Supporting Information

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This appendix is organized as follows. Section 1 discusses in greater detail the coding of bilateral cooperation agreements and the various covariates. Section 2 provides a formal exposition of the stochastic actor-oriented model of network evolution. Section 3 presents results for numerous robustness checks—employing both alternative codings of bilateral agreements and alternative model specifications—and also extends the analysis to additional issue areas. Section 4 explores the topological properties of the network, particularly with regard to scale-freeness and clustering. Sections 5 and 6 list Correlates of War country codes and Rohn's treaty codes, respectively.

1 Data Sources and Operationalization

The source for data on bilateral cooperation agreements is the *World Treaty Index* (WTI) (Rohn 1984). The WTI is the most comprehensive database for international treaties. While legal scholars often draw on the United Nations Treaty Series (UNTS),[1] around half of international agreements are never registered with the UNTS or are registered only after substantial delay. Bilateral agreements, in particular, are least likely to be reported.[2] Such missing data are problematic for inferential network analysis; due to the interdependencies present in network data, exclusion of just a few observations can substantially affect statistical inferences.[3] The WTI provides coverage of virtually all known agreements—including UNTS agreements and tens of thousands of unregistered agreements—and thus largely avoids missingness problems.

Even so, the unique characteristics of bilateral agreements mean that, within the WTI, data coverage for recent years is often quite sparse. This sparseness of coverage is due primarily to two factors. First, as mentioned above, even when countries register agreements with the UNTS, they often wait years or decades to do so.[4] Consequently, data sets that incorporate the UNTS as a source—as well as, of course, the UNTS itself—generally provide better coverage further back in time, while coverage deteriorates for more recent years. Second, for agreements unreported to the UNTS, scholars must rely on country publications. Individual countries vary substantially in the frequency and reliability with which they publish treaty lists. Some publish annual lists of treaties in force, while others publish such lists only every few decades or not at all. For these reasons, completeness of coverage for the current version of the WTI is extremely high up until the late 1970s

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[1] See United Nations Treaty Collection (2012).

[2] See Rohn (1984). The UN Charter stipulates that "every treaty and every international agreement entered into by any Member of the United Nations after the present charter comes into force shall as soon as possible be registered with the Secretariat and published by it." However, this stipulation is routinely ignored.

[3] On consequences of missing network data, see Gile and Handcock (2006); Kossinets (2006); Robins, Pattison, and Woolcock (2004).

[4] Further, the period between a treaty's registration and its eventual publication in the UNTS may last an additional five to ten years (Rohn 1984)—though EIF dates of recently registered treaties suggest this gap is closing.

but deteriorates after 1980. Although the database is continually updated (see, e.g., Bommarito, Katz, and Poast 2012; Pearson 2001), post-1980 updates rely heavily on the UNTS and therefore inherit its coverage problems. I opt for the more conservative approach and restrict the analysis to the post-World War II period ending in 1980, for which data coverage is maximally complete.[5] (The first year of the temporal sample varies between 1940 and 1949, depending on the coding of the dependent variable; e.g., the models in the main paper are estimated on data for the 1947–1980 period.) Analysis of more recent data will become possible as countries publish updated treaty lists and/or improve reporting of treaties to the UNTS. In any case, this temporal sample provides an excellent testing ground for the hypotheses, as the decades immediately following World War II are precisely the period during which bilateral agreements initially proliferated. Furthermore, Section 3 shows that, even with less complete data coverage, the main empirical findings apply to the entire 1950–2000 period.

In choosing the treaty categories for the analysis—commodities, military, sciences, and fisheries—I relied upon five criteria. First, the selected issue areas must involve major fields of international relations and enjoy some salience in IR scholarship. The selected issues represent the larger categories of economic relations, security relations, cultural relations, and environmental relations, respectively. Second, the issues must entail potentially confounding coordination and collaboration dilemmas, i.e., there must exist a nontrivial risk of cooperation failure. This excludes various administrative and aid agreements that are overtly asymmetric or merely procedural—and thus not representative of a typical cooperation problem. Third, for the sake of drawing comparisons across categories, the issue areas must be comparable in terms of the number of agreements involved. The selected categories range in size from 335 to 486 treaties, which is a relatively small variance. This criterion excludes agreement categories that number well into the thousands (e.g., general trade and cultural exchange agreements), as well as numerous smaller categories that number only in the tens. Fourth, agreements should not be limited only to specific segments of the temporal period. This criterion excludes, among others, economic agreements of more recent vintage, such as BITs and PTAs. Finally, the issue areas must attract some degree of attention from leaders, policymakers, or domestic audiences. In short, they should be politically relevant, such that we might reasonably expect a leader from one country to be influenced by the agreements entered into force by others. The selected issue areas satisfy each of these criteria. Even so, as shown in Section 3 of this appendix, network influences are apparent in numerous additional issue areas.

Coding of the dependent network variable presents novel challenges. Most commonly, dichotomous network ties are coded as either present or absent, such that $y_{ij} = 1$ for all periods in which a network tie exists between i and j, and equals zero otherwise. In the case of bilateral agreements, such a coding would require precise information on the duration of each agreement. However, because relatively few countries publicly report the expiration of their agreements, and because bilateral agreements do not attract the same outside scrutiny as do multilateral agreements, the details of their intended duration and current legal status are often known only to member states and relevant third parties. Indeed, many countries do not publish treaty instruments themselves, but publish only such basic information as title, entry-into-force date, and membership status. Nonetheless, a random sample of 100 available treaty instruments revealed that the median agreed treaty length is 10 years. Approximately 40% of agreements are indefinite, while only about 8% last less than three years. In general, then, the $\tau = 3$ coding used in the main paper creates a

[5] The only other large-scale study of bilateral agreements of which I am aware, by Garriga (2009), limits analysis to the 1950–1979 period for the same reason.

stronger test of the hypotheses, as it ignores agreements that continue to exercise influence beyond the three-year mark. At the same time, the historical evidence discussed in the main paper suggests that network influences are most apparent within the first few years of a treaty's entry into force, which means that the $\tau = 3$ criterion captures network effects when they are most likely to be influential. Sensitivity analyses conducted in Section 3 of this appendix show that using a different criterion—such as $\tau = 1$, $\tau = 5$, $\tau = 10$, etc.—does not substantively change the main results.

The data coding follows a few basic rules. First, I exclude agreements that involve nonstate actors (e.g., the IAEA) or political units that lack legal sovereignty (e.g., Hong Kong). Second, I code the creation of a network tie based on the agreement's entry-into-force (EIF) date. Date of signature—i.e., "formalization"—is an alternative criterion;[6] however, given that most of the agreements I analyze don't require ratification, EIF and signature dates are often identical or very close together. In any case, using date of signature in place of EIF makes little difference in the results. Third, if a country experienced a regime change in the interim since an agreement's EIF date, I code that agreement as no longer in effect. For this purpose, "regime change" is defined as a change in Polity score of at least ± 5 points on the 21-point Polity scale. Dropping this criterion or changing the definition of regime change does not substantively change the results. Fourth, if a dyad signs multiple agreements in a single issue area, I code ties of three years in duration for each agreement. E.g., if i and j, over a nine-year period, sign agreements at t_1, t_4, and t_7, they will be coded as having a network tie for the entire period. In practice, given the specificity of the issue areas under study, such redundant agreements are typically confined to isolated pairs of highly cooperative states (e.g., France and Germany, United States and Canada, etc.); in such cases, the coding of a continuous network tie for the entire period accurately reflects the high level of cooperation between these countries.

As noted in Section 2, these coding restrictions necessitate corresponding restrictions in the network model. The empirical results are nonetheless robust to alternative codings, as I show in Section 3. An especially important alternative is to code network ties as enduring indefinitely from the observation moment in which they are created. That is, once i and j sign an agreement, their network tie remains in place for the duration of the temporal sample.[7] This coding builds on two insights. First, although bilateral agreements are, in the aggregate, virtually universal, within specific issue areas they are often quite limited; e.g., the number of bilateral commodities or fisheries agreements currently in place is far smaller than the number of dyads that could potentially create such agreements. Thus, the move from a state of no agreement to a state of bilateral cooperation is far more significant than are minor gradations in levels of cooperation. Second, the random sample of treaty instruments shows that a large number of agreements, about 40%, are in fact indefinite, or are at least intended to be so. And finite agreements are often renewed or reinstated, further extending their duration. This coding thus allows us to determine whether the initial onset of bilateral cooperation between states is conditional on network influences, regardless of the number of agreements those states subsequently create. This approach is similar in spirit (though not in its formal properties) to survival or hazard models, where instead of modeling the time to an event, we model the changes in the network that presage that event—specifically, the structure of the network for which i and j are most likely to accede to their first bilateral cooperation agreement.[8]

[6] Garriga (2009) uses date of formalization rather than EIF dates.

[7] This restriction assumes monotonicity in network ties. See Ripley, Snijders, and Preciado (2012).

[8] To more closely approximate a survival scenario, the dependent network variable may also be coded "in reverse," where a given ij dyad is assumed to be present only while i and j lack a network tie, and the dyad subsequently

I present results for this alternative coding in Section 3.

