			
1	152 (.04)					
2	144 (.04)	71 (.09)				
3	27 (.02)	92 (.14)	79 (.66)			
Region	CN	MA	NE	NW	SO	SW
Central (CN)	44 (.13)					
Mid-Atlantic (MA)	24 (.05)	29 (.17)				
Northeast (NE)	31 (.03)	45 (.06)	143 (.17)			
Northwest (NW)	11 (.02)	7 (.02)	6 (.01)	44 (.23)		
South (SO)	14 (.02)	32 (.06)	17 (.01)	10 (.02)	48 (.12)	
Southwest (SW)	12 (.08)	6 (.05)	4 (.02)	27 (.23)	6 (.04)	4 (.27)

Note: Density in parentheses.

$A_{1,NW}$–$B_{1,NE}$ teams).[12] This pattern, however, does not hold for strongly power-imbalanced teams from the same region, such as $A_{3,NW}$–$B_{1,NW}$ dyads. Although strongly power-imbalanced teams from the same region are less likely to compete than mutually dependent *and* power-balanced teams from nonadjacent regions (−2.34 log-odds for $A_{3,NW}$–$B_{1,NW}$ dyads versus −0.86 log-odds for $A_{3,NW}$–$B_{3,NE}$ dyads), strongly power-imbalanced teams from the same region are more likely to compete than the majority of other mutually dependent and power-balanced teams from nonadjacent regions (e.g., $A_{2,NW}$–$B_{2,NE}$ and $A_{1,NW}$–$B_{1,NE}$ = −4.69 and −5.71 log-odds, respectively).

Interestingly, these differential patterns of tie formation largely hold for adjacent regions as well. Only the following dyads from adjacent regions deviate from the findings outlined above: A_{NE}–B_{MA} dyads and A_{MA}–B_{SO} dyads. We also find that A_3–B_2 dyads (or, weakly power-imbalanced teams) from the same region are less likely to compete than A_3–B_3 dyads from adjacent regions (we find the opposite effect for A_3–B_3 dyads from nonadjacent regions). All told, the probability that two power imbalanced teams from the same region compete increases as the geographic distance between mutually dependent alternatives increases (hypothesis 4).

Model 2 explores the robustness of these findings by including absolute difference in rank and controlling for GWESP, GWDSP, and GWD. The absolute difference in rank parameter is statistically significant and negative. Since this parameter is negative, it explains the tendency for two teams, *A* and *B*, to not compete as the difference in rank between *A* and *B* increases. This indicates that there is a strong tendency for teams to compete based on similarities in rank, which supports hypotheses 1 and 2. The GWESP parameter is statistically significant and positive, which describes the tendency for triadic closure and higher-order triangles to form in the network. The scaling parameter, α, suggests that the log-odds of forming

[12] Predicted probability calculated as follows: $\exp(\beta)/(1+\exp(\beta))$.

Table 4
Tie formation in Ultimate: ERGM parameter estimates and standard errors.

Parameters	Model 1		Model 2	
	Estimate	SE	Estimate	SE
Edges	3.16***	.27	−1.21*	.50
Status mix (A_1–B_1)	−4.85***	.26	−2.41***	.29
Status mix (A_2–B_1)	−4.81***	.26	−2.32***	.29
Status mix (A_2–B_2)	−3.83***	.27	−2.03***	.29
Status mix (A_3–B_1)	−5.50***	.31	−2.39***	.32
Status mix (A_3–B_2)	−3.22***	.27	−1.66***	.28
Status mix (A_3–B_3)	(Referent)		(Referent)	
Region mix (A_{CN}–B_{CN})	−.38[a]	.20	.15	.10
Region mix (A_{CN}–B_{MA})	−1.93***	.26	−.88***	.20
Region mix (A_{MA}–B_{MA})	−.22	.24	.37**	.13
Region mix (A_{CN}–B_{NE})	−2.21***	.22	−.94***	.14
Region mix (A_{MA}–B_{NE})	−1.45***	.19	−.65***	.11
Region mix (A_{CN}–B_{NW})	−3.21***	.38	−1.67***	.32
Region mix (A_{MA}–B_{NW})	−3.67***	.46	−1.93***	.42
Region mix (A_{NE}–B_{NW})	−4.02***	.45	−1.95***	.41
Region mix (A_{NW}–B_{NW})	.06	.21	.38**	.15
Region mix (A_{CN}–B_{SO})	−2.81***	.31	−1.33***	.26
Region mix (A_{MA}–B_{SO})	−1.54***	.22	−.54***	.13
Region mix (A_{NE}–B_{SO})	−2.97***	.28	−1.32***	.21
Region mix (A_{NW}–B_{SO})	−3.20***	.37	−1.48***	.33
Region mix (A_{SO}–B_{SO})	−.53**	.18	.08	.08
Region mix (A_{CN}–B_{SW})	−1.78***	.38	−.78**	.29
Region mix (A_{MA}–B_{SW})	−2.72***	.54	−1.30**	.49
Region mix (A_{NE}–B_{SW})	−3.44***	.57	−1.64**	.54
Region mix (A_{NW}–B_{SW})	−.47[a]	.28	−.06	.22
Region mix (A_{SO}–B_{SW})	−2.71***	.49	−1.15*	.45
Region mix (A_{SW}–B_{SW})	−.61	.68	−.28	.63
Region mix (A_{NE}–B_{NE})	(Referent)		(Referent)	
Abs. diff. (rank/10)			−.16***	.02
GWESP (α = .75)			1.27***	.10
GWDSP (π = .75)			−.04**	.01
GWD (λ = .3)			1.61**	.59
BIC	3472		2943	
AIC	3285		2728	

Note: SE = standard errors.
[a] $p < .10$ (two-tailed tests).
* $p < .05$ (two-tailed tests).
** $p < .01$ (two-tailed tests).
*** $p < .001$ (two-tailed tests).

higher-order triangles beyond 6-triangles is close to zero.[13] In other words, lower- and higher-order triangles are prevalent in the network but two connected teams, *A* and *B*, are not more likely than chance to form a 7-triangle.

GWDSP, on the other hand, is statistically significant and negative. The negative GWDSP parameter shows that teams do not have a strong tendency towards higher-order competition coupling, which is the tendency for two unconnected teams, *A* and *B*, to compete against the same unconnected teams *C*, *D*, and *E*. The GWESP parameter in conjunction with the GWDSP parameter indicates a propensity for balance and triadic closure in the network. Model 2 also shows GWD to be statistically significant and positive: teams are likely to form multiple competitions with unconnected teams (i.e., higher-order *k*-stars), but the log-odds of forming a higher-order star beyond a 4-star is relatively close to zero.[14] In short, positive GWESP and GWD parameters alongside negative edge and GWDSP parameters point to preferential attachment at the local level that yields a core-periphery structure at the global level. In this type of global network structure, some teams are part of a densely connected core, while other teams are part of a sparsely connected periphery, where core teams are well-connected to peripheral teams but peripheral teams are not well-connected to either core or other peripheral teams. Interestingly, what our disassortative mixing terms show is that the sparsely connected peripheral nodes in our network are, by-and-large, low- and middle-status teams,

[13] $1.27 \times (1 - \exp(-0.75))^{\gamma} = 1.27 \times 0.53^{\gamma}$, where γ equals the number of shared partners between linked teams *A* and *B*. For instance, the log-odds of completing a triangle when no triangles exist is 1.27×0.53^0, while the log-odds of completing a 2-triangle when a triangle exists is 1.27×0.53^1 and the log-odds of completing a 3-tirangle when a 2-triangle exists is 1.27×0.53^2 and so on (see Hunter, 2007).

