The Networked Peace: Intergovernmental Organizations and International Conflict

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Appendix

1 Modularity Maximization

In this appendix, we explain the formal definition of modularity and the algorithm we use to maximize it. The concept of modularity can be formally described by the equation:

$$Q = \sum_i \left(e_{ii} - b_i^2\right)$$

where e_{ii} refers to the proportion of ties that both originate and end in cluster i. The parameter b is defined as $\sum_j e_{ij}$, where e_{ij} refers to the proportion of ties that originate in cluster i but end in cluster j. As the structure of a network becomes more modular, the proportion of edges (e_{ii}) that span two nodes within a single cluster increases relative to the proportion of edges (e_{ij}) that span nodes that lie within different clusters, therefore leading to an increase in the modularity score, Q. To maximize modularity, we use the algorithm developed by Blondel et al. (2008), which was shown by Lupu and Traag (2013) to provide substantively useful and meaningful results when applied to the network of state connections. We do not specify, ex ante, the number of clusters in the international system; instead, the results indicate the number of clusters and the distribution of states into those clusters that maximizes the modularity score.

Assume we are given a graph (or network) $G = (V, E)$ with n nodes (or vertices) V and m links (or edges) E, with weights w on the links. The edges in this network are directed, meaning they are asymmetric (i.e., state A's trade dependence on state B may be different from state B's trade dependence on A). The $n \times n$ adjacency matrix of the graph G can then be defined as $A_{ij} = w_{ij}$ whenever there is a directed link (ij), and $A_{ij} = 0$ otherwise. The incoming degree of a node i (i.e., the number of nodes that connect to node i) is denoted by $k_i^{in} = \sum_j A_{ji}$ and the outgoing degree (i.e., the number of nodes to which node i connects) by $k_i^{out} = \sum_j A_{ij}$.

Assume each node i is assigned to a cluster σ_i. The modularity of such a partition can be defined as:

$$Q(\{\sigma\}) = \sum_{ij}(A_{ij} - p_{ij})\delta(\sigma_i, \sigma_j), \tag{1}$$

where $\delta(\sigma_i, \sigma_j) = 1$ if and only if $\sigma_i = \sigma_j$, i.e., where i and j are in the same cluster (Newman and Girvan, 2004; Reichardt and Bornholdt, 2006). Let p_{ij} be an expectation value of an ij link that is taken to be:

$$p_{ij} = \frac{k_i^{out} k_j^{in}}{m}. \tag{2}$$

for a directed network (Leicht and Newman, 2008). This p_{ij} is used to compare a random null model to the empirical trade network, in this case with similar degrees.

Consider the graph $G = (V, E_1, E_2, \ldots, E_T)$ where $E_1, \ldots, E_T$ the represents the links at time $1, \ldots, T$ between the nodes V. We denote by $A_{t,ij}$ the associated adjacency matrix for each ij link at time t. The modularity formula as given in Equation 1 can then be extended slightly to yield:

$$Q(\{\sigma\}) = \sum_t \sum_{ij} (A_{t,ij} - p_{t,ij}) \delta(\sigma_{t,i}, \sigma_{t,j}), \tag{3}$$

where $\sigma_{t,i}$ now represents the cluster of node i at time t.

Over the past few years, many algorithms for optimizing modularity have been suggested (for an overview see Fortunato, 2010; Porter, Onnela and Mucha, 2009). Because the problem is NP-hard (Brandes et al., 2006) it is unlikely that there is an efficient algorithm to solve the optimization problem perfectly. There are, however, some algorithms that are both efficient (i.e., they run in almost linear time) and effective (i.e., they can correctly identify clusters in test settings) (Lancichinetti, Fortunato and Radicchi, 2008; Lancichinetti and Fortunato, 2009). The so-called Louvain method developed by Blondel et al. (2008) is especially suitable for optimizing modularity. In brief, the Louvain method works as follows. We start out by assigning each node to its own cluster, such that at the start there are as many clusters as there are nodes. We loop (randomly) over all nodes and add them to a cluster that increases the modularity as much as possible. Then we form a new graph in which each node represents the clusters found at the previous level, with links between these new nodes representing the weights between each cluster in the old graph. In this way, smaller and smaller graphs are obtained, with nodes representing cluster (and possibly sub-clusters). The algorithm ends when modularity can no longer be increased.

