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# The geometry of security: Modeling interstate alliances as evolving networks

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**Abstract**

In this article, it is argued that interstate alliances function as public costly signals of state intentions to cooperate militarily, and as such, they should be expected to influence state expectations within dyads, between dyads, and across time. Accurate statistical modeling of interstate military alliances thus requires that researchers escape the assumption of independent units of observation, which is built into most of the statistical tools currently used by international relations scholars, as such models can be expected to produce unbiased parameter estimates in this domain only if the decisions to create and dissolve interstate alliances are formulated in isolated dyadic bubbles. The use of stochastic actor-oriented models, combined with Markov simulations of network evolution, is shown to be a productive alternative method of modeling interstate alliances, which allows the researcher to avoid the assumption of dyadic independence by incorporating theory-driven assumptions about patterns of extra-dyadic interdependence directly into the functional form of the statistical model. The results demonstrate that triadic patterns of amity and enmity exercise powerful influence over the selection of alliance partners and the evolution of the global alliance network. The results also show that failure to incorporate patterns of extra-dyadic interdependence into our statistical models of interstate alliance decisions is likely to result in biased parameter estimates.

**Keywords**

dyadic interdependence, international security, military cooperation, network analysis, statistical inference

## Introduction

Data on the relationships and interactions that arise between states, the data that lie at the foundation of most quantitative studies in the field of international relations, present a bedeviling array of difficulties to the researcher who would seek to make reliable causal inferences. Whether the object of study is the onset of armed disputes, the construction of international financial institutions, or the attempt to secure military cooperation via the negotiation and ratification of treaties, the behaviors of interest are nearly always the result of *interdependent* decisions by states. While such interdependencies can take a variety of forms, they all generate severe difficulties for statistical inference because they generate observed variables which violate one of the foundational assumptions of nearly every statistical estimator currently in use in our discipline: namely, the conditional independence of observations.

This is the basis of the critique launched by Signorino (1999), arguing that the use of standard logistic regression to analyze conflict onset events can be expected to produce biased parameter estimates because such events are the result of strategic interactions between states. Because the occurrence of any particular dyadic outcome is a function of each state's assessment of the likely future actions of the other state, the resulting observations are also mutually dependent, creating complex nonlinearities between the independent and dependent variables that standard estimation approaches simply assume away. The solution he proposes combines a random utility model with an extensive form representation of a given strategic interaction to produce a maximum likelihood estimator which more closely matches the functional form of the data generating process.

This seminal contribution to the statistical analysis of international interactions has greatly advanced the broader methodological project of bridging the gap between formal models and empirical evidence. However, the need for alignment between the functional form of a data generating process and a corresponding statistical estimator is not restricted to the special case of interdependencies generated by strategic anticipation, but rather represents a basic fact about our ability to generate unbiased causal inferences from observational data (Smith, 1996; Achen, 2002; de Marchi, 2005). Biased parameter estimates will result any time the functional form of the statistical model is not consistent with the data generating process

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(see Signorino & Yilmaz, 2003). Unfortunately, the application of Signorino's solution requires the imposition of game theoretic assumptions that are ill-suited to describing interactions in which the quantities of interest are generated not by strategic equilibria, but by the dynamic evolution of complex systems.

The field of international relations, and the social sciences more broadly, thus find themselves in need of a wider menu of options for combining formal and statistical models, a menu which would map formalized classes of data generating processes to classes of statistical estimators which approximate their corresponding functional forms. As the full realization of such a methodological agenda lies well beyond the scope of this single article, the present study seeks instead to make a modest contribution to its fulfillment by introducing for the first time to international relations and political science a statistical approach to the modeling of dyadic interdependencies originally developed for the analysis of longitudinal social network data (Snijders, 1996).

Substantively, I focus on the dynamic process of alliance formation and dissolution because it highlights an important empirical domain where scholars currently lack a coherent means through which to bring their formal and statistical models into congruence. My goal is neither to develop a complete model of alliance formation and dissolution, nor to develop a 'silver bullet' statistical estimator which could be applied naïvely to all forms of interdependence encountered in international relations data. In fact, given the vast diversity of interactive processes present in the international system, we have good reason to doubt that such an estimator is possible, even in principle. Rather, the goal is to point in the direction of one potential path by which a better menu of options could begin to be constructed.

That path begins by representing the global military alliance system as a dynamic network of interdependent ties between states. To model shifts in the patterns of such ties, I propose an application of what Snijders (1996, 2001) refers to as a *stochastic actor-oriented* approach to the modeling of longitudinal network data. This approach combines a random utility model with Markov simulations of network evolution, making possible the explicit incorporation of extra-dyadic interdependencies into a regression model in which alliance ties are both a reflection of underlying state interests and a response to the evolving network of ties between other states. By characterizing the global alliance system as a network which evolves from the interdependent decisions of individual states, this approach allows the researcher to derive the functional form of the statistical estimator directly from theoretically driven assumptions about the utility functions of states engaged in alliance formation decisions.

While a wide variety of extra-dyadic interdependencies could be modeled within this framework, the present study focuses on the impact of triadic patterns of military conflict and cooperation, as these are the most basic violations of dyadic independence that could be observed in alliance formation decisions. As I will argue more fully below, these extra-dyadic effects arise because interstate alliances are public events and therefore alter expectations about the likely contours of future conflicts, even for witnesses who are external to a given pact. These altered expectations in turn influence the subsequent selection of alliance partners, creating a system of complex interdependencies in which alliance decisions influence each other across dyadic boundaries, rather than being formulated in isolated dyadic bubbles. It is in this sense that we can speak of the alliance network as 'evolving', as state actions are taken in response to a shifting environment, which those very same actions are simultaneously constructing.

The remainder of the paper proceeds as follows. In Section 1, I review the existing theoretical and empirical literature on interstate alliances and explain why alliance treaties must generate the kinds of extra-dyadic interdependencies that cannot be adequately captured through standard forms of regression analysis. In Section 2, I examine alternative statistical frameworks for the analysis of dyadic interdependencies and discuss why they are inadequate to capture the dynamic process of alliance formation and dissolution. In Section 3, I describe how the stochastic actor-oriented approach can be productively applied to the study of interstate alliances by incorporating network statistics into the definition of a state's utility function and using simulations of network evolution to estimate parameterized weights for each component of that utility function. In Section 4, I present empirical results from stochastic actor-oriented models of alliance network evolution estimated for the period 1950–2000 and compare them to the results of standard logistic regressions estimated for the same period. The results demonstrate that triadic interdependencies are powerful and enduring components of the state decisions that drive changes in the structure of the global alliance network, and that these interdependencies are inadequately captured by the statistical methods that are currently standard in the field.