[14] $1.61 \times (1 - \exp(-0.3))^{\gamma} = 1.61 \times 0.26^{\tau}$, where τ equals the number of unlinked teams connected to team *A*. For instance, the log-odds of completing a 1-star when no star exists is 1.61×0.26^0, while the log-odds of completing a 2-star when a 1-star exists is 1.61×0.26^1 and the log-odds of completing a 3-star when a 2-star exists is 1.61×0.26^2 and so on.

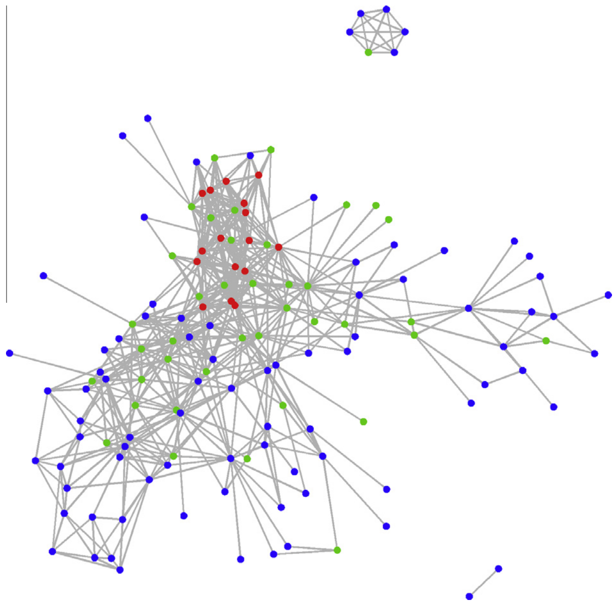

Fig. 4. 2005 Pre-series competitions with high-status (red), middle-status (green), and low-status teams (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

while middle- and high-status teams constitute our densely connected core of nodes (see Fig. 4). Similar sorts of core-periphery structures are found in co-authorship networks, voting-similarity networks, and transportation networks.[15]

Finally, model 2 reveals that parameter estimates for disassortative mixing by status and region differ from those found in model 1; most notably, the coefficients in model 2 decrease in size and the log-odds of tie formation for A_3–B_1 dyads parallel A_1–B_1 dyads. Note, however, that the status inequalities in tie formation found in model 2 are similar to those found in model 1 once the effect of absolute difference in rank is considered. For instance, the log-odds of tie formation for A_3–B_1 dyads and A_1–B_1 dyads are -2.39 and -2.41, respectively. Once we consider the absolute difference in rank between a high-status team (say of rank 1.0) and any low-status team (say of rank 11.0), the log-odds that these two teams compete is $-2.39 + (10 \times -0.16)$, or -3.99. Likewise, the log-odds that any two low-status teams compete (say of rank 10.0 and 12.0) is $-2.41 + (2 \times -0.16)$, or -2.73. In other words, disassortative mixing by status in addition to absolute difference in rank yields status inequalities similar to those found in model 1, which suggests that the dyadic independent network dynamics observed in model 1 are robust to *k*-triangles, *k*-twopaths, and *k*-stars. These findings support laboratory experiments that confirm the utility of power-dependence theory as well as graph-theoretic representations of structure—GWESP, GWDSP, and GWD—in predicting power distributions in exchange networks (see Cook et al., 1983; Yamagishi et al., 1988). In short, mutual dependence in conjunction with power imbalance fuels competition in Ultimate despite the existence of lower- and higher-order network processes.[16]

To assess model fit, we rely on statnet's goodness-of-fit measures (GoF). Fig. 5 illustrates a series of GoF plots comparing the observed network to 100 simulated networks based on parameter estimates found in model 2. Within each cell, the original data is represented by a solid, dark line and the simulated networks are depicted by two faint gray lines and boxplots. All in all, the 100 simulated networks derived from model 2 parameter estimates conform well to the four observed network summary statistics (i.e., network degree, dyad-wise shared partners, edge-wise shared partners, and minimum geodesic distance).

3.3. Descriptive and inferential analysis of geographic mobility

While the previous section concerned power-use and network formation, we now turn to the analysis of power-use and geographic mobility in Ultimate. Table 5 provides descriptive statistics and reveals that the mean travel and tournament attendance during the 2005 pre-series was 0.64 and 1.98, respectively. This shows that less than half of the 2005 open, club

[15] To explore nodal attribute and actor-specific effects, models 1 and 2 were computed with a sociality term that measured the *undirected degree* of each node and a nodefactor term that measured the *factor attribute main effect* of new teams that formed in 2005. We found the following: model 2 with the sociality dummy variables failed to converge to a unique solution regardless of the MCMC estimation values, and the nodefactor dummy for new teams that formed in 2005 became statistically insignificant once we included nodal attribute mixing dummy variables for status. As a result, these terms were excluded from the final models.

[16] To assess the statistical robustness of our findings, we also modeled 2005 pre-series tie formation in Ultimate as counts (see Krivitsky, 2012 for a generalization of ERGMs to valued networks). We found the binary ERGM results presented in Table 4 to be statistically robust to valued ties. A discussion of ERGMs for counts and a table of results can be found in Appendix B.

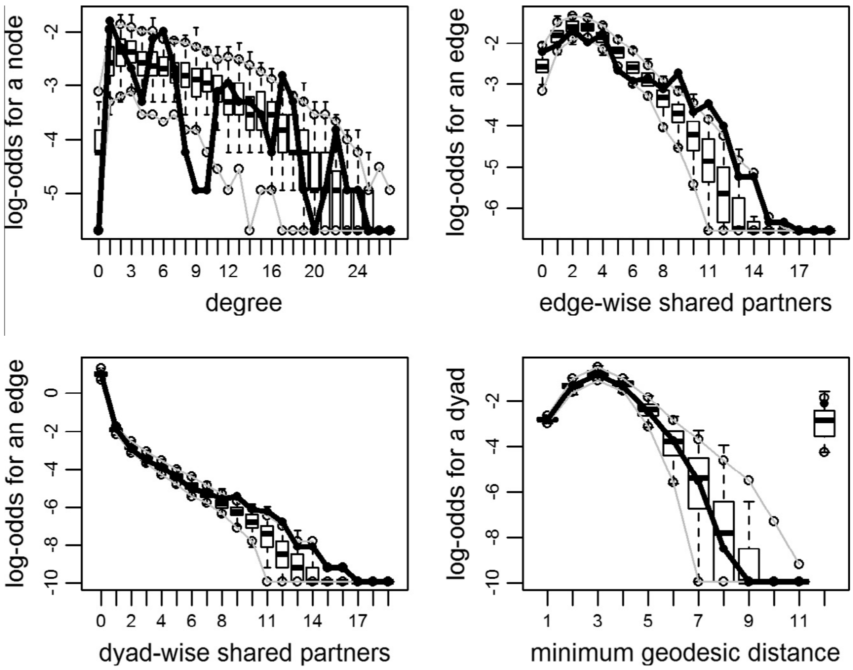

Fig. 5. Goodness-of-fit plot for model 2, Table 4 parameter estimates.