Formally, the algorithm works by first removing node i from its cluster, and then calculating the effect on the modularity measure of adding node i to a cluster–possibly the same one. The effect on modularity of putting node i in cluster r in time t can be written as:

$$\Delta Q(\sigma_{t,i} \to r) = \sum_t (m_{t,ir} + m_{t,ri}) - ([m_{t,ir}] + [m_{t,ri}]), \tag{4}$$

where $m_{t,ir} = \sum_j A_{t,ij} \delta(\sigma_{t,j}, r)$ denotes the total weight from node i to cluster r, with $m_{t,ri}$ defined similarly, and $[m_{t,ir}] = \sum_j p_{t,ij} \delta(\sigma_{t,j}, r)$ the expected weight from i to r with again

$[m_{t,ri}]$ defined similarly. Each node is then added to the cluster for which this effect on modularity is maximal.

After we have completed the first level, we aggregate the clusters into nodes for a new graph, and define the weight of the links between these new nodes dependent on the clusters. Considering clusters r and s, the total weight from cluster r to s can be written as $m_{t,rs} = \sum_{ij} A_{t,ij}\delta(\sigma_{t,i}, r)\delta(\sigma_{t,j}, s)$. Using this as the weight of the link between node r and s in the new network, the expected value of this link can then be written as:

$$p_{t,rs} = \frac{k_{t,r}^{out} k_{t,s}^{in}}{m_t} \tag{5}$$

$$= \sum_{ij} A_{t,ij}\delta(\sigma_{t,i}, r) \sum_{ij} A_{t,ij}\delta(\sigma_{t,j}, s)\frac{1}{m_t}, \tag{6}$$

which is exactly the expected value of the links between clusters r and s in the old network. Hence, joining nodes r and s in the new network corresponds to joining clusters r and s in the old network. Doing so for all type of links then gives us a correct new network, upon which we can iteratively apply the method described above. We stop the procedure if we can no longer increase modularity.

We find that IGO clusters tend to be reasonably stable over time. Throughout the period under examination, the number of distinct IGO clusters varies between 3 and 4, with the higher number of clusters being more common towards the end of the period—presumably as a result of the increase in the number of states in the international system. There is, however, significant variation in the extent to which states switch between different clusters. Some pairs of states—e.g., France and Spain, or Colombia and Venezuela—have shared membership in the same IGO cluster throughout the entire period. Indeed, their experience turns out to be fairly typical: of the pairs of states that belonged to the same IGO cluster in 1965, we find that 55% of them still shared membership in the same cluster by 2000. At the same time, many pairs of states (e.g., the United States and Syria, or the United Kingdom and Afghanistan) have never belonged to the same cluster. However, some pairs of states—presumably those at the borders of the clusters—do not follow this trend. For instance, Canada and Thailand experienced a total of 11 transitions in and and out of a common cluster between 1960 and 2000 period. Other examples of dyads that show a high degree of turnover in this respect include South Africa-South Korea and Indonesia-Cambodia.

As noted above, multiple algorithms have been proposed for maximizing modularity. Some algorithms may be more suitable for a given network than others, i.e., some may perform better at maximizing modularity. Because the purpose of these algorithms is to identify the network partition that maximizes modularity, if different algorithms identify different such partitions, one should choose the result with the largest modularity. We have used the Louvain algorithm because, for our data, it detected partitions with larger levels of modularity than other algorithms. For each year, Figure 1 provides the maximum modularity value generated by the Louvain algorithm and compares this value with those produced by the leading eigenvector (Newman, 2006), fast and greedy (Clauset, Newman and Moore, 2004), walktrap (Pons and Latapy, 2005), spinglass (Reichardt and Bornholdt, 2006), and edge betweenness (Newman and Girvan, 2004) algorithms . For each year, the Louvain method performs better than all the other algorithms at maximizing modularity.