Exogenous Covariates

To account for the numerous possible external influences on bilateral cooperation, I include controls across security, economic, political, and geographic issue areas (as well as additional controls in the robustness checks in Section 3 of this appendix).[9] The baseline model includes five dyadic covariates. DISTANCE, measured as the natural log of the distance between i and j's capital cities (Gleditsch and Ward 2001), controls for the fact that, ceteris paribus, distant states cooperate less. Further, because shared borders play a fundamental role in both conflict and cooperation, I include CONTIGUITY, a dummy variable that equals one if i and j share a border or are separated by less than 400 miles of water, zero otherwise (Correlates of War Project 2006). IGOS indicates the number of shared IGO memberships between i and j (Pevehouse, Nordstrom, and Warnke 2004). States who share many IGO memberships may find it easier to cooperate (Russett, Oneal, and Davis 1998); or, conversely, IGOs may substitute for bilateral agreements and thus decrease the need for bilateral cooperation (Small and Singer 1973). TRADE is log-transformed trade dependence between i and j in year 2000 dollars (Barbieri and Keshk 2012). In accordance with the "weak link" specification, this measure is operationalized as the lower of i or j's trade dependence on the other.[10] Because international institutions are often designed to "manage economic interdependence among their members" (Russett and Oneal 2001: 213), higher levels of trade should promote cooperation. Finally, ALLIANCE is a dummy variable that equals one if i and j share a defense treaty, neutrality pact, or entente, zero otherwise (Leeds et al. 2002). Alliances indicate both ex ante trust and similarity in foreign policy preferences (cf. Bueno de Mesquita 1975; Kydd 2001), either of which may improve conditions for cooperation.

I also include three monadic covariates. DEMOCRACY measures regime type using the 21-point Polity IV index, rescaled such that 20 indicates a fully democratic regime and 0 indicates a fully autocratic regime (Gleditsch 2007; Jaggers and Gurr 1995). CAPABILITIES measures military strength using Correlates of War CINC scores, which are based on state-level energy consumption, iron and steel production, military expenditures, military personnel, total population, and urban population (Singer 1987; Singer, Bremer, and Stuckey 1972). DEVELOPMENT measures economic development using per-capita gross domestic product in year 2000 dollars, log transformed (Gleditsch 2002). These covariates control for the unilateral preference of states for partners who are highly democratic, militarily powerful, and/or economically developed. For each monadic covariate I also include a dyadic ij interaction, which controls for the tendency of states that are mutually democratic, mutually powerful, and/or mutually wealthy to cooperate more.

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drops out of the network or "dies" once a tie is initially created. The results from this estimation are comparable to those from a model that assumes upward monotonicity.

[9] I do not control for variations in ratification procedures across states because the vast majority of bilateral agreements do not require ratification.

[10] An alternative approach is to include total dyadic trade rather than trade dependence. This specification also consistently yielded significant and substantively large estimates.

2 Model of Network Evolution

This section summarizes the formal properties of the stochastic actor-oriented model (SAOM) of network evolution.[11] I first exposit the standard specification of the SAOM, and I then discuss the variant of the model employed in the main analyses, which accommodates nondirected network ties and emphasizes tie creation over maintenance or dissolution.

Assume a network, represented as the $n \times n$ matrix $\mathbf{Y}$, where the y_{ij} entries define undirected ij ties ($i, j = 1, \ldots, n$). $\mathbf{Y}$ is observed at m points in time, resulting in a time series $\mathbf{Y}(t_m)$ of network observations, where $m \geq 2$ and $t_1 < t_2 < \ldots < t_m$. χ defines the set of all $\mathbf{Y}$ over m, and $\mathbf{y} = \mathbf{Y}(t)$. Each observation is assumed to represent a discrete moment in an unobserved continuous process of network evolution (Snijders 1996). Between observation moments, the network is assumed to change incrementally, one tie at a time. Each incremental change constitutes a "ministep." In standard specification of the SAOM, actors may either extend new ties, retract existing ties, or maintain the status quo. The evolution of this network is thus described by (1) the *opportunity* for an actor to change its outgoing ties and (2) the *actual change* or ministep made by that actor (Snijders 2005: 224).

A given i's *opportunity* for change is stochastically determined by a rate function, $\lambda_i(\mathbf{y})$, assumed to follow an exponential model (Snijders 2005: 224). The *actual change* made by i is defined by an objective function, $f_i(\mathbf{y})$. The objective function is the heart of the model. Given the opportunity, i changes its network ties so as to maximize the $f_i(\mathbf{y})$ function (Snijders 2001: 367). Thus, $f_i(\mathbf{y})$ represents i's preference distribution over χ, or, put differently, $f_i(\mathbf{y})$ represents the utility that i derives from various network configurations. (As detailed below, in symmetric networks, the objective function also applies to any j partner with whom i wishes to form an agreement.)

Let $\mathbf{y}(i \to j)$ represent the network that results from $\mathbf{y}$ when i changes its tie to j, either by creating a new tie or dissolving an existing one. Then $f_i(\mathbf{y})$ is the value that i attaches to particular network configuration $\mathbf{y}$, and $f_i(\mathbf{y}(i \to j))$ is the value that i attaches to the alternative network configuration $\mathbf{y}(i \to j)$. Let U_{ij} be a random variable that contains the residual part of the tendency of i toward j (i.e., a random error term). In choosing to change a tie, i follows a decision rule such that it will change its tie to whichever j ($j \neq i$) maximizes the function $f_i(\mathbf{y}(i \to j) + U_{ij})$. This is considered a "myopic stochastic optimization rule" (Snijders 2005: 225). In short, actors choose network ties that generate the most utility.

If we assume that U_{ij} is drawn from a type I extreme value distribution,[12] we can then specify the probability that i makes a change to a particular y_{ij} tie, given that i does in fact make a change of some kind in its network ties, as

$$p_{ij}(\mathbf{y}) = \frac{\exp(f_i(\mathbf{y}(i \to j)))}{\sum_{\substack{k=1 \\ k \neq i,j}}^{n} \exp(f_i(\mathbf{y}(i \to k)))}, (j \neq i), \tag{1}$$

which is the same probability function used in multinomial logistic regression (Maddala 1983). In

[11] This summary draws heavily on Snijders (1996, 2001) and especially Snijders (2005).

[12] This is a common assumption in random utility models. See Snijders (2001: 368).

short, i evaluates the network and considers the utility of changing its tie to j, relative to the utility of changing its tie to k other actors (i.e., the remaining actors in the network), and chooses to change its tie to whichever j maximizes that value.

Together, the rate and objective functions define a continuous-time Markov chain over the space χ on the set of n actors in the network, with an intensity matrix defined as:[13]

$$\begin{aligned} q_{ij}(\mathbf{y}) &= \lim_{dt \downarrow 0} \frac{1}{dt} \mathrm{P}\{\mathbf{Y}(t+dt) = \mathbf{y}(i \to j) | \mathbf{Y}(t) = \mathbf{y}\} \\ &= \lambda_i(\mathbf{y}) p_{ij}(\mathbf{y}). \end{aligned} \tag{2}$$

The continuous-time Markov Chain reflects the above-stated assumption that network evolution occurs as a series of incremental changes or ministeps by actors in their network ties, of which we only observe the accumulation at discrete moments in time (Snijders 2001: 366). The $q_{ij}(\mathbf{y})$ intensity matrix is thus the rate at which an actor takes ministeps—i.e., the probability that i will take a ministep in the short interval $(t, t+dt)$—multiplied by the probability that, if i does take a ministep, it makes a change to the y_{ij} tie (Snijders 2005: 227).

The rate and objective functions must be filled in with a specific model. They depend on unknown parameters ρ and β, estimated from available data (Snijders 2001: 372). $\rho = (\rho_1, \ldots, \rho_{m-1})$ is a vector of length $m-1$ that describes the rate of change from one observation moment to the next, assuming that this rate is the same for all actors.[14] The estimated ρ parameters, which are always positive and significant, indicate the rate at which actors are given opportunities to change their ties between observation moments.[15]

The other parameter, $\beta = (\beta_1, \ldots, \beta_L)$, is a vector of weights (i.e., coefficients) that assigns value to different aspects of the network. This parameterization allows the objective function to be represented as a weighted sum,

$$f_i(\beta, \mathbf{y}) = \sum_{h=1}^{L} \beta_h s_{ih}(\mathbf{y}), \tag{3}$$

where the functions $s_{ih}(\mathbf{y})$ are L meaningful aspects of the network to which i assigns value according to $\beta = (\beta_1, \ldots, \beta_L)$. Importantly, these functions, in addition to including network effects like preferential attachment and triadic closure, can also include monadic and dyadic covariates (Snijders 2005: 228). Thus, when an actor changes its network ties, it is influenced by both structural network effects and exogenous monadic and dyadic effects. Estimating the probability of $i \to j$ collaboration is a matter of estimating the $m-1$ parameters of the rate function and the L parameters of the objective function. Importantly, the first observation moment (t_1) is not itself

13 See Snijders (2005: 225).

14 The assumption that the rate of change is equal for all actors simplifies the model but is not essential. It may be possible, for example, that the rate at which actors change their outgoing ties varies according to monadic properties, such as wealth, democracy, or capabilities. These possibilities, however, are beyond the scope of this paper and must be reserved for future research.