## Alliances, alignments, and interests

Military alliances have long been recognized as one of the central means through which states in the international system structure their relationships and actions. Moreover, in recent years the field of international relations has witnessed a proliferation of studies investigating the effects of alliances on state behavior (see Sprecher & Krause, 2006, for a recent review). Scholars have examined the role played by alliances in the outbreak of conflict (Smith, 1995; Gibler, 2008; Kimball, 2006), the deterrence of aggression (Leeds, 2003a), the decision by third parties to intervene in pre-existing conflicts (Leeds, 2003b; Smith, 1996; Gartzke and Gleditsch, 2004), and the promotion of trade (Long, 2003; Long & Leeds, 2006). However, our understanding of how and why particular alliance partners are chosen in the first place remains relatively sparse.

An *alliance* is a formal, written agreement between two or more states in which they agree to some form of coordinated military action in the event of a future conflict. Alliances have long been characterized, especially by the neorealist school, as reflections of pre-existing state interests (Waltz, 1979). Indeed, it has become common practice to use measures of alliance portfolio similarity as indicators of shared interests between states (Signorino & Ritter, 1999; Gibler & Rider, 2004). In characterizing such interests, early work on the formation of interstate military alliances focused on the logic of balancing, whether in the form of a balance of *power* (Waltz, 1979) or a balance of *threat* (Walt, 1987).[1] For balancing theorists such as Waltz and Walt, alliances are formed primarily *against* specific external threats and thus are primarily driven by systemic patterns of capabilities and conflicts. Morrow (1991) has also argued that there may be strong incentives towards dyadic power asymmetry in military alliances, as such ties allow states to pursue mutually productive trade-offs between security and autonomy.

Further examinations of the shared interests that drive the selection of particular alliance partners have gone beyond the effects of power and threats, to examine the role played by regime type. Siverson & Emmons (1991) find that there is a general tendency for democracies to ally with each other at significantly larger rates than other states. Simon & Gartzke (1996) argue that we should actually expect a tendency toward politically asymmetric alliances because they have the advantage of combining the complementary strengths of democracies (stable, transparent commitments) and autocracies (quick mobilization of defense). Lai & Reiter (2000) find that after 1945 similar regimes of all types are more likely to ally with each other,[2] as are states with culturally similar populations and states separated by smaller geographic distances.

In all these analyses, the conditions for alliance formation are generally treated as identical to the conditions for productive military cooperation. However, as Morrow points out, 'anything that an alliance allows during wartime can also be accomplished without a prewar alliance' (2000: 64). To take actions on behalf of another state during war does not require a pre-existing agreement, nor does it require that the agreement be written and public. Why then do states sometimes choose to formalize their intentions to engage in military cooperation in the form of written, public treaties?

The answer that has become generally accepted in the literature is that such public formalization allows states to generate effects that would not be possible through private assurances. This is due to the ability of public treaties to mobilize 'audience costs' (Fearon, 1994), which allow states to more credibly reveal their underlying interests. While such interests are always present, the anarchic nature of the international system makes the credible revelation of those interests quite difficult, as states will frequently have strong incentives to misrepresent their beliefs and intentions. Audience costs alter such strategic calculations because audiences, whether domestic or international, can be expected to impose costs on states and their leaders if they renege on publicly constituted international commitments (Fearon, 1994; Gaubatz, 1996; Leeds, 1999, 2003a; Smith, 1998). By providing a fulcrum to which the reputations of states and their leaders can be attached, alliance treaties thus generate costly signals that allow states to make more reliable inferences about the intentions of their alliance partners (Morrow, 2000).

However, the public nature of alliance treaties means that the perceptions and expectations they generate cannot be limited to the members of the alliance, but must also influence witnesses who are external to a given pact. As Snyder argues, an interstate alliance 'focuses and specifies the otherwise diffuse strategic interests that are generated by anarchy itself' (1997: 25), which implies that 'the relation between interests and alliances is some mixture of reflection and creation' (Snyder, 1997: 25). Alliance treaties are tools used by states to generate altered expectations about the likely contours of future conflicts. These altered expectations in turn influence the subsequent selection of alliance partners, creating a system of complex interdependencies in which alliance decisions influence each other across dyadic boundaries, rather than being formulated in isolated dyadic bubbles. In other words, the audience cost mechanism implies that alliance formation decisions should be subject to strong forms of extra-dyadic interdependence, through which alliances themselves influence the formation of other alliances.

## Dyadic interdependence

Subjecting this conjecture to empirical scrutiny, however, poses serious difficulties, as the statistical techniques used in nearly all quantitative studies of alliance formation – logit, probit, survival models, etc. – require the modeler to assume that all observations are independent across dyads, conditional on the explanatory variables (Greene, 2003: 68; see also Wasserman & Faust, 1994: 634, 658–662). If state A's decision to form an alliance with state B were always made without any consideration of the likely patterns of military cooperation outside their dyad, then this assumption of dyadic independence might be tenable. However, if the presence of an alliance between state B and state C at time $t$ alters the expectations of state A and thereby influences A's decision to form an alliance with B at time $t + 1$, then the situation is far more complicated.

This is immediately apparent if one examines the history of interstate diplomatic maneuvers. For instance, while Russia was negotiating the infamous Molotov–Ribbentrop Pact with Germany, it was simultaneously engaged in discussions with the United Kingdom and France about the formation of an anti-Fascist alliance against Germany (see Carr, 1952). In his eventual decision to side with Nazi Germany in August 1939, Stalin was forced to consider not only his ideological distaste for Hitler's regime, but also the propensity for alternative blocs to form and the contours of the forces which would be arrayed against him if he sided with the United Kingdom and France. Indeed, it was precisely this style of calculation which led Russia to impose a Pact of Defence and Mutual Assistance on the

[1] For an important critique, see Schweller (1994). See also Sweeney & Fritz (2004).

[2] However, in an important critique, Gibler & Wolford (2006) find that if the dependent variable is changed to alliance formation rather than alliance presence, the key driver is not regime type but territorial threats, with democratization following after such threats are resolved.