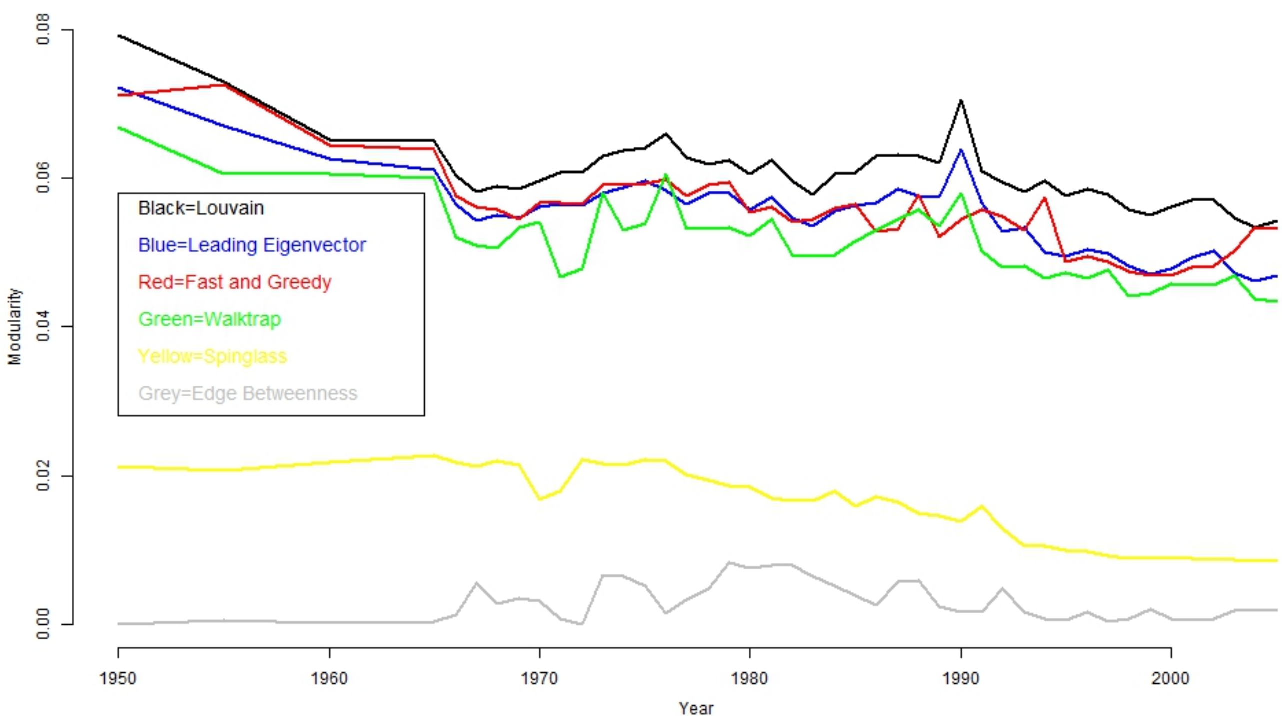

Figure 1: Comparison of Modularity Maximization by Competing Algorithms

2 Maps of IGO Clusters with Regional IGOs Excluded

Figure 2 shows the IGO clusters in 1965, 1980, and 2000 based on an IGO network that excludes regional IGOs. As we might expect, there is significantly less geographic clustering when we exclude regional IGOs from the analysis. Overall, the most powerful and economically developed states consistently join similar IGOs and form a single IGO cluster throughout the time period. As of 1965, this excludes many less-developed African, Asian and Latin American states. By 2000, however, more states have become integrated into the main IGO cluster, including China and much of Latin America. Nonetheless, much of Africa continues to be in a different IGO cluster, a particularly striking result given that the African IGOs are not included in this analysis.