15 Since the rate parameters are substantively uninteresting, they are not reported in the tables.

modeled, but is instead taken as the "starting point" for network evolution (Snijders, van de Bunt, and Steglich 2010: 46).

To capture the data generating process underlying bilateral agreements, this standard model must be adjusted in two ways. First, because bilateral agreements require mutual consent, a given i cannot simply change ties at will; the intended target, j, must also concede to the agreement. We thus assume that i proposes a tie to whichever j maximizes the $f_i(\beta, \mathbf{y})$ objective function, and the tie is created only if j agrees. Specifically, if $\mathbf{y}^+(i,j)$ represents the network *with* the proposed ij tie, and $\mathbf{y}^-(i,j)$ represents the network *without* the ij tie, then the probability of j confirming i's proposal is given by[16]

$$p_{ij}^{(j)}(\mathbf{y}) = \frac{\exp(f_j(\beta, \mathbf{y}^+(i,j)))}{\exp(f_j(\beta, \mathbf{y}^-(i,j))) + \exp(f_j(\beta, \mathbf{y}^+(i,j)))}. \tag{4}$$

In other words, the more utility j derives from a particular ij tie, as determined by applying the objective function to j, the greater the probability of the tie being created. This particular method of modeling symmetric ties is known as "unilateral initiative and reciprocal confirmation" (Ripley, Snijders, and Preciado 2012). While it is not the only means of imposing symmetry on the network,[17] it well represents real-world processes of bilateral treaty formation, where states condition their cooperative endeavors on mutual gains. Manger, Pickup, and Snijders (2012) employ this assumption to model preferential trade agreements, and Warren (2010) uses it to model military alliances.

Second, in the standard specification, actors maximize the objective function by either creating or terminating a tie. In this sense, the objective function can be defined as an "evaluation function" (Snijders 2005), where actors evaluate the current state of the network and change their ties so as to generate the most utility, and the estimated β parameters necessarily apply equally to tie creation and termination. However, the theory advanced in the main paper offers no theoretical expectations regarding termination of bilateral agreements. As well, the operationalization of the dependent network variable determines tie duration exogenously. The goal of the analysis is to assess the effect of network influences on tie creation. I thus incorporate into the model a so-called "endowment function," denoted $g_i(\gamma, \mathbf{y})$, which allows actors to respond differently to tie termination than tie creation. Specifically, for the termination of network ties, the endowment function is defined as

$$g_i(\gamma, \mathbf{y}) = \sum_{h=1}^{L} \gamma_h s_{ih}(\mathbf{y}), \tag{5}$$

while for the creation of network ties, $g_i(\gamma, \mathbf{y}) = 0$. The objective function of the model is then given as the sum of the evaluation and endowment effects,

$$f_i(\beta, \mathbf{y}) + g_i(\gamma, \mathbf{y}), \tag{6}$$

[16] See Snijders (2008).

[17] See Snijders (2008) and Ripley, Snijders, and Preciado (2012) for discussion of other methods.

which is a more general specification of Eq. 3, where parameters are allowed to differ according to creation or termination.[18] The estimated γ_h parameters then indicate whether the network effects and/or covariates act differently on termination than on creation. More importantly, inclusion of the endowment function means that the β parameters of the evaluation function now capture the impact of network influences and covariates only on creation of new ties.[19] In this context, the endowment function is only meant to improve inferences regarding network tie creation. As such, the γ_h estimates themselves are simply artifacts of the coding scheme and are substantively uninteresting (and they are not reported in the tables).[20]

Identification of the SAOM derives from the key assumption that when i takes a ministep (i.e., creates a new network tie), it does so independently of all other actors, conditional on the current structure of the network and exogenous covariates (Snijders 2005: 224–225). That is, the model assumes that simultaneous influences are not actually "instantaneous" (cf. Hays, Kachi, and Franzese Jr 2010: 413). Rather, causality rests on temporal sequencing, wherein an actor first takes account of the structure of the network, and then changes its network tie accordingly (Snijders, Steglich, and Schweinberger 2007). That change then becomes part of the network and thus influences the ministeps of subsequent actors. The total network change between observation moments is simply the accumulation of these ministeps. In this way, the model allows statistical inferences to be drawn even from ties that appear to emerge in a single observation moment (e.g., an ikj triad that is null at t_1 but fully complete at t_2). This ability to model seemingly simultaneous outcomes is an important distinction between the SAOM and models that incorporate only lagged network variables.

Because this model is too complex for direct calculation of probabilities, it is most commonly estimated through simulation (Snijders 2001). The principle of estimation utilized here is method of moments, which determines parameters by minimizing the difference between the expected and observed values of the $s_{ih}(\mathbf{y})$ network functions. The observed values are, of course, given by the data. The expected values are not known ex ante and are thus drawn from simulations of the Markov chain. Let $\mathbf{y}^{\text{obs}}(t_m), m = 1, \dots, M$ denote the observed networks. Starting from a given $\mathbf{y}^{\text{obs}}(t_m)$ network, larger values of the β_h parameters should result in larger values of the associated s_{ih} network statistic at observation moment t_{m+1}. The goal of simulation is to locate those β_h parameter values that, when a given s_h network statistic is summed over all i and m in the network, yields an expected value of s_h equal to the observed value (Snijders 2005: 235). Specifically, for a given s_h function, the "target value," based on the observed data, is

[18] Alternatively, the evaluation function may be dropped altogether, and a "creation function," denoted $c_i(\zeta, \mathbf{y})$, incorporated alongside the endowment function. $c_i(\zeta, \mathbf{y})$ is defined analogously to $g_i(\gamma, \mathbf{y})$, except that $c_i(\zeta, \mathbf{y}) = 0$ for termination of ties, whereas $g_i(\gamma, \mathbf{y}) = 0$ for creation of ties. The objective function is then given as the sum of the creation and endowment effects. Indeed, the objective function defined in Eq. 3 represents the special case where $\zeta_h = \gamma_h = \beta_h$ (Ripley, Snijders, and Preciado 2012). Nonetheless, although this specification requires the γ_h estimates of the endowment function to be interpreted differently than in Eq. 6, the ζ_h estimates of the creation function are in fact equivalent to the β_h estimates of Eq. 6. See Snijders (2001); Snijders, Steglich, and Schweinberger (2007).

[19] For further discussion, see Ripley, Snijders, and Preciado (2012); Snijders (2001); Snijders, Steglich, and Schweinberger (2007).

[20] I also estimated models that included only the $c_i(\zeta, \mathbf{y})$ creation function (see fn. 18) and altogether excluded the $g_i(\gamma, \mathbf{y})$ function, such that the $f_i(\beta, \mathbf{y})$ objective function is defined entirely by tie creation. The ζ_h parameter estimates from this model are comparable to those reported in the main paper, though somewhat diminished in magnitude. According to Snijders (2001: 385), this approach is less desirable than including endowment effects alongside either creation or evaluation effects.

$$s_h^{\text{obs}} = \sum_{m=1}^{M-1} \sum_{i=1}^{n} s_{ih}(\mathbf{y}^{\text{obs}}(t_{m+1})), (h = 1, \dots L). \tag{7}$$

Consider the simple case where $M = 2$. In general, the "distance" between two networks, $\mathbf{x}$ and $\mathbf{y}$, is defined as

$$\|\mathbf{x} - \mathbf{y}\| = \sum_{i,j} |x_{ij} - y_{ij}|. \tag{8}$$

Applying the same principle, the observed distance between our $m = 2$ networks, denoted v_1, is

$$v_1 = \|\mathbf{y}^{\text{obs}}(t_2) - \mathbf{y}^{\text{obs}}(t_1)\|. \tag{9}$$

The simulation would in this case proceed by taking the initial observed network, $\mathbf{y}^{\text{obs}}(t_1)$, and simulating the Markov chain described in Eq. 2 until the first time point, R_1, where

$$\|\mathbf{Y}(R_1) - \mathbf{y}^{\text{obs}}(t_1)\| = v_1. \tag{10}$$

The relevant s_h statistics can then be calculated from this $\mathbf{Y}(R_1)$ simulated network in the same manner as for the observed network (i.e., according to Eq. 7). The estimation uses a Robbins-Monro Markov-chain Monte Carlo (MCMC) algorithm to search the parameter space and locate the vector $\hat{\beta}$ for which the observed and expected values of these statistics are equal.[21] Finally, the estimation holds β constant at $\hat{\beta}$ and performs additional simulations to estimate the covariance matrix, cov$\hat{\beta}$, using a likelihood ratio / score function variant of the delta method, which Schweinberger and Snijders (2007) show to be unbiased, N-consistent, and much less computationally intensive than, e.g., bootstrapping or resampling.[22] Taking the square roots of the diagonal elements of cov$\hat{\beta}$ yields the standard errors of $\hat{\beta}$ (Snijders 2005: 237). Since the estimates of β_h generated by the simulation are approximately normally distributed (Snijders, van de Bunt, and Steglich 2010), null hypotheses can be tested with a simple t-statistic, $t_h = \dfrac{\hat{\beta}_h}{\text{s.e.}(\hat{\beta}_h)}$, in the standard normal distribution (Snijders 2005: 238).