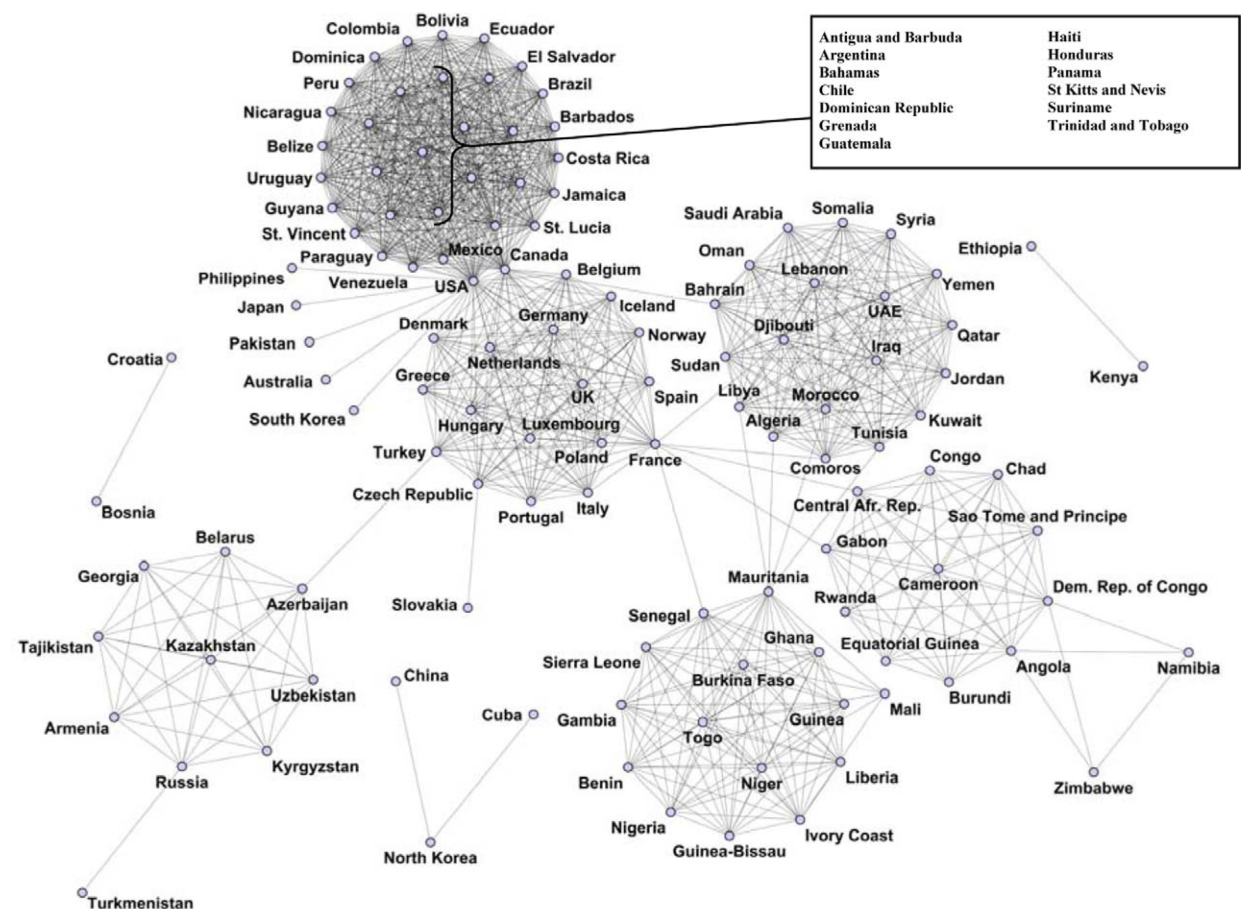


Figure 1. Interstate alliance network, 2000

Based on data from the Alliances Treaties and Obligations Project (ATOP). Links represent the presence of at least one alliance commitment, operationalized as the union of the *offense* and *defense* categories in the ATOP dataset. Countries with no alliance commitments are excluded from the diagram.

Baltic states to prevent their potential incorporation into a broader European bloc which might oppose Soviet interests (Vizulis, 1990).

The importance of dyadic interdependencies in alliance formation decisions is also apparent if one examines a snapshot of the network of alliance ties a given point in time. Figure 1 displays the structure of the interstate alliance network in the year 2000. Each node in the diagram is a state, and each edge represents the presence of an alliance treaty obligating a pair of states to coordinated military activities. The nodes are arrayed using a force-directed layout algorithm (Kamada & Kawai, 1989; Fruchterman & Reingold, 1991), which automatically reveals clusters of nodes with similar patterns of ties. Examination of the diagram reveals, among other patterns, a number of densely interconnected regional blocs with relatively few external ties, the continuing relationship of former colonial powers to their periphery, and the structural isolation of the few remaining communist countries. The highly structured and clearly non-random arrangement of the nodes reveals just how heroic the standard assumption of dyadic independence really is. While the structure revealed in the diagram certainly arose from a sequence of separate alliance formation decisions over the course of many years, it is difficult to imagine that such a structure could arise if the decisions underlying it were purely independent of each other.

Such interdependencies, if simply assumed away, represent a kind of functional form misspecification analogous to that identified by Signorino (1999) for the case of strategic interdependencies. Because alliance treaties induce novel expectations within dyads, between dyads, and across time, the structure of the alliance network is constantly evolving in response to itself. When faced with such a situation, standard regression techniques will not only result in severely biased parameter estimates, but will also fail to capture many of the most critical aspects of the decisionmaking processes underlying the formation of interstate alliance ties.[3]

Several methods have been proposed to deal with interdependence structures in dyadic data. Social network theorists have developed a family of statistical models known as

[3] See Signorino & Yilmaz (2003) for a trenchant discussion of the biases that result from functional form misspecification, which can be characterized as a form of omitted variable bias.

exponential random graph models (ERGM), which allow the researcher to estimate an autologistic regression model in which the log odds of the probability that a relational tie is present are regressed linearly on functions of the other relational ties in the network, thereby avoiding the assumption of dyadic independence (Wasserman & Pattison, 1996; Anderson, Wasserman & Crouch, 1999; Robins et al., 2007). However, ERGM models are restricted observations at a single point in time and are therefore incapable of modeling the dynamic elements of a network structure which evolves substantially over time.