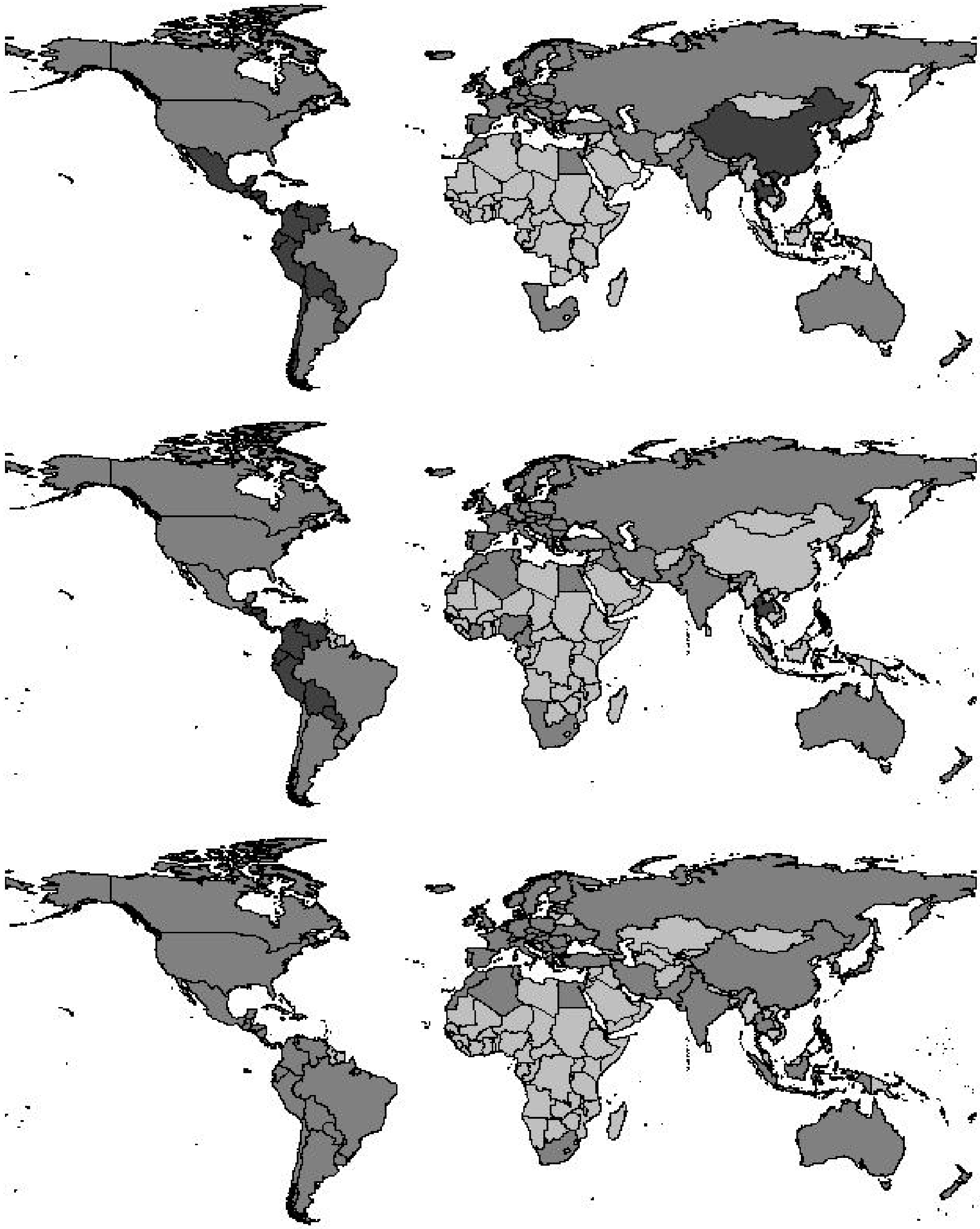

Figure 2: IGO clusters in (from top to bottom) 1965, 1980 and 2000 with regional IGOs excluded.

2.1 Maps of IGO Clusters with Minimalist IGOs Excluded

Figure 3 shows the IGO clusters in 1965, 1980, and 2000 based on an IGO network that excludes minimalist IGOs. There is a significant amount of geographic clustering in these results, arguably more so than in the results based on the full IGO network. By 2000, there are distinct IGO clusters in Latin America, Africa, and much of Asia. The fourth IGO cluster in 2000 includes many "Western" states, Japan and parts of Central Asia. The result indicates that, with respect to IGOs with meaningful structures, there is both a consistent regionalism in IGO membership behavior and a clear distinction between the global North and South.