3 Robustness Checks and Additional Issue Areas

This section provides sensitivity analyses for the various alternative codings of the dependent network variable discussed in Section 1, as well as robustness checks for a variety of additional

[21] See Snijders (2005: 236–237). The algorithm typically converges in 1,000–2,500 iterations, depending on the complexity of the model, number of nodes, number of ties, and number of observation moments. I report these iterations at the bottom of the tables.

[22] Ripley, Snijders, and Preciado (2012) recommend 2,000–4,000 additional iterations to estimate s.e.(β). I typically use 5,000 iterations, as reported in the tables.

control variables. I also extend the analysis beyond the four issue areas covered in the main paper.

Robustness Checks and Sensitivity Analyses

I first extend the analysis from the 1950–1980 period to the entire 1950–2000 period.[23] The results of these estimations are shown in Table 1. Although data coverage for the post-1980 period is relatively less complete than for earlier periods, the main results hold not only for the aggregate AGREEMENT category, but also for each of the four constituent categories. Indeed, in some cases, the estimates for the 1950–2000 model are more precise than the estimates from the main paper. These results confirm that network influences are not merely Cold War artifacts but are instead an ever-present feature of bilateral cooperation. Interestingly, some of the exogenous covariates produce substantially different estimates in the post-Cold War period. For example, the democracy controls, which proved insignificant in the main model, are now positive and significant, which suggests that the 1980–2000 period witnessed an increase in cooperation by and between democratic regimes—though this trend appears to have had no dampening effect on the network influences.

I next conduct a sensitivity analysis using alternate codings of the dependent network variables. The first three columns of Table 2 show the results for varying the $\tau = 3$ restriction, where agreements are presumed to endure and exercise influence for just one year ($\tau = 1$), five years ($\tau = 5$), or ten years ($\tau = 10$). The results from these alternate codings generally mirror those from the main paper. Interestingly, while the substantive effects of triadic closure and degree centrality differ little between the $\tau = 1$ and $\tau = 5$ codings, they are noticeably smaller for the $\tau = 10$ coding, which reinforces the assumption that network influences are most apparent within the first few years of an agreement's formation. More generally, the estimates confirm that the results reported in the main paper are not artifacts of the coding scheme.

The remaining columns of Table 2 explore the coding discussed at the end of Section 1, wherein network ties, once created, are assumed to endure indefinitely. This data construction bears similarities to dynamic synthetic networks, often studied by network physicists, wherein the network continuously expands in size and network ties, once created, are permanent (e.g., Barabási and Albert 1999). To accommodate this restriction, the model incorporates an "up only" monotonicity constraint, such that ties are only permitted to move in an upward direction and cannot be retracted (Ripley, Snijders, and Preciado 2012).[24] The results show that, in most cases, network influences are strongly apparent. TRIADCLOSURE remains significantly positive in the aggregate coding and each of the constituent categories, with the exception, interestingly, of commodity agreements. The DEGREE effect remains significantly positive in all categories.

Table 3 shows the results for additional robustness checks to the main network model. First, to control for sociocultural influences on cooperation, I include dummy variables that capture shared religion, shared language, or shared ethnicity (Gartzke and Gleditsch 2006). Of the three, only LANGUAGE significantly affects the probability of bilateral cooperation—though in a negative, rather than a positive, direction. At the same time, none of the estimates for network influence

[23] Note that, because the WTI lists no new commodities agreements past 1996, the COMMODITY model covers only the 1950–1996 period.

[24] Since the DENSITY effect defines the balance between "up only" and "down only" probabilities, it is formally undefined for these models. I simply fix the effect to zero or exclude it altogether.

Table 1: Effect of Network Influence on Creation of Bilateral Agreements (1950–2000)

	AGREEMENT	MILITARY	COMMODITY†	SCIENCES	FISHERIES
DENSITY	-2.332^{***}	-3.135^{***}	-3.052^{***}	-2.752^{***}	-3.016^{***}
	(0.043)	(0.109)	(0.121)	(0.069)	(0.106)
TRIADCLOSURE	0.505^{***}	0.48^{**}	0.431^{*}	0.718^{***}	0.884^{**}
	(0.048)	(0.151)	(0.197)	(0.126)	(0.311)
PREFATTACHMENT	0.06^{***}	0.186^{***}	0.177^{***}	0.145^{***}	0.258^{***}
	(0.005)	(0.021)	(0.025)	(0.013)	(0.032)
DISTANCE	0.002	0.029^{***}	0.000	0.015^{**}	-0.006
	(0.003)	(0.006)	(0.006)	(0.005)	(0.006)
CONTIGUITY	0.715^{***}	0.535^{***}	0.486^{***}	0.43^{***}	1.277^{***}
	(0.075)	(0.132)	(0.144)	(0.117)	(0.133)
IGOS	0.013^{***}	0.024^{***}	0.037^{***}	0.017^{***}	0.01
	(0.003)	(0.005)	(0.006)	(0.004)	(0.005)
ALLIANCE	0.021	0.394^{***}	-0.344^{**}	0.028	0.139
	(0.068)	(0.112)	(0.13)	(0.094)	(0.123)
TRADE	0.184^{***}	0.235^{***}	0.207^{***}	0.212^{***}	0.116^{***}
	(0.011)	(0.025)	(0.023)	(0.016)	(0.019)
DEMOCRACY	0.01^{*}	0.05^{***}	0.013	-0.027^{***}	0.009
	(0.005)	(0.01)	(0.01)	(0.007)	(0.009)
DEM × DEM	0.001^{**}	0.000	0.000	0.002^{***}	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
CAPABILITIES	3.099^{***}	0.568	3.508^{***}	3.415^{***}	2.97^{***}
	(0.236)	(0.506)	(0.384)	(0.348)	(0.486)
CAP × CAP	-1.884	1.834	-2.005	-1.123	-2.619
	(1.515)	(1.817)	(2.007)	(1.737)	(2.699)
DEVELOPMENT	0.135^{***}	0.2^{*}	-0.081	0.086	0.379^{***}
	(0.036)	(0.081)	(0.073)	(0.05)	(0.074)
DEV × DEV	-0.03	-0.006	-0.026	-0.029	-0.06
	(0.019)	(0.046)	(0.04)	(0.026)	(0.044)
Iterations β	1,361	1,685	1,136	1,529	1,359
Iterations s.e.(β)	5,000	5,000	5,000	5,000	5,000

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parentheses. $N_{1950} = 75$; $N_{2000} = 170$. † 1950–1996 period only. Estimates indicate effect on network tie creation, based on stochastic actor-oriented model of network evolution. All t-ratios for deviations from targeted values < 0.1 (excellent convergence).

is affected by these controls. I also add a control for shared preferences or "affinity." Developed by Gartzke (1998), this measure uses voting in the United Nations General Assembly to infer (dis)similarities in the foreign policy preferences of states. Intuitively, we might expect that bilateral cooperation is greatest between countries that share preferences. However, the AFFINITY estimate is significantly negative rather than positive. The network influences, on the other hand, remain positive and highly significant. To account for hegemony effects and Cold War dynamics, I include dummy variables for the United States and the Soviet Union, which capture the preference of states for ties to the US and USSR, respectively. Given the high degree centrality of both the US and USSR, we might expect that when either state is the prospective target of a tie, the probability of tie creation increases. In a simple "covariates only" specification, where network influences are excluded, the estimates for both effects (not shown) are insignificant. However, after introducing

Table 2: Alternate Codings of Dependent Network Variable (1950–1980)

	Agreement[a]	Agreement[b]	Agreement[c]	Agreement[d]	Military[d]	Commodity[d]	Sciences[d]	Fisheries[d]
Density	−2.339***	−2.342***	−1.789***	–	–	–	–	–
	(0.05)	(0.05)	(0.068)	–	–	–	–	–
TriadClosure	0.772***	0.778***	0.366***	0.431***	1.48***	0.014	0.365***	0.449***
	(0.14)	(0.144)	(0.043)	(0.077)	(0.099)	(0.08)	(0.09)	(0.124)
PrefAttachment	0.056***	0.056***	0.048***	0.053***	0.042**	0.101***	0.111***	0.082***
	(0.006)	(0.006)	(0.006)	(0.013)	(0.015)	(0.023)	(0.014)	(0.01)
Distance	−0.001	−0.001	−0.008	0.000	0.025	0.014**	0.025***	−0.003
	(0.004)	(0.004)	(0.005)	(0.012)	(0.015)	(0.005)	(0.007)	(0.006)
Contiguity	0.698***	0.696***	0.688***	0.998***	1.288***	0.744***	0.638***	0.915***
	(0.079)	(0.079)	(0.12)	(0.257)	(0.313)	(0.14)	(0.162)	(0.137)
IGOs	0.021***	0.021***	0.02***	0.045**	0.128***	0.042***	0.027***	0.031***
	(0.004)	(0.004)	(0.006)	(0.014)	(0.019)	(0.006)	(0.008)	(0.006)
Alliance	0.007	0.007	−0.037	−0.553*	−1.337***	0.031	−0.007	−0.189
	(0.067)	(0.067)	(0.108)	(0.248)	(0.292)	(0.107)	(0.131)	(0.112)
Trade	0.181***	0.182***	0.172***	0.287***	0.341***	0.123***	0.194***	0.06***
	(0.012)	(0.012)	(0.016)	(0.046)	(0.058)	(0.026)	(0.02)	(0.015)
Democracy	0.000	0.000	−0.002	−0.014	−0.021	−0.004	−0.059***	−0.031***
	(0.005)	(0.005)	(0.007)	(0.016)	(0.019)	(0.009)	(0.01)	(0.008)
Dem × Dem	0.001	0.001	0.001	0.002	0.004**	−0.001*	−0.002**	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capabilities	3.497***	3.5***	2.704***	3.116***	5.389***	3.251***	2.158***	3.975***
	(0.244)	(0.239)	(0.38)	(0.872)	(1.042)	(0.338)	(0.313)	(0.28)
Cap × Cap	−0.34	−0.358	−9.088*	−4.04	9.492	2.558	−1.038	−0.192
	(1.284)	(1.264)	(4.516)	(14.082)	(16.78)	(2.137)	(1.691)	(1.689)
Development	0.223***	0.223***	0.147**	−0.063	−0.147	−0.135	0.066	0.16*
	(0.04)	(0.041)	(0.055)	(0.136)	(0.154)	(0.072)	(0.085)	(0.075)
Dev × Dev	−0.029	−0.03	−0.062*	0.202**	0.126	0.221***	0.157**	0.067
	(0.021)	(0.021)	(0.03)	(0.078)	(0.089)	(0.045)	(0.049)	(0.047)
Iterations β	1,964	2,129	1,797	1,954	2,179	1,830	2,071	1,788
Iterations s.e.(β)	5,000	5,000	5,000	5,000	5,000	5,000	5,000	5,000