Table 5
Descriptive statistics and proportion of travel by status.

Variable	μ	SD	Min	Max	μ Travel
Travel	.64	.96	0	4	–
Low status	.60	–	0	1	.27
Middle status	.29	–	0	1	.81
High status	.09	–	0	1	2.62
Elite-high status	.02	–	0	1	0
Matches	9.72	8.29	1	32	–
Rank	6.98	3.91	.1	12.3	–
Tournament attendance	1.98	1.23	1	5	–

N: low status = 84; middle status = 41; high status = 13; elite-high status = 3.

pre-series tournaments a team attended were outside of their own region. We can also see that the mean number of matches was 9.72 (min 1, max 32) and that the mean rank was 6.98 (recall, rank equals RRI divided by 10). In other words, teams attended, on average, 1.98 tournaments that yielded 9.72 total competitions. Note that unlike our ERGM edges term, our matches variable includes redundant competitions.

According to our power-dependence model of tie formation and geographic mobility, we expect a small cadre of high-status teams to travel very little or not at all, which is exactly what we find: three high status teams did not travel outside of their region during the 2005 pre-series, while the remaining thirteen high-status teams traveled to a great extent (mean = 2.62). Interestingly, these three teams were the top-three 2004 RRI teams who also advanced to the 2004 national championship. Based on these observations, we construct a new status category, "elite-high status," that only includes this small cadre of non-traveling, high-status teams. All other status categories, including low and middle status, remain the same, except that our high status category now excludes the small cadre of non-traveling, high-status teams. Descriptively, then, we can see that 60% of the sample is low status, 29% is middle status, 9% is high status, and 2% is elite-high status (see Table 5).

Table 6 presents estimates for a series of nested Poisson regression models predicting extra-regional travel as a function of status, matches, and rank. Since we expect stable unmeasured factors to produce patterns of correlations among errors of observations within regions, we use a robust-cluster estimator of the standard errors by region to account for this bias throughout. Model 1 reveals that all three status dummy variables are statistically significant and exhibit a nonmonotonic relationship with travel (see hypothesis 5); that is, as one moves from low status to high status, travel rates increase but

Table 6
Geographic mobility in Ultimate: Poisson regression parameter estimates and standard errors.

Parameter	Model 1		Model 2		Model 3	
	Estimate	SE	Estimate	SE	Estimate	SE
Low status	−1.21**	.45	−.92*	.39	−.77*	.36
Middle status	−.53*	.24	−.36**	.14	−.30*	.13
Elite-high status	−15.14***	1.07	−16.55***	1.06	−15.16***	1.03
High status	(Referent)		(Referent)		(Referent)	
Matches			.02	.01	.01	.02
Rank					−.04	.10
Constant	−.48***	.08	−.91*	.40	−.69	.74
Pseudo-R^2	.11		.11		.12	
Wald χ^2	251.34		338.66		606.49	

Note: exposure variable = total tournament attendance; SE = robust-cluster standard errors by region.
$N = 141$.
* $p < .05$ (two-tailed test).
** $p < .01$ (two-tailed test).
*** $p < .001$ (two-tailed test).

approach zero for elite-high-status teams, which yields the following inequalities in travel: high status > middle status > low status > elite-high status.[17] Models 2 and 3 bolster these results: matches and rank are statistically insignificant and do not substantively alter the findings found in model 1.

In summary, the relationship between travel and status is nonmonotonic: low- and elite-high-status teams are less likely to travel than their middle- and high-status counterparts because of power imbalances and geographic divisions. Altogether, the analysis of tie formation and geographic mobility in Ultimate reveals the following: elite high-status teams do not travel to compete but, ironically, are well connected across geographic space; high-status teams, on the other hand, frequently travel and exhibit a great number of extra-regional ties; middle-status teams travel some but have very few extra-regional connections; and low-status teams rarely travel and are primarily confined to intra-regional ties of propinquity.

4. Discussion

We began this article by discussing one of Georg Simmel's classic propositions: regardless of their innumerable diversity—be it cosmopolitan, multiplex, simplex, or local—social networks form on the basis of values and propinquity. Our personal interests and preferences, in addition to our spatial location, impact who we know and in what capacity, and when taken aggregately can produce a diverse constellation of network structures.

We investigated this classic premise by generating hypotheses derived from assumptions and concepts found in power-dependence theory and the social exchange tradition, by using a hitherto unanalyzed data set of a complete network of competitive social actors, and by utilizing innovative network methods. Our analysis not only demonstrates support for Simmel's theory of sociation, but also shows that certain mechanisms proposed by power-dependence theory add depth and understanding to his explanation: actors form relationships based on shared values and social propinquity, and do so while keeping elements of mutual dependence and power imbalance in mind.

In the case of Ultimate, we assume that teams depend on and cooperatively choose competitors to solidify or increase status. We also assume that Ultimate teams desire status and money but prefer to increase status at a minimal monetary cost. When teams are equipped with such preferences and resources, and status is based on a relative ranking system, then social exchange produces a network of competitions in which the status of competing teams is equivalent and comparable. The mechanisms that generate this process are mutual dependence and power balance: two teams are likely to compete as sum status increases, as relative status differences decrease, and as the availability of status equivalent alternatives decrease. The general implication is that middle-status actors are more likely to bridge the status divide than low- and high-status actors who are more likely to exchange exclusively within and immediately below their status ranking—in the case of high-status actors—or exclusively within and immediately above their status ranking—in the case of low-status actors.