Hoff & Ward (2004) propose a random effects estimator which decomposes the error term into sender, receiver, and dyadic components to allow for correlation within dyads and across dyads with common members. Their model also allows for certain third-order dependencies using an inner product of unobserved latent characteristic vectors. This approach has the advantage of producing unbiased parameter estimates in the face of a wide variety of dyadic interdependence structures, but it achieves this by relegating those interdependencies to atheoretical error terms. If such interdependencies were merely nuisances standing in the way of unbiased estimation of other parameters of interest, then this approach would be quite applicable. However, for our purposes here it is the structure and dynamics of the interdependencies themselves which are the parameters of interest, and this approach gives us no means by which to estimate such quantities.[4]

Signorino (1999) incorporates interdependence into his strategic logit specification in a more theoretically explicit way. He shows that the logit quantal response equilibrium developed by McKelvey & Palfrey (1998) can be used to derive maximum likelihood estimators directly from the structure of an extensive form game tree. By utilizing information about the number of players, their utility functions, and the order of moves, such an estimator incorporates the recursive interdependencies created by anticipatory strategic actions into the functional form of the statistical model. Unfortunately, the derivation of the strategic logit estimator requires that all relevant interactions between agents be characterized by an extensive form game. This in turn requires that the modeler make stringent assumptions about the calculative and anticipatory abilities of agents, while also necessitating that the interactions have a firm endpoint from which an equilibrium (even if it is only reached probabilistically) can be backward-induced. However, there are strong reasons to doubt that an accurate extensive form representation exists for the interactions that produce the network of international alliances. Such a game theoretic setup would have to somehow represent as many as 196 separate agents, each making interdependent anticipatory decisions about dozens of potential alliance partners. The interconnected web of linkages is in a constant state of evolution, with agents responding to an ever-changing landscape of constraints which their own actions are simultaneously constructing. There is thus no endpoint from which agents could backward-induce an equilibrium solution, nor any reason to expect that such an equilibrium exists.

## Alliance formation as network evolution

We are therefore in need of a modeling framework that allows us to incorporate extra-dyadic interdependencies in a theoretically explicit way, while allowing for non-game theoretic assumptions about agents and their interactions. The solution proposed here will be a variant of what Snijders (1996) refers to as *stochastic actor-oriented models*. Within this framework, the international structure of alliance ties is conceptualized as a continuously evolving network which is observed in a series of discrete snapshots. Changes in the network are assumed to be driven by the decisions of agents (states), who seek to maximize a utility function based on their preferred configuration of linkages and the influences generated by the pre-existing pattern of alliance commitments. The agents are boundedly rational, both in the sense that they maximize utility with stochastic error and in the sense that they condition their choices on the current structure of the network rather than attempting to make predictions about the future structure of the network. The goal of the model is to use real-world data on the structure of the interstate alliance network, observed at discreet intervals over several decades, to determine the form of the underlying utility function that is most likely to have produced the observed array of alliance decisions. This is accomplished by (1) specifying a candidate utility function composed of weights on different aspects of network structure, (2) simulating the pattern of tie formation and dissolution that would result if states relied on that utility function, (3) comparing that simulated pattern to the decisions observed in the real-world data, then repeating (1)–(3) with new candidate utility functions until a specification is found that minimizes the discrepancies between the simulated and observed data. The advantage of this framework is that it provides the necessary foundation for both a formal model of the process of alliance formation and a mode of statistical estimation that allows a modeler to incorporate theoretically derived assumptions about structures of dyadic interdependence directly into the functional form of the statistical estimator.[5]

Let $\mathbf{X} = (X_{ij})$ be an $n \times n$ matrix where $X_{ij}$ represents the relation directed from actor $i$ to actor $j$ $(i, j = 1, \ldots, n)$. If the relation is dichotomous, then $X_{ij} = 1$ indicates the presence of a tie and $X_{ij} = 0$ represents the absence of a tie. Here, the relation in question is an alliance agreement, so $X_{ij} = 1$ can be interpreted as $i$ making a written commitment to $j$ to undertake joint

[4] Similarly, the spatial-lag approach advocated by Franzese & Hays (2007) assumes the exogeneity of the connectivity matrix (i.e. the lines along which interdependence is experienced). Although this allows far more accurate estimation of other parameters of interest, it does not allow one to investigate the process by which changes in the connectivity matrix influence each other.

[5] The mathematical foundations for this approach were first developed by Snijders (1996), and were then further elaborated by Snijders & van Duijn (1997) and Snijders (2001, 2005a). I draw heavily on these sources for the following discussion.

military actions. This is equivalent to representing the network as a directed graph, with each agent as one of $n$ nodes, each alliance tie as an arc from $i$ to $j$, and $\mathbf{X}$ as the adjacency matrix for the network. The goal of the model is to explain changes over time in the structure of the adjacency matrix.

Consider a time series $x(t_m), t_m \in \mathrm{T}$ of network observations for a constant set $\{1, \ldots, n\}$ of actors, where the set $\mathrm{T} = \{t_1, \ldots, t_M\}$ of observation times is finite and $\mathrm{M} \geq 2$. We will assume that this time series of network observations is embedded in an unobserved continuous-time process of network evolution $x(t)$, where $t_1 \leq t \leq t_M$. If we define $\chi$ as the set of all $n \times n$ matrices with elements 0 or 1, then the process of network evolution can be fully described by the combination of a family of rate functions,

$$\lambda_i(\theta, x), i = 1, \ldots, n, \quad x \in \chi \tag{1}$$

which represent the rate at which actor $i$ is able to change her outgoing relations, and a family of objective functions,

$$f_i(\theta, x), i = 1, \ldots, n, \quad x \in \chi \tag{2}$$

which describe the stochastic decision rules she uses to evaluate the desirability of different network configurations. The parameter of the statistical model is $\theta = (\rho, \beta)$, where $\rho = (\rho_1, \ldots, \rho_{M-1})$ is a vector of change rates and $\beta$ is a vector of parameterized weights which $i$ applies to particular aspects of a network's configuration. We will denote as $x(i \mapsto j)$ the network that results when the single element $x_{ij}$ is changed to $1 - x_{ij}$ (i.e. the network that results when the tie from $i$ to $j$ is changed from 0 to 1, or from 1 to 0). When the current network is $x$, actor $i$ has the choice between changes to $x(i \mapsto j)$ for all $j \neq i$.

The objective function maximized by $i$ is thus given by:

$$f_i(\beta, x(i \mapsto j)) + U_i(t, x, j) \tag{3}$$

where $U_i(t, x, j)$ is a random variable representing the non-systematic components of $i$'s utility function. This produces a kind of random utility model in which $i$'s choices are a function of the other links in the network, her preferences over different network configurations, and a random error term. If we assume that $U_i(t, x, j)$ is drawn from a type I extreme value distribution, then the probability that actor $i$ chooses to change her relation $x_{ij}$ to actor $j$ is given by the multinomial logit expression:

$$p_{ij}(\theta, x) = \frac{\exp\left(f_i(\beta, x(i \mapsto j))\right)}{\sum_{h=1, h \neq j}^{n} \exp\left(f_i(\beta, x(i \mapsto h))\right)} \quad i, j = 1, \ldots, n, i \neq j \tag{4}$$

This transition rule defines a continuous-time Markov chain, with an intensity matrix which is defined by:

$$q_{ij}(x) = \lim_{dt \to 0} \frac{\mathrm{P}\{X(t + dt) = x(i \mapsto j) | X(t) = x\}}{dt} i, \quad j = 1, \ldots, n, i \neq j \tag{5}$$

which here is given by:

$$q_{ij}(x) = \lambda_i(\theta, x) p_{ij}(\theta, x) \tag{6}$$

where $\lambda_i(\theta, x)$ is a function which represents the rate at which actor $i$ is able to change her outgoing relations and $p_{ij}(\theta, x)$ is given by equation (4). The specification presented here will assume that for each time period $(t_m, t_{m+1})$ the rate function is constant across actors; that is, $\lambda_i(\theta, x) = \rho_m$.