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parentheses. [a] $\tau = 1$; [b] $\tau = 5$; [c] $\tau = 10$; [d] $\tau =$ indefinite. $N_{1950} = 75$; $N_{1980} = 150$. Estimates indicate effect on network tie creation, based on stochastic actor-oriented model of network evolution. All t-ratios for deviations from targeted values < 0.1 (excellent convergence).

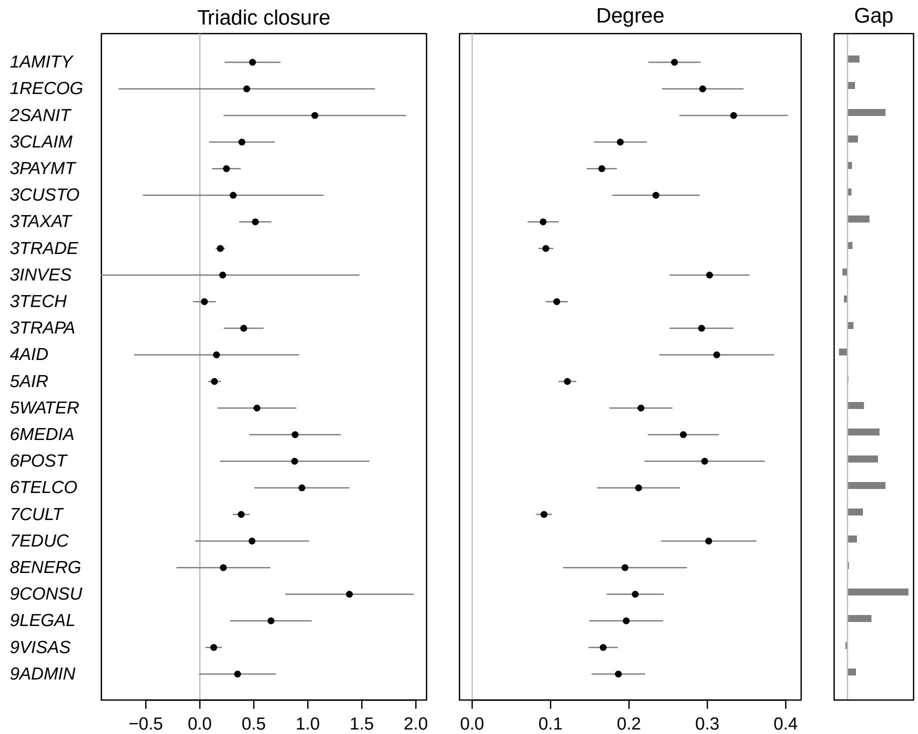
Table 3: Additional Robustness Checks (1950–1980)

	Agreement	Agreement	Agreement	Agreement	Agreement	Agreement
Density	−2.138***	−2.146***	−2.135***	−2.134***	−2.135***	−2.112***
	(0.052)	(0.052)	(0.053)	(0.053)	(0.056)	(0.053)
TriadClosure	0.556***	0.558***	0.555***	0.573***	0.473***	0.551***
	(0.059)	(0.058)	(0.058)	(0.059)	(0.064)	(0.062)
PrefAttachment	0.051***	0.05***	0.05***	0.046***	0.083***	0.054***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)
Distance	−0.004	−0.004	−0.004	−0.004	−0.001	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Contiguity	0.73***	0.762***	0.742***	0.746***	0.667***	0.704***
	(0.094)	(0.096)	(0.094)	(0.095)	(0.095)	(0.093)
IGOs	0.021***	0.021***	0.021***	0.022***	0.02***	0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Alliance	−0.079	−0.009	−0.039	−0.007	0.09	−0.06
	(0.083)	(0.088)	(0.084)	(0.086)	(0.085)	(0.083)
Trade	0.184***	0.189***	0.184***	0.181***	0.184***	0.182***
	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Democracy	0.003	0.001	0.003	0.002	0.014*	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Dem × Dem	0.001	0.001	0.001	0.001*	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capabilities	3.288***	3.216***	3.3***	3.267***	4.753***	2.993***
	(0.265)	(0.262)	(0.263)	(0.259)	(0.281)	(0.299)
Cap × Cap	−1.614	−1.507	−1.681	−1.757	−2.828	−1.76
	(1.611)	(1.618)	(1.637)	(1.676)	(1.905)	(1.72)
Development	0.144**	0.15***	0.146**	0.137**	0.135**	0.138**
	(0.046)	(0.045)	(0.046)	(0.048)	(0.048)	(0.047)
Dev × Dev	−0.053*	−0.056*	−0.052*	−0.044	−0.048	−0.053*
	(0.024)	(0.025)	(0.024)	(0.024)	(0.026)	(0.024)
Religion	−0.005					
	(0.066)					
Language		−0.342**				
		(0.119)				
Ethnicity			−0.255			
			(0.132)			
Affinity				−0.311**		
				(0.115)		
USA					−2.361***	
					(0.237)	
USSR						0.472*
						(0.219)
Iterations β	1,994	2,102	2,053	2,126	2,101	1,963
Iterations s.e.(β)	5,000	5,000	5,000	5,000	5,000	5,000

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors in parentheses. $N_{1950} = 75$; $N_{1980} = 150$. Estimates indicate effect on network tie creation, based on stochastic actor-oriented model of network evolution. All t-ratios for deviations from targeted values < 0.1 (excellent convergence).

network influences, as shown in the last two columns of Table 3, the estimate for USA becomes strongly *negative*. States do not prefer ties to the US. Rather, they prefer ties to high-degree partners. Controlling for degree centrality reveals that prospective partners in fact *avoid* the United States. The estimate for USSR, on the other hand, is weakly positive, suggesting that, at least for the 1950–1980 period, the USSR did indeed attract cooperative partners beyond its high degree centrality. Most importantly, for both hegemony effects, the estimates of network influence remain

Figure 1: Effects of Triadic Closure and Degree Centrality across Treaty Categories



Note: Dots are point estimates. Lines are 95% confidence intervals. Models include same covariates as Model 2 of main paper (estimates not shown). "Gap" panel shows estimates for PrefAttachment subtracted from TriadClosure. See Section 6 of this SI for treaty codes.

substantively unchanged; nodal heterogeneity clearly matters, but it does not appear to undermine the network influences. As a final consideration, I also estimated a simplified "rule of three" model (Achen 2002), which includes only the network influences. The estimates of network effects in this specification (not shown) were even larger and more precise than in the full model. I also estimated separate models for each one of the network effects (i.e., with either of TriadClosure or PrefAttachment excluded) and again obtained larger, more precise estimates.

Testing Additional Issue Areas

While the four issue areas discussed in the main paper—commodities, military, science, and fisheries—represent key areas of bilateral cooperation, they are by no means exhaustive. Rohn (1984) identified over 90 distinct categories. Many of these contain too few agreements to obtain reliable network estimates, while others concern issues—such as relief/rescue missions and humanitarian aid—that are highly asymmetric or do not involve traditional cooperation problems. I nonetheless obtained good estimates for 24 additional categories. Notably, some of these categories, such as telecommunications and postal services, have been previously identified by scholars as key areas of of coordination (e.g., Krasner 1991; Morrow 1994).