We also demonstrate that these patterns are conditional on propinquity. As the geographic space between mutually dependent teams increases, so do the monetary costs of competition. The consequence is that status congruent pairings become less enticing and more undesirable, leading to fewer competitions among mutually dependent teams divided by geography, which increases the availability of all local teams. When this occurs, teams are more likely to forsake extra-local mutually dependent competitions in favor of local power imbalanced competitions. More broadly interpreted, high-status actors seek out exchanges with proximal low- and middle-status actors when the social distance between middle- and high-status actors is too great. This does not suggest, however, that low- and middle-status actors are increasingly able to bridge the status divide. In reality, the global status hierarchy is reproduced in a local context writ small where low- and

[17] These differences are statistically significant: a joint test rejects the null hypothesis that the coefficients are equal ($\chi^2 = 241.76$; df = 2; $p < .001$).

middle-status actors are more confined to local exchange with other low- and middle-status actors, while high-status actors are better connected to other high-status actors across geographic space. This is because low- and middle-status actors have fewer available status-improving alternatives than high-status actors, which reduces the benefits of traversing geographic space more for low- and middle-status actors than for high-status actors.[18]

Finally, we find that geographic mobility—an outcome of power-use—is a function of status within the Ultimate community. As noted previously, geographic distance between teams increases the monetary costs of competition. To reduce these costs, elite-high-status teams use structural positions of power to gain distributional bargaining advantages. This power-use allows elite-high-status teams to leverage favorable monetary outcomes and produce a highly stratified travel schedule: all non-elite high-status teams are more likely to travel to compete than elite-high-status teams. Middle- and low-status teams, on the other hand, have very little to no bargaining power, producing counterintuitive power outcomes. These teams, like elite-high-status teams, rarely travel to compete even if they are willing to pay for travel, since higher status teams have little rank to gain and a great deal of rank to lose by competing against them and low-status teams have little rank to gain and money to lose to travel and compete against other low-status teams. The analysis of geographic mobility coupled with our findings on network formation paints a stratified picture of power-use in Ultimate: because of distributional bargaining advantages, high-status teams are well connected across geographic space and low-status teams are more confined to ties of propinquity, while elite-high- and low-status teams travel less than their middle- and high-status counterparts who exhibit the most geographic mobility.

4.1. Implications

The idea that power-dependence theory can explain network formation has interesting theoretical and empirical implications. First, our work highlights the importance of integrating individual interests into the general theoretical framework of social network analysis (SNA) (e.g., Wellman, 1983), which is often ignored by this tradition. One of the paradigm's unifying analytic assumptions is the principle that "*networks structure collaborative and competitive activities to secure scarce resources*" (Wellman, 1983, p. 178). In conditions of limited resources, actors compete for access to them and, as a result, form coalitions or factions to monopolize their consumption. By limiting outsider access, factions secure resources for their members while inflating its value.

The implication is that competition over scarce resources leads to the formation and evolution of network structure: coalitional ties shift through time to gain greater access to goods in short supply. Yet, the mechanisms that produce these outcomes remain unresolved. While some SNA scholars identify vacancy chains (White, 1970) and structural embeddedness (Feld, 1997; Granovetter, 1985) as possible sources, others point to structural balance (Heider, 1958) or brokerage positions (Burt, 1992). Note that with the exception of structural balance, each of these proposed mechanisms is a higher-order, top-down process that emphasizes structural position over agency.

Although structural positions are important, they often identify and describe network structure and their accompanying constraints on actors *ad hoc* without detailing *a priori* how or why actors choose particular courses of action, the engine of network formation and evolution. To have a complete and logically concrete model of network formation, then, SNA scholars must include an explicit causal component at the actor-level (Cook et al., 1983; Cook and Whitmeyer, 1992; Cook and Yamagishi, 1992). Otherwise the internal logic of SNA models suffer from circular and tautological reasoning. The theoretical model we employ overcomes these issues and offers a set of transformational mechanisms built on explicit microfoundations that combine to produce network-level outcomes—what Coleman (1990) called the *interdependence of actions*. Keep in mind, however, that higher-order triangles, twopaths, and stars are central to tie formation in Ultimate, which suggests that the global structure of social networks depends on characteristics of actors (rationality), relations (power and dependence), and structure (triadic closure and stars).

Second, our work speaks to the broad literature on social stratification and inequality by detailing concrete relational mechanisms and proximity mechanisms (Rivera et al., 2010) for Robert Merton's (1968) *Matthew Effect* (or what is generally referred to as *cumulative advantage*), where actors who possess certain status characteristics can exercise their status to reproduce or gain even more status. We find that this process of cumulative advantage stems not from structural features of society (see DiPrete and Eirich, 2006), but from powerful actors who dictate terms of exchange, which solidifies their advantage, reproduces their status, and reinforces the lower status of the less powerful. And although the Matthew Effect implies that the "the rich get richer and the poor get poorer", we show that this effect is conditional on propinquity; geographic divisions limit status improving alternatives for low-status actors and, consequently, further constrain the upward status mobility of low-status actors.[19]

As a result, we expect systems of stratified network connections and processes of cumulative advantage similar to those found in Ultimate when (a) status resources are relative, (b) exchange domains fall within power-dependence theory's scope

[18] Although greater access to resources might explain rates of extra-regional travel among high-ranking teams, this account seems implausible since Ultimate is an amateur sport where teams receive very little resources from sponsors. Measurable evidence of these factors, however, is unavailable with the present data. This issue should nevertheless be brought to the reader's attention.

[19] Alternatively, teams might be low status, and remain low status, not because of cumulative advantage but because of their relative inexperience or consistently poor performance. A statistical analysis of tie formation and status mobility through time is necessary to adjudicate between these two competing arguments. We thank the anonymous reviewer for bringing this alternative argument to our attention.

conditions, (c) actors have alternative exchange relations, and (d) actors are embedded within negatively connected exchange networks. Under such conditions, the expectation is that high-status actors with many available alternatives will exchange globally, while low-status actors with few available alternatives will exchange locally. These exchange domains range from religious and political communes to kite flying groups and amateur rock climbing associations to academic departments such as sociology, history, and political science. With respect to the latter, Burris (2004) recently investigated PhD hiring practices of American sociology departments and found that top 20 departments accounted for nearly 70% of total faculty hired; that highly prestigious, or "top 5", departments exhibited the greatest inbreeding and endogamy for hiring practices; and that aspiring, or "next 15", departments displayed some of the greatest upward and downward mobility of any of the ranked departments (see Table 3, p. 249). Burris' findings are strikingly consistent with those found in the case of Ultimate, where high-status teams generally compete with other high-status teams (i.e., inbreed) and middle-status, or aspiring, teams are most successful at crossing the status divide, either downward or upward (see Manger et al. (2012) for an alternative empirical application).