The objective function can be defined as a sum of utilities derived from various characteristics of the network structure $s_{ik}(x)$, weighted by a parameter vector $\beta = (\beta_1, \ldots, \beta_L)$,

$$f_i(\beta, x) = \sum_{k=1}^{L} \beta_k s_{ik}(x). \tag{7}$$

The functions $s_{ik}(x)$ represent those aspects of the network structure that actor $i$ views as relevant when making a decision about the construction or elimination of a tie. The weights $\beta_k$ are statistical parameters indicating the relative importance of each corresponding network characteristic to $i$'s decision, holding all else constant.

Hence, if we have $M$ longitudinal observations of a given network, the estimation problem consists of estimating the values of $M-1$ rate parameters and an $L$-dimensional vector of network parameters. While the resulting model will generally be intractable to maximum likelihood estimation, Snijders (1996, 2001) shows that the parameters in such a model can be estimated using the method of moments, minimizing the difference between the expected values of the chosen network statistics and their observed values, summed over $M-1$ time intervals. The observed values are given by the real-world data, but because the expected values of the network statistics cannot be calculated explicitly, they are estimated from simulations of network evolution, while using a variant of the Robbins–Monro (1951) Markov-chain Monte Carlo algorithm to search the parameter space. For each time period $t_m$, the algorithm takes the current network configuration as given and searches for values of $\beta$ which result in expected values of the network statistics $s_{ik}(x)$ in time period $t_{m+1}$ which are as close as possible to the observed values of $s_{ik}(x)$ in time period $t_{m+1}$.[6] If factor $k$ is actually important in real-world alliance decisions, then the algorithm will find that simulations driven by utility functions that include a stronger $\beta_k$ weight (that is, utility functions that place more emphasis on factor $k$) will do

[6] Note that because the interstate alliance network is an undirected network, in which $x_{ij} = x_{ji}$ and $(i \mapsto j)$ implies $(j \mapsto i)$, the simulations must transform the individual utilities given by equation (3) into joint dyadic decisions. Following the advice of Snijders (2005b), this is accomplished by including a proposal stage and a confirmation stage in each joint decision. At each decision opportunity, actor $i$ evaluates all possible tie changes $(i \mapsto j)$ and chooses its most preferred change as defined by equation (3). If this change represents the formation of a new tie, the change is proposed to $j$ and implemented along with its reciprocal only if $j$ also views the change as a utility increase. If it represents the dissolution of a tie, the dissolution of both the tie and its reciprocal is carried out unilaterally.

a better job of reproducing the alliance patterns observed in the real world.

Having used these network simulations to find the $\beta$ vector which minimizes the divergences between the observed and expected values (that is, the weighted utility function that produces patterns of network evolution most like those observed in the data), the algorithm runs additional simulations while holding $\beta$ constant to estimate the covariance matrix of $\beta$.[7] Assuming the parameter estimates $\hat{\beta}_k$ are approximately normally distributed, hypothesis testing can then proceed through the same t-statistics used in standard regression analysis. In this way, the functional form of the statistical test is derived directly from the assumptions concerning dyadic interdependence that different modelers choose to incorporate into their theories of network evolution. Moreover, whereas previous efforts have focused separately on dependent variables defined by the presence of alliance ties, the formation of alliance ties, or their dissolution, the dependent variable analyzed here effectively combines formation and dissolution into a single object of analysis. Because the simulation algorithm is based on comparisons between $x(t_m)$ and $x(t_{m+1})$, where $t_m \in \{t_1, \ldots, t_{M-1}\}$, the starting position of the network is inherently taken as given, and only events of tie formation or tie dissolution can influence the parameter estimates.[8] The goal of the model is to use such events to reveal the underlying utility function that is most likely to have produced the observed array of alliance decisions.

## Modeling interstate alliances

Given this framework, the heart of the modeling enterprise comes to revolve around the selection of the relevant network statistics which the modeler believes agents use to evaluate the desirability of a given configuration of linkages. This requires theoretically-driven assumptions about the patterns of dyadic interdependence that are likely to result from the alliance decisions of individual states. In other words, it is a question of which functions $s_{ik}(x)$ will be included in the objective function given by equation (7). The most basic of these functions, which we can label the 'Density' effect, controls for the general propensity of states to form alliance ties. Analogous to a constant term in standard regression analyses, it is necessary for accurate estimation of the other effects, but on its own it contains little substantive content. The relevant network parameter is given by:

$$s_{i1}(x) = \sum\nolimits_j x_{ij}.$$

The more substantively relevant functions can be divided into two general categories: dyadic effects and extra-dyadic effects. I will examine each in turn, showing how hypotheses about the nature of alliance formation decisions can be translated into the language of network statistics.

### *Dyadic Effects*

At the level of individual dyads, the literature reviewed in Section 1 indicates that a variety of factors may be associated with the selection of alliance partners, including geographic distance, relative capabilities, regime similarity, cultural similarity, trade, and conflict. To capture these effects, each factor is incorporated into *i*'s objective function by constructing a network function $s_{ik}(x)$ in which an independent variable measured for dyad *ij* is interacted with the presence of a tie from *i* to *j*. The most fundamental of these determinants is the geographic distance between *i* and *j*, both because salient threats tend to emerge from close neighbors and because close neighbors tend to be best positioned to offer assistance. This implies that we should add a term to *i*'s utility function that interacts the presence of a tie between *i* and *j* with the geographic *Distance* between them:[9]

$$s_{i2}(x) = \sum\nolimits_j x_{ij} DISTANCE_{ij}.$$

There are also strong theoretical reasons to believe that the distribution of power between states will exercise influence over their alliance decisions. To capture this factor, each state's level of material power is measured using Singer, Bremer & Stuckey's (1972) Composite Index of National Capability (CINC). The *Capability Ratio* of dyad *ij* is given by the log of the stronger state's CINC score divided by the weaker state's score: $CapRat_{ij} = \log\left(\frac{CINC_S}{CINC_W}\right)$, generating a variable which becomes larger as the dyad's power levels become more unbalanced. This is included in the model by adding a term to *i*'s utility function which interacts the presence of a tie between *i* and *j* with the *Capability Ratio* of dyad *ij*:

$$s_{i3}(x) = \sum\nolimits_j x_{ij} CapRat_{ij}.$$

Much prior evidence indicates that states also have preferences about the regime type of their alliance partners and, in particular, that they seek partners with similar levels of democracy to their own. *Polity* measures each state's level of democracy using

[7] The parameter search stage generally converges after 3,000–4,000 simulation runs. In the models presented here, the covariance estimation stage always consists of an additional 1,000 runs.