The estimated coefficients and standard errors for TriadClosure and PrefAttachment (labeled as "Degree") are shown in Figure 1. The estimate for TriadClosure is positive in all categories and statistically significant at $p < .05$ in 17 of the categories, including agreements in taxation and fiscal evasion (3TAXAT), patents and copyrights (3PATEN), general nonspecific trade (3TRADE), air and water transport (5AIR, 5WATER), mass media (6MEDIA), postal services (6POST), telecommunications (6TELCO), cultural and artistic exchange (7CULT), administrative and legal areas (9CONSU, 9LEGAL, 9VISAS), and others. Degree effects are even more consistently significant; no matter the issue, states prefer to cooperate with high-degree partners. The difference in significance between the two effects may be due to the fact that less active states—of which there are many in the bilateral cooperation network—generally have few opportunities for triadic closure, as they have few "friends of friends" connections to draw upon. In such cases, the degree centrality of potential targets becomes a more important consideration; since there are nearly always some high-degree states to look toward, preferential attachment should be more apparent across a wider variety of networks.[25] At the same time, as indicated by the third panel in Figure 1—and consistent with my expectation from Hypothesis 2—the substantive impact of triadic closure is nearly always greater than the impact of degree centrality, regardless of issue area; while degree centrality attracts partners, states especially prefer agreements with countries that have ties to their existing partners.

4 Topology of the Bilateral Cooperation Network

As with other network models, such as exponential random graph models (Robins et al. 2007), the SAOM connects local interdependent processes—e.g., triadic closure, preferential attachment—to global network structures. Yet, as an "actor-oriented" model, the SAOM especially emphasizes individual initiative; network interdependencies are a direct consequence of utility maximization by individual actors (Snijders, van de Bunt, and Steglich 2010). This feature of the model makes it especially attractive for the study of international relations, where actors often possess substantial agency. Nonetheless, a large body of work in network analysis focuses instead on the large-scale statistical properties of networks.[26] These approaches emphasize network topology, or the macro-level arrangement of nodes and ties.

Much of this recent literature explores so-called "scale-free" networks.[27] The key consideration in identifying a scale-free network is the "nodal degree" of the individual actors, i.e., the number of network ties possessed by each node. If a network is scale free, the probability distribution of nodal degrees follows a power law, such that the network has a small number of very high-degree or "popular" nodes and a large number of much less popular nodes. A second commonly studied topological feature of networks is clustering, perhaps best known from the "small world" model developed by Watts and Strogatz (1998), where most nodes are not connected to one another directly but can be reached in a small number of steps via mutual acquaintances.[28] More generally,

[25] An important area for future research is to explore how the substance and significance of triadic closure varies according to the density of the network.

[26] For overviews, see Albert and Barabási (2002); Newman (2003*b*); Newman, Barabási, and Watts (2006).

[27] Studies of scale-free networks are far too numerous to summarize here. See Barabási and Albert (1999) for the seminal contribution.

[28] Specifically, a small-world network is one in which the average distance between nodes is proportional to the

clustering refers to the extent of transitivity or closure in a network, defined in terms of the number of fully closed triangles of actors (Holland and Leinhardt 1970).

The analysis in the main paper focuses on local processes of network selection—rather than emergent network properties—for two reasons. First, much of our current understanding of emergent properties is based on extremely large networks, such as internet router systems (Faloutsos, Faloutsos, and Faloutsos 1999), electrical power grids (Albert, Albert, and Nakarado 2004), the world wide web (Barabási and Albert 1999), cellular and metabolic networks (Jeong et al. 2000), academic coauthorships (Newman 2001), and so on. Such networks typically consist of thousands, millions, or even billions of nodes, and they may have no upper limit on growth. Ease of observation in many of these networks results in thousands of unique cross sections of data, yielding a massive, fine-grained time series of observations. As well, the nodes themselves are typically "like units," functionally undifferentiated or otherwise highly homogenous, making the inclusion of covariates largely unnecessary. In contrast, the bilateral cooperation network is small, consisting of, at most, 150 nodes, which limits the ability of analysts to tease out distinctive network topologies.[29] Yet, despite their smaller number, these nodes are heterogeneous, necessitating consideration of covariates; if these covariates compete for influence with network effects, then the distinctive topologies associated with particular selection processes may not emerge.[30] For example, Fowler, Dawes, and Christakis (2009) find that nearly half of the indegree of individuals can be explained by genetic variation, and de Blasio, Seierstad, and Aalen (2011) similarly find that unit heterogeneity overwhelms preferential attachment. In short, given the characteristics of the bilateral cooperation network, any evidence drawn from the topology of that network should be interpreted with caution.[31]

Second, current standards of inquiry in political science privilege causal mechanisms. Taken alone, network topologies reveal little about the underlying mechanisms that produced those topologies. Indeed, "the mere fact that a nodal degree distribution follows a power law actually implies nothing either about the mechanism giving rise to it or about its particular architecture" (Keller 2005: 1061).[32] While scale-free networks are often linked to preferential attachment processes, scholars have identified numerous alternative selection processes that yield comparable degree distributions (e.g., Dangalchev 2004; Li et al. 2005; Newman 2005). Similarly, extensive network clustering clearly reflects a tendency toward closure in social relations, but a variety of distinctive closure mechanisms could be responsible for such an outcome (Newman, Barabási, and Watts 2006; Watts 1999; Watts and Strogatz 1998). More generally, inferring micro-level mechanisms from macro-level structural properties commits the classic ecological fallacy. By focusing the analysis on how local structural forces impact network selection, I keep causal mechanisms at the forefront while still

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logarithm of the number of nodes in the network (Watts and Strogatz 1998).

[29] In reference to a network of 306 nodes (more than twice as many as my largest network), Barabási and Albert (1999) state that "the relatively small size of the system [...] severely limits the data quality."

[30] On a related point, Snijders (2011: 503) notes that, "For most types of networks between human individuals this [the scale-free property] does not seem realistic because various constraints will limit the frequency of occurrence of very high degrees."

[31] Note, however, that this argument in no way implies that network influences are not apparent in bilateral cooperation. It simply means that these influences may not generate distinctive topological properties. In fact, the cooperation network more closely resembles traditional small-scale social networks (e.g., classes of schoolchildren, interlocking corporate directorates, etc.), which have for decades been studied as interdependent systems, even if their topologies aren't particularly interesting.

[32] This fact was readily recognized by the earliest analysts of power-law distributions, such as Yule (1925), Simon (1955), and Merton (1968).

incorporating important structural features of the network.

With these caveats in mind, I explore the topological properties of the bilateral cooperation network, focusing on the aggregate AGREEMENT coding. Figures 2 and 3 illustrate the structure of the network at two points in time. I argue in the main paper that triadic closure and preferential attachment drive selection of bilateral partners. Each of these processes carries implications for the overall topology of the network. As discussed above, under ideal conditions, preferential attachment leads to a scale-free network.[33] We have many reasons to suspect that IR networks stray far from these ideal conditions. Finding evidence of a scale-free architecture despite these inhospitable conditions thus bodes well for Hypothesis 2—especially in combination with the SAOM's strong evidence for preferential attachment. Triadic closure, on the other hand, represents a form of homophily, where similarities between nodes are defined in terms of shared partners rather than shared nodal attributes (Newman 2002, 2003*a*). Under ideal conditions, homophily should lead to clustering beyond that which we'd expect to see in a random network.

Taken separately, scale-free and clustered networks—and the corresponding attachment and closure processes—might appear contradictory. This is not the case, however. Clustering in scale-free graphs is in fact so pervasive as to be nearly universal.[34] As observed by Ravasz and Barabási (2003): "The scale-free property and clustering are not exclusive: for a large number of real networks, including metabolic networks, the protein interaction network, the World Wide Web, and even some social networks, the scale-free topology and high clustering coexist."[35] In short, an enormous array of real-world networks exhibit both a power-law degree distribution and nontrivial amounts of clustering. The goal of the present analysis is to determine if these features also characterize the bilateral cooperation network.

I first examine the network for evidence of scale-free topology. Such networks are characterized by the degree distribution

$$p(x) \propto x^{-\alpha}, \tag{11}$$

where x indicates nodal degree (i.e., each individual actor's number of network ties) and α is a scaling parameter. Typically, though not always, α lies in the range $2 < \alpha < 3$. As Newman (2005: 325) notes, "Identifying power-law behavior in either natural or manmade systems can be tricky." I employ the method of Clauset, Shalizi, and Newman (2009), which estimates the α parameter using maximum likelihood techniques while also estimating the minimum x value for which the power-law distribution accurately describes the data.[36] This is currently the most reliable method