Third, our findings contribute to a growing body of research in administrative science concerned with the geographic proximity of organizations, industry-wide network structure, and resource dependence theory. This literature shows that (a) the spatial distribution and geographic dispersion of firms influences economic exchange and market activities (Sorenson and Stuart, 2001; Stuart and Sorenson, 2003a,b), (b) social structure and interdependence are critical for interorganizational tie formation (Gulati, 1995), and (c) mutual dependence and power imbalance predicts inter-industry mergers and acquisitions (Casciaro and Piskorski, 2005). To our knowledge, however, no study has yet to synthesize elements of all three and explore how power imbalances, mutual dependencies, and spatial proximity impact interorganizational tie formation and geographic mobility. Thus, our findings contribute to this broader literature in organizational science and support the view that interorganizational tie formation is amenable to power-dependence processes and geographic propinquity.[20]

4.2. Limitations

The present study is not without limitations. To conduct our analysis, we assumed that status was exogenous to the exchange relation and that tie formation (or competition) was endogenous. However, to the extent that an endogenous variable produces an exogenous variable (i.e., joint endogeneity), parameter estimates are biased and inconsistent. Moreover, it is plausible that competition is path dependent and contingent on prior network structures or institutionalized competitions. This is an issue since many of the Ultimate teams we observe have competed in the past. These prior interactions might somehow influence or dictate with whom teams compete and, as a result, potentially bias parameter estimates and standard errors. All of which potentially undermines discussions of causality.

In relation to the first issue, status is a consequence of competition: winners generally gain rank while losers generally lose rank, where rank is an attribute teams use to gauge their place in the social hierarchy. However, the association between status and competition in Ultimate is more temporal than simultaneous, potentially eliminating issues of joint endogeneity. To illustrate: series competitions at time 1 generate new rankings (and hence status), which fuels pre-series competitions at time 2, while results from pre-series competitions at time 2 influence series rankings at time 3 and so on. This pattern does not weaken our fundamental point about the role of status in network formation. Instead, it suggests that while competition does indeed produce status, the endogeneity bias is not simultaneous but sequential and temporal, varying between and not within seasons—an indication that status can be treated as exogenous in our models.

This discussion of joint endogeneity parallels the second issue of network path dependence and institutionalized competitions. We argue and show that mutual dependence and power imbalance, in addition to geographic constraints, produces network structure in Ultimate. Yet, unobserved and historically contingent rules about competition schedules or habitual dyadic competitions over time might inhibit or facilitate tie formation beyond that of power and dependence, which would confound the results. To address this alternative argument, we randomly chose two pre-series tournaments (i.e., *Labor Day Championships* and *Boston Invitational Elite Open*) and analyzed their attendance from 2004 to 2010. If Ultimate competitions are, in fact, institutionalized and independent of choice, we would expect consistent tournament attendance across time. But this is not what we find: only one team attended *Labor Day Championships* every year for seven straight years, while three teams did so for the *Boston Invitational*.[21] This suggests inconsistent tournament attendance across time and supports our power-dependence argument of network formation. Yet, only by systematically observing temporal patterns of competitions is it possible to overcome and address issues of joint endogeneity, network path dependence, and institutionalized competitions. Thus, future research should employ recent advances in longitudinal network methods—such as stochastic actor-based models (Steglich et al., 2010)—to shed light on the dynamic casual processes involved in the formation of Ultimate competition networks.

4.3. Conclusion

Our findings reveal how power, dependence, and propinquity dictate tie formation and geographic mobility in the pursuit of status. The primary goal of our study was to develop and test a power-dependence model of Georg Simmel's classic

[20] Although recent studies outside of administrative science have explored some of these processes, none have explored all three (see Manger et al., 2012; Zhu et al., 2013).

[21] Both tournaments usually draw 16 of the highest ranking teams from across the nation every year.

proposition that networks form on the basis of shared values and social propinquity. Our secondary goal was to reinvigorate Richard Emerson's original motivation: to explain and account for structure and structural change with assumptions and concepts found in power-dependence theory (Emerson, 1972a,b). That is, to treat network structure as the *explanandum* and power-dependence as the *explanans* (see Cook and Gillmore, 1984; Willer, 1987 for applications). The "big data" revolution in the social sciences (Lazer et al., 2009) along with advents in the statistical analysis of social networks (Steglich et al., 2010) should propel more research and theoretical developments from the social exchange tradition in this direction. We hope the present manuscript is a welcome first step.

We now end this article where we began, by invoking Georg Simmel. Simmel argued that groups form on the basis of two disparate processes: values and propinquity. People who share some common value and location seek each other out and unintentionally establish a social network on that account. Relationships formed in this way have implications not only for the satisfaction of individual interests, but also for the realization of collective welfare, group cohesion, national identity, and even moral order. Although we demonstrate what Simmel expected, that our companions and associates, our place in the social hierarchy, and our sense of solidarity are the unintended product of social space and individual interests, these effects are entirely conditional on power and dependence.

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Appendix A

ERGMs define the probability of a network with a given set of nodes as,

$$\text{prob}(\mathbf{Y} = \boldsymbol{y}) = \left(\frac{1}{k}\right) \exp\left[\sum_A \eta_A g_A(y)\right] \tag{A.1}$$

where $\mathbf{Y}$ is an n x n matrix of ties (n = population size), and each tie is a random variable Y_{ij} equal to 1 if there is a tie from node i to node j, and 0 otherwise. The observed value of the random variable Y_{ij} is specified as y_{ij} with $\mathbf{y}$ the matrix of observed ties. In Eq. (A.1) above, $g_A(y)$ is a network statistic (or model covariate) corresponding to configuration A, equal to 1 if the configuration is observed, and 0 otherwise. Each network statistic $g_A(y)$ is associated with an unknown parameter to be estimated, η_A, which determines the impact of configuration A on network formation for the observed network.

While Eq. (A.1) concerns the probability of an entire social network, for ease of interpretation, we consider an alternative form of the model re-expressed as the conditional log-odds (logit) of individual ties,

$$\text{logit prob}(Y_{ij}|Y_{ij}^c) = \sum_A \eta_A \delta g_A(y) \tag{A.2}$$

where $\delta g_A(y)$ is the amount by which $g_A(y)$ changes when a single tie, Y_{ij}, is toggled from 0 to 1, conditional on the rest of the network Y_{ij}^c. Based on Eq. (A.2) above, if forming a tie increases g_A by 1, then *ceteris paribus* the log-odds of that tie forming increases by η_A. For example, if A refers to a 2-star, then η_A represents the increase (or decrease) in log-odds of a tie being formed that would create exactly one 2-star. Each η_A indicates whether the observed network exhibits greater (positive coefficient) or lesser (negative coefficient) amounts of A than expected by chance, conditional on other configurations in the model.

Appendix B

Note that the ERGMs presented in Table 4 are limited to binary data: the presence or absence of a tie. This excludes the analysis of valued networks, where edges consist of counts or ranks. Such valued networks might include tallies of e-mail messages, instances of social interaction, or duration and volume of trade. Dichotomizing this data to conform to a classic binary ERGM framework, however, loses such information and may introduce bias.

For the present manuscript, the network data we use consists of valued edges: teams could and did compete with the same team multiple times throughout the 2005 pre-series. In fact, 466 edges in our pre-series network constitute 1 competition, while 78 edges constitute 2 competitions and 21 edges constitute 3 competitions. In other words, ties in our network can be modeled as counts. As a result, we follow recent developments in the analysis of valued ERGMs and model valued ties in our network with a zero-modified Binomial reference distribution using the *statnet* package in R (Krivitsky, 2012).