[8] Gibler & Wolford (2006) examine the importance of differentiating alliance presence from alliance formation, arguing that researchers should focus on alliance formation as the dependent variable rather than alliance presence. While this makes sense in the context of logistic regression, such a characterization of the dependent variable would not work in the present context, as it would only capture dependencies between alliance formation events which occurred in the same year. Moreover, the estimation technique used here avoids the difficulties they note with using alliance presence as a dependent variable, as any alliance ties that remain constant over time will not influence the parameter estimates.

[9] Distance is measured as capital-to-capital distance (Small & Singer, 1982) for non-contiguous states and 0 for contiguous states. Robustness checks indicate that the use of alternative distance metrics, such as Gleditsch & Ward's (2001) minimum distance measure, generates substantively identical findings.

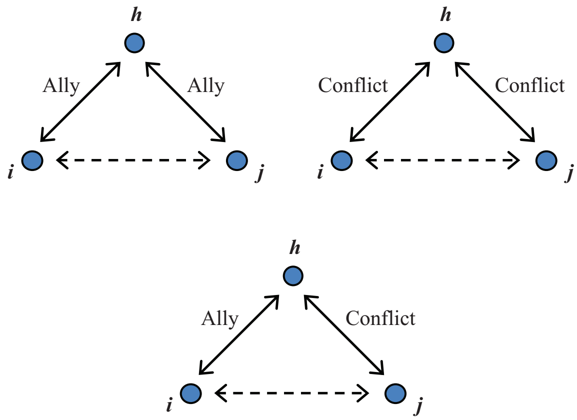


Figure 2. Triadic interactions of amity and enmity

the standard 21-point scale derived from the Polity IV dataset (Marshall & Jaggers, 2002). To capture the tendency towards regime similarity, I predicate $i$'s preferences for alliance partners on the degree of similarity between $i$ and $j$'s *Polity* scores:

$$s_{i4}(x) = \sum_j x_{ij} sim_{ij}^{POL}$$

where $sim_{ij}^{POL}$ is a similarity score defined as $sim_{ij}^{POL} = \frac{\Delta - |POLITY_i - POLITY_j|}{\Delta}$, with $\Delta$ representing the observed range of the covariate, $\max_{ij}|POLITY_i - POLITY_j|$.

To estimate the impact of cultural similarities, I use the COW project's Cultural Composition of Interstate System Members data set (Henderson, 1997) to code a dichotomous variable *Language*, which equals 1 if the most commonly spoken language is the same in both states. To capture the effects of economic interdependence, *Trade* is measured as the log of the total trade volume (imports plus exports) between $i$ and $j$ (Gleditsch, 2002). Both factors are included in $i$'s utility function in an analogous fashion:

$$s_{i5}(x) = \sum_j x_{ij} Language_{ij}$$

$$s_{i6}(x) = \sum_j x_{ij} Trade_{ij}.$$

Finally, the most direct indicator of dyadic security interests is the observed behavior of states in militarized disputes. To capture the effects of recent hostilities, the dichotomous variable *Conflict* equals 1 if $i$ and $j$ have engaged each other in a militarized interstate dispute in the last 10 years.[10] Hence we have:

$$s_{i7}(x) = \sum_j x_{ij} Conflict_{ij}.$$

[10] Constructed using Maoz's (1999) dyadic version of the Militarized Interstate Dispute database (Jones, Bremer & Singer, 1996) and EUGene software (Bennett & Stam, 2000).

*Extra-dyadic effects*

Up to this point, the factors included in the model have all treated each dyad $ij$ as if it operated independently. However, we have good reasons to believe that alliance decisions are not formulated in isolated dyadic bubbles. As explained in Section 1, alliance treaties are public costly signals and can therefore be expected to alter the expectations of states, even beyond the dyad engaged in a particular interaction. Similarly, militarized conflicts between states are also public costly signals that can be expected to influence the calculations of third parties. Interactions between these indicators of amity and enmity should therefore be expected to exercise influence on state behavior in an extra-dyadic manner. The advantage of the stochastic actor-oriented approach is that any form of such extra-dyadic interdependence can be characterized as a network statistic and factored into the model as an element in agent $i$'s utility function, allowing us to move beyond the analysis of independent dyads while remaining theoretically grounded. To simplify the presentation, I focus exclusively on the set of triadic interactions between amity and enmity, as these constitute a minimum demonstration of the insufficiency of analyzing independent dyads.

As shown in Figure 2, there are three possible forms that such triadic interactions might take, in which the decision to form an alliance between $i$ and $j$ is also a function of their relations with some third party $h$.[11] The *Ally–Ally* relationship captures the conventional wisdom that ties should be transitive, that is, that the friend of my friend is more likely to also be my friend:

$$s_{i8}(x) = \sum_j x_{ij} \max_h (x_{ih} x_{jh}).$$

The *Conflict–Conflict* relationship represents the logic of joint threats, central in much of the previous literature, in which the enemy of my enemy is more likely to be my friend:

$$s_{i9}(x) = \sum_{j \neq h} x_{ij} (Conflict_{ih} Conflict_{hj}).$$

Finally, the *Ally–Conflict* relationship asks whether an alliance is more or less likely with the enemy of my friend:

$$s_{i10}(x) = \sum_{j \neq h} x_{ij} (x_{ih} Conflict_{hj}).$$

While these effects certainly cannot represent the full range of possible forms of extra-dyadic interdependence, they represent a natural starting point for analyzing whether the assumption of dyadic independence is a sufficient basis from which to study alliance formation decisions.

[11] These relationships are similar in spirit to those analyzed by Maoz et al. (2007). However, the present study differs by using simulations of interdependent decisions to estimate the parameters of interest, rather than standard logistic regressions that are unbiased only if the independent and dependent variables are sampled independently.

## Models and results

To assess the relevance of these factors to the alliance formation and dissolution decisions of actual states, I estimate the stochastic actor-oriented model of alliance network evolution described above for the period 1950–2000. Data on interstate military alliance commitments were taken from the Alliance Treaty Obligations and Provisions (ATOP) Project (Leeds et al., 2002). Recall that an alliance was defined above as a formal, written agreement between two or more states in which they agree to some form of coordinated military action in the event of a future conflict. I therefore restrict the following analyses to written agreements which include explicit promises of offensive or defensive military support in the event of a future conflict. Alliance ties of the form $x_{ij} = x_{ji} = 1$ are thus coded as the union of the *offense* and *defense* categories in the ATOP data set.[12] I exclude agreements which are restricted to mere neutrality, non-aggression, or consultation obligations, since they do not commit states to any joint military actions and therefore are likely to be subject to a different data generating process.