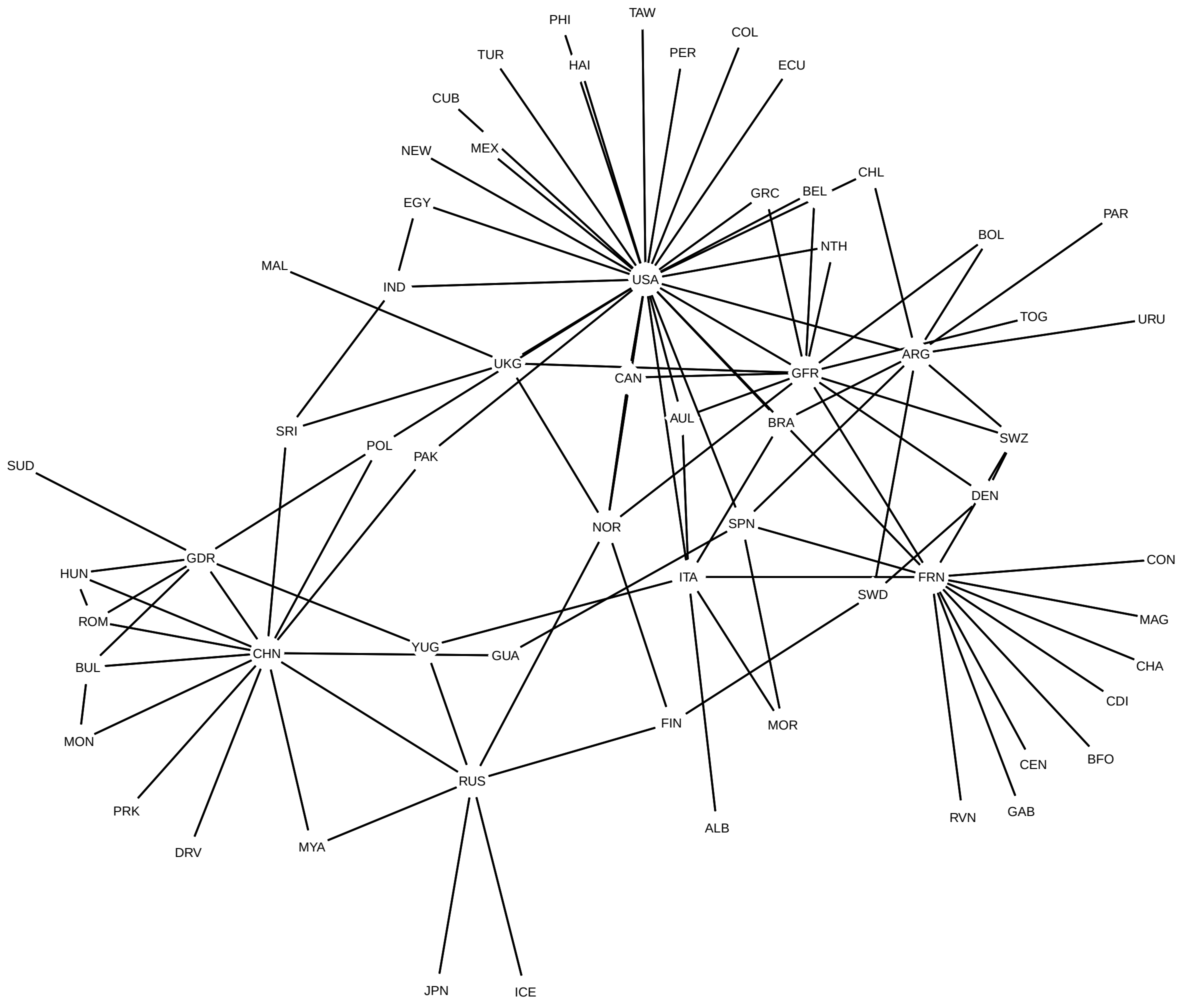
[33] The archetypical Barabási-Albert model assumes both preferential attachment and growth. As the network grows in size, new nodes attach to existing nodes in proportion to their degree centrality. Without growth, the network becomes saturated and the nodal degree distribution tends toward a Gaussian rather than a power law. (But see Xie, Zhou, and Wang (2008) for exceptions.) Additionally, the model assumes that the network never loses actors, and network ties, once established, never disappear. See Barabási and Albert (1999).

[34] More specifically, the scale-free topology conflicts with clustering only if the rules of network formation stipulate that actors follow a preferential attachment strategy *to the exclusion of all other strategies.* In that case, clustering declines with the size of the network. But this result is simply an artifact of the model. Indeed, the inability of the Barabási-Albert model to produce a level of network clustering similar to that seen in real-world networks is a widely recognized weakness (Klemm and Eguiluz 2002*b*).

[35] This intriguing feature of complex networks has prompted a substantial body of research. This literature is far too large to exhaustively summarize, but examples include Chen and Chen (2007); Dell'Amico (2006); Holme and Kim (2002); Jacob and Mörters (2012); Klemm and Eguiluz (2002*a*,*b*); Ravasz and Barabási (2003).

[36] Empirical network data typically only follow a power law in the tail of the degree distribution, where x is some

Figure 2: Full Network, AGREEMENT Coding, 1960

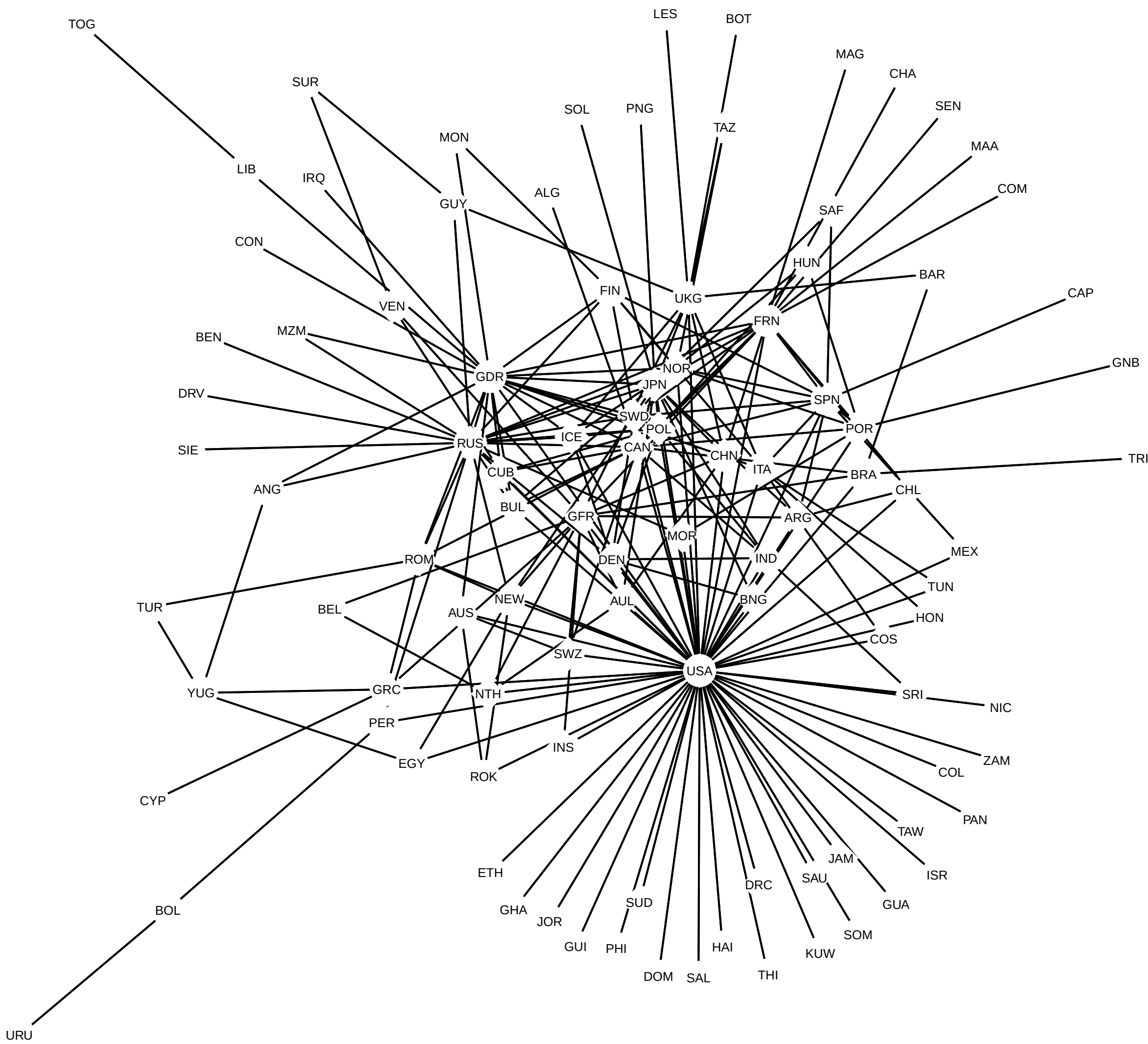


Note: Nodes are countries. Lines indicate bilateral cooperation agreements. Isolates not shown.

of estimating power-law distributions. This approach also incorporates a goodness-of-fit test in the form of a modified "p-value," $0 \leq p \leq 1$, generated by comparing the observed network data to synthetic data drawn from a hypothesized underlying power-law distribution. If the observed data systematically differ from the synthetic data, indicated by a p-value close to zero (the minimum), the model is not a plausible fit to the data. On the other hand, p-values closer to one (the maximum) indicate good fit. (Note that, contrary to the p-values typically used for hypothesis testing, *large* values are desirable here.) Clauset, Shalizi, and Newman (2009) recommend $p \leq 0.1$ as the threshold for rejecting the power-law hypothesis. Thus, p-values greater than this threshold leave a reasonable probability of the data having been drawn from a power-law distribution.

value greater than one (Clauset, Shalizi, and Newman 2009).