Fortunately, many of the dyadic independence terms used in Table 4—disassortative mixing for status and region as well as absolute difference in rank—can be executed in a valued ERGM. But valued ERGMs do depart from binary ERGMs in a number of important respects. First, the "intercept" term in a valued ERGM is *sum*, not *edges* and refers to the log-odds of

Table B1
Tie formation in Ultimate: valued ERGM parameter estimates and standard errors.

Parameters	Model 1		Model 2	
	Estimate	SE	Estimate	SE
Sum	1.25***	.16	.34[a]	.18
Non-zero relations	−1.32***	.15	−1.72***	.15
Status mix (A_1–B_1)	−2.89***	.17	−1.94***	.17
Status mix (A_2–B_1)	−2.89***	.17	−1.83***	.16
Status mix (A_2–B_2)	−2.11***	.17	−1.39***	.16
Status mix (A_3–B_1)	−3.48***	.23	−1.85***	.23
Status mix (A_3–B_2)	−1.73***	.16	−.91***	.16
Status mix (A_3–B_3)	(Referent)		(Referent)	
Region mix (A_{CN}–B_{CN})	−.41*	.16	−.28*	.14
Region mix (A_{CN}–B_{MA})	−1.66***	.22	−1.38***	.20
Region mix (A_{MA}–B_{MA})	−.38[a]	.20	−.16	.18
Region mix (A_{CN}–B_{NE})	−1.76***	.18	−1.45***	.17
Region mix (A_{MA}–B_{NE})	−1.13***	.15	−.97***	.14
Region mix (A_{CN}–B_{NW})	−2.30***	.28	−1.85***	.26
Region mix (A_{MA}–B_{NW})	−2.77***	.38	−2.25***	.37
Region mix (A_{NE}–B_{NW})	−3.37***	.41	−2.71***	.39
Region mix (A_{NW}–B_{NW})	−.04	.16	.13	.14
Region mix (A_{CN}–B_{SO})	−2.24***	.25	−1.79***	.23
Region mix (A_{MA}–B_{SO})	−1.28***	.18	−1.04***	.16
Region mix (A_{NE}–B_{SO})	−2.39***	.23	−2.01***	.21
Region mix (A_{NW}–B_{SO})	−2.38***	.29	−1.83***	.26
Region mix (A_{SO}–B_{SO})	−.40**	.14	−.24†	.13
Region mix (A_{CN}–B_{SW})	−1.42***	.28	−1.19***	.26
Region mix (A_{MA}–B_{SW})	−1.82***	.36	−1.46***	.34
Region mix (A_{NE}–B_{SW})	−2.77***	.50	−2.25***	.47
Region mix (A_{NW}–B_{SW})	−.47*	.20	−.37[a]	.19
Region mix (A_{SO}–B_{SW})	−1.92***	.35	−1.45***	.34
Region mix (A_{SW}–B_{SW})	−.39	.44	−.36	.43
Region mix (A_{NE}–B_{NE})	(Referent)		(Referent)	
Abs. diff. (rank/10)			−.20***	.02
Transitive weights			.80***	.09
BIC	−35,533		−35,782	
AIC	−35,727		−35,997	

Note: SE = standard errors.
[a] $p < .10$ (two-tailed test).
* $p < .05$ (two-tailed test).
** $p < .01$ (two-tailed test).
*** $p < .001$ (two-tailed test).

tie formation during a given time step (or the log-odds of a success for Binomial reference distributions). Second, valued ERGMs can account for zero-inflated tie formation where a few actors in a sparse network have high interaction counts. Zero-modification is modeled in the *statnet* package with the term *nonzero*, which captures the number of non-zero relations in a network. Third, higher-order geometrically weighted terms—GWESP, GWDSP, and GWD—have yet to be implemented for valued ERGMs. Instead, to model triadic closure with valued ERGMs one must employ the flexible *transitive weights* and *cyclical weights* statistics found in the *statnet* package. We model the former, since the *cyclical weights* term is perfectly correlated with the *transitive weights* term in our network. We customize our *transitive weights* statistic by using conservative values for the "twopath", "combine", and "affect" functions.

Table B1 replicates the binary ERGMs presented in Table 4 with valued ERGMs described above. We estimate both models as follows: a Markov chain Monte Carlo (MCMC) sample size of 10,000, a burn-in of 100,000, a thinning interval of 20,000, a Newton-Raphson optimizing steplength of 0.5, and a maximum of 40 iterations. A Hotelling's T^2 test for equality of MCMC-simulated network statistics to observed network statistics revealed convergence; MCMC trace and density plots revealed stable chains; Geweke Z-scores were below 1.96 for all parameters; and, autocorrelation between MCMC draws was approximately zero for all parameters.

In replicating model 1, Table 4 (the dyadic independence model), we find few substantive differences in the results (see Table B1), although many of the coefficients decrease in size and magnitude. This is likely due to the inclusion of a non-zero relations term, which is statistically significant and negative, indicating that there is an excess of zeros in the data relative to the binomial distribution and given the rest of the model. Regardless, the nodal attribute mixing terms found in model 1, Table B1 yield inequalities in tie formation that support hypotheses 1 through 4, where mutually dependent (hypothesis 1) and power balanced (hypothesis 2) ties are more likely to form than mutually independent and power imbalanced ties, respectively; where tie formation varies by geographic propinquity (hypothesis 3); and, where, as the geographic space between mutually dependent alternatives increases, local power imbalanced ties are more likely to form than extra-local mutually dependent ties (hypothesis 4).

In replicating model 2, Table 4 (the dyadic dependence model), we substitute GWESP, GWDSP, and GWD with a *transitive weights* term that statistically controls for triadic closure (see model 2, Table B1). We find that the substantive results presented in model 2, Table B1 for nodal attribute mixing by status and region, as well as absolute difference in rank, is similar to results presented in model 2, Table 4. Once again, the non-zero relations term suggests an excess of zeros, and the transitive weights term is statistically significant and positive. Thus, like for model 2, Table 4, there appears to be a strong transitivity effect—a friend of a friend is a friend—in the 2005 pre-series network.

All in all, the binary ERGM results presented in Table 4 are robust to modeling procedures that treat ties as counts, which further support hypotheses 1 through 4: status resources desired by teams, coupled with the availability of geographically proximal alternatives, create power and dependence that dictates where and with whom teams compete.