Observations of alliance network structure were made at five-year intervals, resulting in a dataset of 11 observation moments. While dividing the data into five-year intervals is somewhat arbitrary, the decision was necessitated by the computational burdens of the technique, which increase rapidly as a function of the number of actors, the number of ties, and the number of observation moments included in the model. To ensure that the selection of these specific observation moments has not influenced the results, I re-ran the same model with the observation intervals shifted backwards by two years (i.e. 1948–1998). As long as the results are substantively congruent between these two models, we can be reasonably confident that we are recovering real factors in the alliance decisions of states, rather than mere artifacts of an arbitrary specification choice.

In order to compare the inferences drawn from the stochastic actor-oriented models of network evolution to the inferences that would be drawn from regression techniques that assume the independence of observations, I also estimate two forms of alternative models for the same time period. First, I estimate a stochastic actor-oriented model that excludes the three extra-dyadic effects but is otherwise identical to the models described above. Second, I estimate two logistic regressions,[13] with one coding the dependent variable as the presence of an alliance tie between $i$ and $j$, and the other coding the dependent variable as the formation (i.e. onset) of an alliance tie between $i$ and $j$.[14]

Results for these five models are presented sequentially in Table I.[15] The two models of alliance network evolution (Models 1 and 2) generate substantively equivalent results, indicating that the selection of particular observation moments has not unduly influenced the results. In these models, the covariates measured at the dyad level generally behave as expected. The statistically significant ($p < 0.05$) dyadic coefficients indicate that states prefer to form alliance ties with partners who are geographically close, are governed by regimes with similar levels of democracy, and whose populations speak the same language. The significant negative coefficient for *Capability Ratio* indicates that states prefer to form alliance ties with partners who possess similar levels of military capabilities, in contrast to the expectations of Morrow (1991). The significant negative coefficient for *Trade Volume* may seem surprising at first glance, but it is congruent with previous research indicating that alliance ties foster subsequent increases in trade levels, rather than the reverse (Long, 2003; Long & Leeds, 2006). This finding extends that logic, indicating that states may prefer to form alliances with partners with depressed levels of trade, where the potential gains of increased cooperation are highest.

The negative and statistically significant coefficient for *Conflict* indicates that at the level of individual dyads, states are disinclined to form alliance ties in the presence of a recent history of militarized conflict. However, the discussion above indicates that we must be cautious when estimating such effects, because both military alliances and militarized disputes are public costly signals that may alter the expectations of third parties who witness the events. The effects of interactions between public amity and public enmity are thus unlikely to be limited to individual dyads. The advantage of stochastic actor-oriented models of network evolution lies in their ability to accurately estimate the extra-dyadic effects of such interactions, while avoiding the assumptions of observational independence that underlie other techniques.

The final three parameters are designed to capture precisely this style of effect, in the form of triadic interactions between amity and enmity. The positive and significant coefficient for

[12] It is important to note that this specification treats multilateral alliance treaties as equivalent to bilateral treaties, with multilateral treaties represented as the joint presence of several bilateral ties. This is a direct consequence of the formal model underlying the estimation algorithm, which assumes that state preferences are dependent on the pattern of pre-existing obligations, but not dependent on how those obligations came into being. Relaxing that assumption by allowing for different impacts depending on treaty type would be an interesting exercise, but one which necessarily lies beyond the scope of this article.

[13] To estimate these models, the network statistics for the extra-dyadic effects described in Section 4 are replaced by dichotomous variables that equal 1 if some third party $h$ exists that satisfies the ally–ally, conflict–conflict, or ally–conflict relationship for $i$ and $j$. It is important to note that these covariates violate the assumption of independent sampling upon which the unbiasedness of the logit estimator is based, and thus in an important sense are misspecified. However, they are nevertheless important for demonstrating the incorrect inferences that will be drawn when standard regression techniques are used to estimate extra-dyadic effects.

[14] See footnote 8.

[15] All network evolution models were estimated using the SIENA software package (version 3.17w) authored by Snijders et al. (2007). The software is free and can be downloaded as part of the StOCNET package at: http://stat.gamma.rug.nl/stocnet/.

Table I. Interstate military alliances, 1950–2000

| | | *Model 1 Network Evol. 1950–2000* | *Model 2 Network Evol. 1948–1998* | *Model 3 Network Evol. 1950–2000* | *Model 4 Logit – Presence 1950–2000* | *Model 5 Logit – Formation 1950–2000* |
|---|---|---|---|---|---|---|
| $s_{i1}(x)$ | Density / Constant | **−2.7181**** | **−2.4801**** | **−0.9708**** | **−5.6314**** | **−7.8179**** |
| | | (0.1172) | (0.0751) | (0.0667) | (0.0587) | (0.2754) |
| Dyadic effects | | | | | | |
| $s_{i2}(x)$ | Distance | **−0.0567**** | **−0.0407**** | **−0.0522**** | **−0.000734**** | **−0.000469**** |
| | | (0.0010) | (0.0005) | (0.0009) | (0.000007) | (0.000028) |
| $s_{i3}(x)$ | Capability Ratio | **−0.0105**** | **−0.0038**** | **0.0020**** | **0.0340**** | **−0.0918**** |
| | | (0.0010) | (0.0008) | (0.0009) | (0.0088) | (0.0372) |
| $s_{i4}(x)$ | Polity Similarity | **0.5919**** | **0.5732**** | **0.4765**** | **1.4515**** | **0.6848**** |
| | | (0.1407) | (0.0990) | (0.1164) | (0.0409) | (0.1645) |
| $s_{i5}(x)$ | Shared Language | **0.6158**** | **0.5658**** | **1.1215**** | **2.3658**** | **-0.9756**** |
| | | (0.1538) | (0.1006) | (0.1266) | (0.0392) | (0.1277) |
| $s_{i6}(x)$ | Trade Volume | **−0.0121**** | **−0.0053**** | **−0.0017**** | **0.0885**** | **−0.2491**** |
| | | (0.0016) | (0.0013) | (0.0015) | (0.0056) | (0.0242) |
| $s_{i7}(x)$ | Conflict | **−1.1403**** | **−0.8682**** | **−0.8076**** | **−0.2326**** | -0.2013 |
| | | (0.1926) | (0.1361) | (0.1868) | (0.0694) | (0.2120) |
| Extra-dyadic effects | | | | | | |
| $s_{i8}(x)$ | Ally–Ally | **3.1966**** | **2.4296**** | | **6.1858**** | **5.0581**** |
| | | (0.1468) | (0.1033) | | (0.0477) | (0.2333) |
| $s_{i9}(x)$ | Conflict–Conflict | 0.0186 | 0.0237 | | **0.5095**** | -0.1050 |
| | | (0.0421) | (0.0319) | | (0.0344) | (0.1253) |
| $s_{i10}(x)$ | Ally–Conflict | **0.0820**** | **0.1214**** | | **-0.0503*** | **-0.4830**** |
| | | (0.0186) | (0.0135) | | (0.0276) | (0.0985) |