Figure 3: Full Network, Agreement Coding, 1980

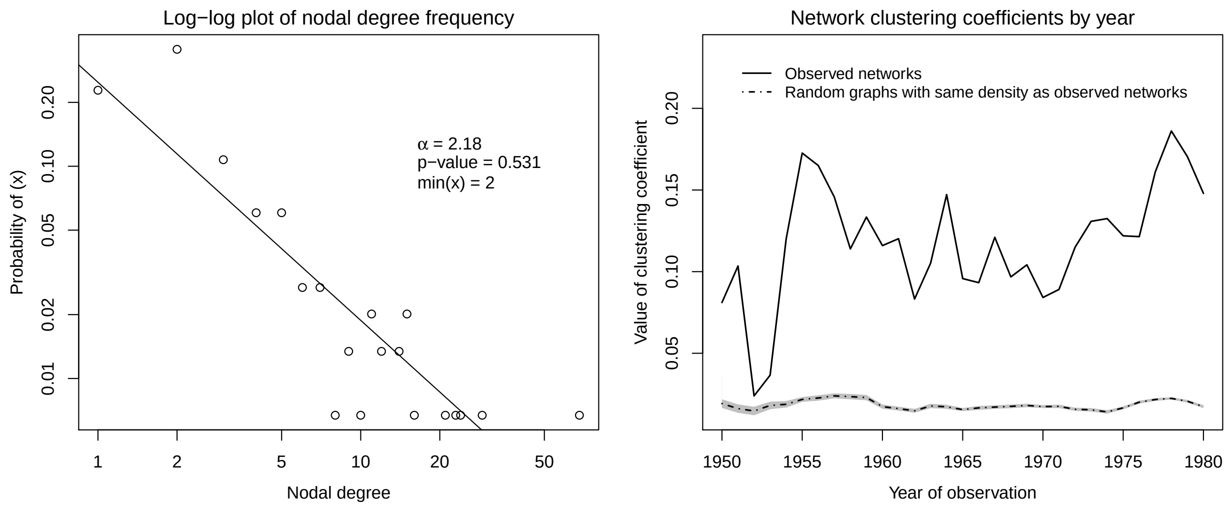


Note: Nodes are countries. Lines indicate bilateral cooperation agreements. Isolates not shown.

The log-log plot in the left-hand panel of Figure 4 illustrates the probability distribution of nodal degrees in the bilateral cooperation network, expressed as the log ratio of nodes in the network that have x connections to other nodes. The estimated $\alpha = 2.18$ clearly falls within the $2 < \alpha < 3$ range commonly found in scale-free networks. As well, the p-value greatly exceeds the recommended 0.10 threshold. The estimated $\min(x) = 2$ indicates that this power-law relationship holds for nodal degrees of 2 or greater. In short, despite its relatively small size, the bilateral cooperation network shows clear evidence of a scale-free topology, further corroborating the hypothesized preferential attachment process.

I next measure the extent of triadic closure within the network using a global clustering coefficient, C_G, which calculates the ratio of transitive triads to potentially intransitive triads. As a ratio,

Figure 4: Scale-Freeness and Clustering in the Bilateral Cooperation Network



Note: In left panel, y-axis is log ratio of nodes with degree x, and x-axis is log of x. The x values are calculated for all 149 actors in the network as mean values for the full 1950–1980 period. In right panel, solid line indicates global clustering coefficients (C_G) in observed network. Dashed line indicates mean C_G in 100 randomly generated networks for each year of observation; gray shading indicates corresponding 95% confidence intervals.

$0 \leq C_G \leq 1$, where larger values of C_G indicate more extensive triadic closure throughout the network. There is no particular threshold value of C_G beyond which a graph is clustered rather than unclustered. Instead, we must determine whether the network exhibits more clustering than would be expected by random chance. To accomplish this comparison, I employ random graph simulations. For each annual t observation of the network, I generate 100 random Bernoulli graphs, where the $p(y_{ij})$ probability of a given network tie in year t is equal to the density of the observed network at year t. I derive the mean clustering coefficient and 95% confidence intervals across all 100 graphs, which together provide, for each year of analysis, an expectation of how much clustering should exist by random chance. The right-hand panel of Figure 4 plots the random graph clustering coefficients (dashed line) against the C_G statistics derived from the observed networks (solid line). For all years of analysis, the network contains nontrivial amounts of clustering. Indeed, aside from a few anomalous years in the early 1950s, the clustering coefficients in the observed network are typically an order of magnitude or more larger than what we'd expect by random chance.

I reemphasize that, given the relatively small size of the network, these results should be interpreted with caution. Nonetheless, they show clear evidence that the topology of the bilateral cooperation network exhibits characteristics consistent with the proposed local network processes, further corroborating the importance of network influences. Taken as a whole, the results show that (1) states preferentially seek ties to highly popular targets, and this preference manifests itself at the macro level with a small number of highly popular states and a large number of peripheral states, and that (2) states also seek ties to partners of partners, and this tendency manifests itself at the macro level with more closed triads than would be expected by random chance.

5 Correlates of War Country Acronyms

Afghanistan (AFG); Albania (ALB); Algeria (ALG); Angola (ANG); Argentina (ARG); Australia (AUL); Austria (AUS); Bahamas (BHM); Bahrain (BAH); Bangladesh (BNG); Barbados (BAR); Belgium (BEL); Belize (BLZ); Benin (BEN); Bhutan (BHU); Bolivia (BOL); Bosnia and Herzegovina (BOS); Botswana (BOT); Brazil (BRA); Brunei (BRU); Bulgaria (BUL); Burkina Faso (BFO); Burundi (BUI); Cambodia (CAM); Cameroon (CAO); Canada (CAN); Cape Verde (CAP); Central African Republic (CEN); Chad (CHA); Chile (CHL); China (CHN); Colombia (COL); Comoros (COM); Congo (CON); Costa Rica (COS); Cuba (CUB); Cyprus (CYP); Czechoslovakia (CZE); Democratic Republic of the Congo (DRC); Denmark (DEN); Djibouti (DJI); Dominican Republic (DOM); Ecuador (ECU); Egypt (EGY); El Salvador (SAL); Equatorial Guinea (EQG); Eritrea (ERI); Ethiopia (ETH); Fiji (FIJ); Finland (FIN); France (FRN); Gabon (GAB); Gambia (GAM); German Democratic Republic (GDR); German Federal Republic (GFR); Ghana (GHA); Greece (GRC); Guatemala (GUA); Guinea (GUI); Guinea-Bissau (GNB); Guyana (GUY); Haiti (HAI); Honduras (HON); Hungary (HUN); Iceland (ICE); India (IND); Indonesia (INS); Iran (IRN); Iraq (IRQ); Ireland (IRE); Israel (ISR); Italy (ITA); Ivory Coast (CDI); Jamaica (JAM); Japan (JPN); Jordan (JOR); Kenya (KEN); Kuwait (KUW); Laos (LAO); Lebanon (LEB); Lesotho (LES); Liberia (LBR); Libya (LIB); Luxembourg (LUX); Madagascar (MAG); Malawi (MAW); Malaysia (MAL); Maldives (MAD); Mali (MLI); Malta (MLT); Mauritania (MAA); Mauritius (MAS); Mexico (MEX); Mongolia (MON); Morocco (MOR); Mozambique (MZM); Myanmar (MYA); Namibia (NAM); Nepal (NEP); Netherlands (NTH); New Zealand (NEW); Nicaragua (NIC); Niger (NIR); Nigeria (NIG); North Korea (PRK); Norway (NOR); Oman (OMA); Pakistan (PAK); Panama (PAN); Papua New Guinea (PNG); Paraguay (PAR); Peru (PER); Philippines (PHI); Poland (POL); Portugal (POR); Qatar (QAT); Republic of Vietnam (RVN); Romania (ROM); Russia (RUS); Rwanda (RWA); Saudi Arabia (SAU); Senegal (SEN); Sierra Leone (SIE); Singapore (SIN); Solomon Islands (SOL); Somalia (SOM); South Africa (SAF); South Korea (ROK); Spain (SPN); Sri Lanka (SRI); Sudan (SUD); Suriname (SUR); Swaziland (SWA); Sweden (SWD); Switzerland (SWZ); Syria (SYR); Taiwan (TAW); Tanzania (TAZ); Thailand (THI); Togo (TOG); Trinidad and Tobago (TRI); Tunisia (TUN); Turkey (TUR); Uganda (UGA); United Arab Emirates (UAE); United Kingdom (UKG); United States of America (USA); Uruguay (URU); Venezuela (VEN); Vietnam (DRV); Yemen Arab Republic (YAR); Yemen People's Republic (YPR); Yugoslavia (YUG); Zambia (ZAM); Zimbabwe (ZIM).

6 Rohn's Treaty Codes

Friendship and amity (1AMITY); diplomacy/recognition (1RECOG); human health (2SANIT); claims, debts, and assets (3CLAIM); payments and currency (3PAYMT); customs duties (3CUSTO); taxation (3TAXAT); general trade (3TRADE); investment guarantee (3INVES); technical cooperation (economic) (3TECH); trade and payments (3TRAPA); unspecified aid (4AID); air transport (5AIR); water transport (5WATER); mass media communications (6MEDIA); postal services (6POST); telecommunications (6TELCO); cultural exchange (7CULT); educational exchange (7EDUC); energy (8ENERG); foreign consulates (9CONSU); legal procedures (9LEGAL); visas and passports (9VISAS); general administration (9ADMIN).

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