References

Berger, J., Fisek, M.H., 2006. Diffuse status characteristics and the spread of status value: a formal theory. Am. J. Sociol. 111, 1038–1079.
Bienenstock, E.J., Bonacich, P., 1992. The core as a solution to exclusionary networks. Social Netw. 14, 231–243.
Blau, P.M., 1964. Exchange and power in social life. J. Wiley, New York.
Blau, P.M., 1977. Inequality and Heterogeneity: A Primitive Theory of Social Structure. Free Press, New York.
Blau, P.M., Schwartz, J.E., 1984. Crosscutting Social Circles: Testing a Macrostructural Theory of Intergroup Relations. Academic Press, Orlando.
Bossard, J.S., 1932. Residential propinquity as a factor in marriage selection. Am. J. Sociol. 38, 219–224.
Burris, V., 2004. The academic caste system: prestige hierarchies in PhD exchange networks. Am. Sociol. Rev. 69, 239–264.
Burt, R.S., 1992. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, Mass.
Butts, C.T., 2003. Network inference, error, and informant (in)accuracy: a Bayesian approach. Social Networks 25, 103–140.
Casciaro, T., Piskorski, M., 2005. Power imbalance, mutual dependence, and constraint absorption: a closer look at resource dependence theory. Adm. Sci. Q. 50, 167–199.
Coleman, J.S., 1990. Foundations of Social Theory. Harvard University Press, Cambridge.
Cook, K.S., Emerson, R.M., 1978. Power, equity and commitment in exchange networks. Am. Sociol. Rev. 43, 721–739.
Cook, K.S., Emerson, R.M., 1987. Social Exchange Theory. SAGE Publications, Beverly Hills, Calif.
Cook, K.S., Gillmore, M.R., 1984. Power, dependence and coalitions. In: Lawler, E.J. (Ed.), Advances in Group Processes. JAI Press, Greenwich, CT, pp. 27–58.
Cook, K.S., Whitmeyer, J.M., 1992. Two approaches to social structure: exchange theory and network analysis. Ann. Rev. Sociol. 18, 109–127.
Cook, K.S., Yamagishi, T., 1992. Power in exchange networks: a power-dependence formulation. Social Netw. 14, 245–265.
Cook, K.S., Emerson, R.M., Gillmore, M.R., Yamagishi, T., 1983. The distribution of power in exchange networks: theory and experimental results. Am. J. Sociol. 89, 275–305.
Corra, M., Willer, D., 2002. The gatekeeper. Sociol. Theory 20, 180–207.
DiPrete, T.A., Eirich, G.M., 2006. Cumulative advantage as a mechanism for inequality: a review of theoretical and empirical developments. Ann. Rev. Sociol. 32, 271–297.
Ekeh, P.P., 1974. Social Exchange Theory: The Two Traditions. Heinemann Educational, London.
Emerson, R.M., 1962. Power-dependence relations. Am. Sociol. Rev. 27, 31–40.
Emerson, R.M., 1964. Power-dependence relations: two experiments. Sociometry 27, 282–298.
Emerson, R.M., 1972a. Exchange theory, Part I: a psychological basis for social exchange. In: Berger, J., Zelditch, M., Anderson, B. (Eds.), Sociological Theories in Progress. Houghton Mifflin, Boston, MA, pp. 38–57.
Emerson, R.M., 1972b. Exchange theory, Part II: exchange rules and networks. In: Berger, J., Zelditch, M., Anderson, B. (Eds.), Sociological Theories in Progress. Houghton Mifflin, Boston, MA, pp. 58–87.
Feld, S.L., 1997. Structural embeddedness and stability of interpersonal relations. Social Networks 19, 91–95.
Foa, U.G., Foa, E.B., 1974. Societal Structures of the Mind. Springfield, Thomas, Ill.
Foa, U.G., Foa, E.B., 1976. Resource theory of social exchange. In: Thibaut, J.W., Spence, J.T., Carson, R.C. (Eds.), Contemporary Topics in Social Psychology. General Learning Press, Morrison, NJ.
Frank, R.H., 1988. Passions within Reason: The Strategic Role of the Emotions. Norton, New York, NY.
Frank, O., Strauss, D., 1986. Markov graphs. Journal of the American Statistical Association 81, 832–842.
Friedkin, N.E., 1986. A formal theory of social power. Journal of Mathematical Sociology 12, 103–126.
Friedkin, N.E., 1992. An expected value model of social power: predictions for selected exchange networks. Social Netw. 14, 213–229.
Goodreau, S.M., 2007. Advances in exponential random graph (p^*) models applied to a large social network. Social Networks 29, 231–248.
Granovetter, M., 1985. Economic action and social structure: the problem of embeddedness. Am. J. Sociol. 91, 481–510.
Griggs, G., 2009a. 'Just a sport made up in a car park?': The 'soft' landscape of Ultimate Frisbee. Social Cult. Geogr. 10, 757–770.
Griggs, G., 2009b. 'When a ball dreams, it dreams it's a Frisbee': The emergence of aesthetic appreciation within Ultimate Frisbee. Sport Soc. 12, 1317–1326.
Griggs, G., 2011. 'This must be the only sport in the world where most of the players don't know the rules': operationalizing self refereeing and the spirit of the game in UK-Ultimate Frisbee. Sport Soc. 14, 97–110.
Gulati, R., 1995. Social structure and alliance formation patterns: a longitudinal analysis. Adm. Sci. Q. 40, 619–652.
Handcock, M.S.D., Hunter, D.R., Butts, C.T., Goodreau, S.M., Morris, M., 2003. statnet: Software Tools for the Statistical Modeling of Network Data.
Hedstrom, P., 1994. Contagious collectivities: on the spatial diffusion of Swedish Trade-Unions, 1890–1940. Am. J. Sociol. 99, 1157–1179.
Heider, F., 1958. The Psychology of Interpersonal Relations. Wiley, New York.
Hoff, P.D., Raftery, A.E., Handcock, M.S., 2002. Latent space approaches to social network analysis. J. Am. Stat. Assoc. 97, 1090–1098.
Holland, P.W., Leinhardt, S., 1976. Local structures in social networks. Sociol. Methodol. 6, 1–45.
Homans, G.C., 1950. The Human Group. Harcourt, New York, NY.
Homans, G.C., 1974. Social Behavior: Its Elementary Forms. Harcourt, New York, NY.
Huberman, B.A., Loch, C.H., Onculer, A., 2004. Status as a valued resource. Social Psychol. Quart. 67, 103–114.
Hunter, D.R., 2007. Curved exponential family models for social networks. Social Netw. 29, 216–230.
Kossinets, G., 2006. Effects of missing data in social networks. Social Netw. 28, 247–268.
Krivitsky, P.N., 2012. Exponential-family random graph models for valued networks. Electron. J. Stat. 6, 1100–1128.
Lawler, E.J., 2001. An affect theory of social exchange. Am. J. Sociol. 107, 321–352.
Lawler, E.J., Yoon, J., 1993. Power and the emergence of commitment behavior in negotiated exchange. Am. Sociol. Rev. 58, 465–481.
Lawler, E.J., Thye, S.R., Yoon, J., 2008. Social exchange and micro social order. Am. Sociol. Rev. 73, 519–542.
Lazarsfeld, P.F., Henry, N.W., 1968. Latent Structure Analysis. Houghton, New York, NY.
Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A.L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., Van Alstyne, M., 2009. Computational social science. Science 323, 721–723.
Leonardo, P., Zagoria, A., 2005. Ultimate: The First Four Decades. Daehan Printing, South Korea.
Lovaglia, M., 1994. Relating power to status. Adv. Group Process. 11, 87–111.
Lovaglia, M.J., 1995. Power and status: exchange, attribution, and expectation states. Small Group Res. 26, 400–426.