Standard errors in parentheses. $^{**}p < 0.05$, $^{*}p < 0.1$.

the *Ally–Ally* relationship indicates that states prefer to form alliance ties with partners who already possess a similar pattern of obligations to their own. In other words, it indicates that the friend of my friend is likely to also become my friend. However, in contrast to the balancing logic predominant in much of the previous scholarship on international alliances, the results indicate that the *Conflict–Conflict* relationship has no statistically significant effect on the likelihood of alliance formation. That is, the enemy of my enemy is not necessarily my friend. This implies that the pressures generated by shared extra-dyadic patterns of alliance ties are more forceful than the pressures generated by shared extra-dyadic patterns of militarized conflict. Also in contrast to the prevailing wisdom is the positive and significant coefficient for the *Ally–Conflict* relationship, which indicates that states are more likely to form alliance ties with the enemies of their existing alliance partners. Thus, while conflict inhibits alliance formation the level of individual dyads, given the proper configuration at the extra-dyadic level, conflict can actually promote alliance formation.

Taken together, these findings indicate that triadic forms of extra-dyadic interdependence are powerful components of the state utility functions underlying alliance formation decisions, strongly implying that models that fail to account for such interdependence will be subject to functional form misspecification and biased parameter estimates. As a robustness check, I also use a variant of the Rao score (RS) goodness-of-fit test suggested by Schweinberger (2005), which uses deviations from the observed data to directly test the null hypothesis of zero extra-dyadic interdependence, $H_0 : \beta_8 = \beta_9 = \beta_{10} = 0$.[16] This parameter restriction is decisively rejected ($p < 0.001$), indicating that the observed data is very unlikely to have been generated by a process involving only independent dyads operating in isolation, and that models making such an assumption are likely to be misspecified.

The deleterious effects of such misspecification can be observed by comparing the results of Models 1 and 2 to alternative specifications that fail to fully account for the interdependence of dyadic observations. In Model 3, I estimate a stochastic actor-oriented model that is identical to Model 1 except for the exclusion of the three extra-dyadic parameters, which amounts to assuming that those parameters are each equal to zero. We can see that as a result of this exclusion, several of our estimates are changed dramatically, including rendering the *Trade Volume* coefficient insignificant and actually flipping the sign on the coefficient for *Capability Ratio*. In Model 4, I estimate a logistic regression with alliance *presence* as the dependent variable, and in Model 5, I estimate a logistic regression with alliance *formation* as the dependent variable, both using the same independent variables as Model 1. These models represent the best attempt that could be made to account for extra-dyadic interdependence using standard regression techniques, by including dummy variables which measure the presence of *Ally–Ally*, *Conflict–Conflict*, or *Ally–Conflict* configurations.[17] The results from both models are in substantial disagreement with the results derived from stochastic actor-oriented models of network evolution. The alliance presence model generates positive and significant coefficients for both *Capability Ratio* and *Trade Volume*, while the alliance formation model generates a negative and significant coefficient for *Shared Language*. Moreover, both the alliance presence model and the alliance formation model yield negative and significant estimates for the *Ally–Conflict* relationship.

These results make clear that functional form misspecification can be neither assumed away nor safely ignored. All parametric statistical techniques carry with them the baggage of functional form assumptions, which exercise powerful influence over our inferences even when there is complete agreement about the underlying data. Unfortunately, the data do not speak for themselves. Different functional form assumptions generate different answers. As a result, the implications derived from Models 3–5, at both the dyadic and extra-dyadic levels, stand in stark contrast to those derived from stochastic actor-oriented models of network evolution that allow for triadic patterns of interdependence between dyads. The strong implication is that when dealing with state interactions constituted by public costly signals, which can be expected to alter expectations at both the dyadic level and the extra-dyadic level, models founded on the assumption of dyadic independence are a poor bet for making reliable inferences.

## Conclusion

The results of both theoretical analysis and empirical investigation thus converge on the realization that the public nature of alliance treaties extends their effects far beyond those states that are party to the agreement itself. As a result, the network of alliance ties is constantly evolving in response to itself, as states find their decisions constrained by a complex structure that their own actions are simultaneously constructing. Furthermore, the extra-dyadic interdependencies that are produced in this way cannot be effectively modeled through statistical frameworks which assume the independence of dyadic observations.

The solution is to model alliance decisions not as independent events, but as elements of a network whose evolution is governed by the actions of individual states whose incentives are driven, at least in part, by the prior actions of other states. By deriving the functional form of the statistical estimator directly from theoretically-driven assumptions about the utility functions of states engaged in alliance formation decisions, this stochastic actor-oriented approach allows for the incorporation of a wide variety of interdependencies – both within dyads, between dyads, and across time – into our theories and our empirical tests. Indeed, the flexibility of this framework is one of its primary advantages. Nearly any form of dyadic interdependence could

[16] This is analogous to an F-test in standard regression analysis.

[17] See footnote 13.

be characterized by a network statistic in an agent's utility function and added as a parameter to the resulting statistical model.

With this in mind, we should remember that the models presented here have undoubtedly missed important elements of the data generating process. Indeed, it would be quite surprising if triadic interactions of amity and enmity were the only form of extra-dyadic interdependence to influence the formation of alliance ties. In future work, these models could be extended to consider alternative specifications of the relevant forms of dyadic interdependence, as well as additional sources of variation in state utility functions, such as differences between types of alliance treaties (offensive vs. defensive, bilateral vs. multilateral, etc.) and differences across time periods. To risk restating the obvious, the goal of the models presented here was not to construct a final, all-encompassing vision of the alliance formation process. Rather, the goal was to further the methodological agenda of providing international relations and political science with a broader menu of options that allow us to more closely approximate the ideal of statistical estimators whose functional form matches the functional form of corresponding data generating processes. In doing so, I hope to have also demonstrated that strict game theoretic assumptions about agent interactions are far from the only means through which such syntheses can be achieved.

## Replication data

A replication archive containing data and specification files is available at: http://www.prio.no/jpr/datasets and http://www.camberwarren.net.

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