Lusher, D., Koskinen, J., Robins, G., 2012. Exponential Random Graph Models for Social Networks: Theory, Methods, and Applications. Cambridge University Press, Cambridge, MA.
Manger, M.S., Pickup, M.A., Snijders, T.A.B., 2012. A hierarchy of preferences: a longitudinal network analysis approach to PTA formation. J. Conflict Resolut. 56, 853–878.
Markovsky, B., Willer, D., Patton, T., 1988. Power relations in exchange networks. Am. Sociol. Rev. 53, 220–236.
Meeker, B.F., 1971. Decisions and exchange. Am. Sociol. Rev. 36, 485–495.
Merton, R.K., 1968. The Matthew effect in science. The reward and communication systems of science are considered. Science 159, 56–63.
Molm, L.D., 1997. Coercive Power in Social Exchange. Cambridge University Press, New York, NY.
Molm, L.D., 2003. Power, trust, and fairness: comparisons of negotiated and reciprocal exchange. In: Thye, S.R., Lawler, E.J. (Eds.), Advances in Group Processes: Power and Status. Elsevier, Oxford, UK, pp. 31–65.
Molm, L.D., Cook, K.S., 1995. Social exchange and exchange networks. In: Cook, K.S., Fine, G.A., House, J.S. (Eds.), Sociological Perspectives on Social Psychology. Allyn and Bacon, Boston, MA, pp. 209–235.
Molm, L.D., Peterson, G., Takahashi, N., 1999. Power in negotiated and reciprocal exchange. Am. Sociol. Rev. 64, 876–890.
Molm, L.D., Takahashi, N., Peterson, G., 2000. Risk and trust in social exchange: an experimental test of a classical proposition. Am. J. Sociol. 105, 1396–1427.
Molm, L.D., Collett, J.L., Schaefer, D.R., 2007. Building solidarity through generalized exchange: a theory of reciprocity. Am. J. Sociol. 113, 205–242.
Pattison, P., Wasserman, S., 1999. Logit models and logistic regressions for social networks: II. Multivariate relations. Br. J. Math. Stat. Psychol. 52, 169–193.
Pfeffer, J., Salancik, G.R., 1978. The External Control of Organizations: A Resource Dependence Perspective. Harper & Row, New York.
Rivera, M.T., Soderstrom, S.B., Uzzi, B., 2010. Dynamics of dyads in social networks: assortative, relational, and proximity mechanisms. Ann. Rev. Sociol. 36, 91–115.
Robbins, B., 2004. 'That's Cheap'. the rational invocation of norms, practices, and an ethos in Ultimate Frisbee. J. Sport Social Iss. 28, 314–337.
Robbins, B.G., 2012. Playing with fire, competing with spirit: cooperation in the sport of ultimate. Sociol. Spect. 32, 270–290.
Robins, G., Pattison, P., Kalish, Y., Lusher, D., 2007a. An introduction to exponential random graph (p^*) models for social networks. Social Netw. 29, 173–191.
Robins, G., Snijders, T., Wang, P., Handcock, M., Pattison, P., 2007b. Recent developments in exponential random graph (p^*) models for social networks. Social Netw. 29, 192–215.
Schaefer, D.R., 2012. Homophily through nonreciprocity: results of an experiment. Soc. Forces 90, 1271–1295.
Simmel, G., Wolff, K.H., 1950. The Sociology of Georg Simmel. Free Press, Glencoe.
Simpson, B., Willer, D., 2002. Applications of elemental theory to structures of antiquity. In: Chew, S.C., Knottnerus, J.D. (Eds.), Structure, Culture, and History: Recent Issues in Social Theory. Rowman and Littlefield Publishers, Inc., Oxford, UK, pp. 231–256.
Skvoretz, J., Lovaglia, M.J., 1995. Who exchanges with whom: structural determinants of exchange frequency in negotiated exchange networks. Social Psychol. Quart. 58, 163–177.
Skvoretz, J., Willer, D., 1993. Exclusion and power: a test of four theories of power in exchange networks. Am. Sociol. Rev. 58, 801–818.
Snijders, T.A.B., 2011. Statistical models for social networks. Ann. Rev. Sociol. 37, 131–153.
Snijders, T.A.B., Pattison, P.E., Robins, G.L., Handcock, M.S., 2006. New specifications for exponential random graph models. Sociol. Methodol. 2006 (36), 99–153.
Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. Am. J. Sociol. 106, 1546–1588.
Steglich, C., Snijders, T.A.B., Pearson, M., 2010. Dynamic networks and behavior: separating selection from influence. Sociol. Methodol. 40, 329–393.
Stolte, J.F., 1988. From micro-exchange to macro-exchange structure: measuring power imbalance at the exchange network level. Social Psychol. Quart. 51, 357–364.
Stolte, J.F., Emerson, R.M., 1977. Structural inequality: position and power in exchange structures. In: Hamblin, R.L., Kunkel, J.H. (Eds.), Behavioral Theory in Sociology. Transaction Books, New Brunswick, NJ, pp. 117–138.
Stuart, T.E., Sorenson, O., 2003a. Liquidity events and the geographic distribution of entrepreneurial activity. Adm. Sci. Q. 48, 175–201.
Stuart, T., Sorenson, O., 2003b. The geography of opportunity: spatial heterogeneity in founding rates and the performance of biotechnology firms. Res. Policy 32, 229–253.
Thye, S.R., 2000. A status value theory of power in exchange relations. Am. Sociol. Rev. 65, 407–432.
Thye, S.R., Willer, D., Markovsky, B., 2006. From status to power: new models at the intersection of two theories. Soc. Forces 84, 1471–1495.
Van de Rijt, A., Macy, M.W., 2006. Power and dependence in intimate exchange. Soc. Forces 84, 1455–1470.
Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.
Wasserman, S., Pattison, P., 1996. Logit models and logistic regressions for social networks. I. An introduction to markov graphs and p^*. Psychometrika 61, 401–425.
Wellman, B., 1983. Network analysis: some basic principles. Sociol. Theory 1, 155–200.
White, H.C., 1970. Chains of Opportunity. Harvard University Press, Cambridge, Mass.
Willer, D., 1987. Theory and the Experimental Investigation of Social Structures. Gordon and Breach Science Publishers, New York, NY.
Yamagishi, T., Gillmore, M.R., Cook, K.S., 1988. Network connections and the distribution of power in exchange networks. Am. J. Sociol. 93, 833–851.
Zhu, M.X., Huang, Y., Contractor, N.S., 2013. Motivations for self-assembling into project teams. Social Netw. 35, 251–264.