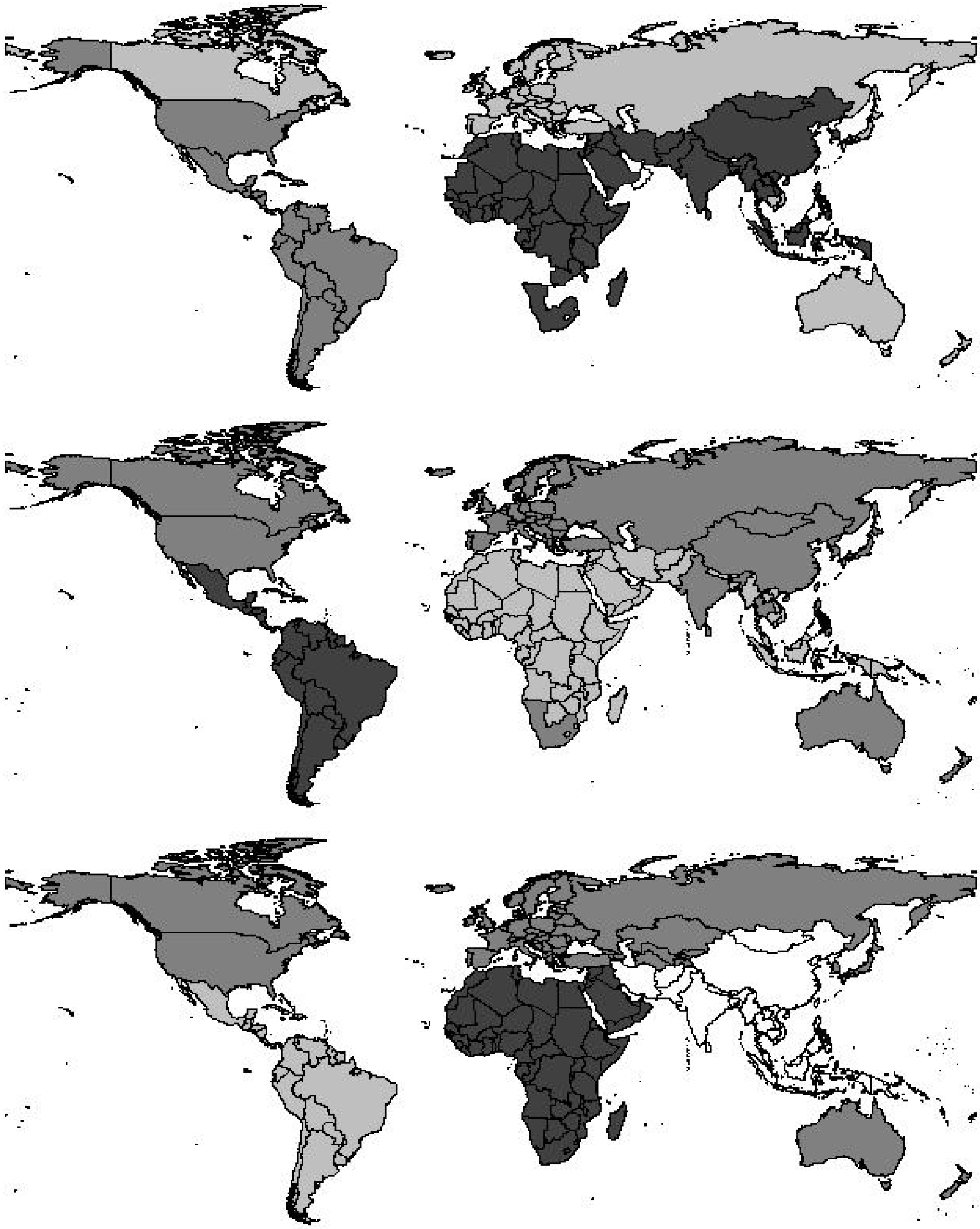

Figure 3: IGO clusters in (from top to bottom) 1965, 1980 and 2000 with minimalist IGOs excluded.

3 Baseline Models

Table 1: Conflict Models - Baseline

	(1) All IGOs	(2) Structured IGOs	(3) Non-Regional IGOs
Joint IGO Membership	0.011*	0.017	0.018*
	(0.005)	(0.010)	(0.007)
Embassy	0.615***	0.593***	0.605***
	(0.156)	(0.157)	(0.156)
Diplomatic Mission	0.345	0.376*	0.319
	(0.190)	(0.191)	(0.191)
Openness (Low)	0.026	0.028	0.024
	(0.020)	(0.020)	(0.020)
Trade Dependence (Low)	-15.021	-14.445	-15.012
	(8.388)	(8.109)	(8.384)
Polity (Low)	-0.045***	-0.043***	-0.046***
	(0.010)	(0.011)	(0.010)
Contiguity	2.579***	2.608***	2.591***
	(0.248)	(0.246)	(0.245)
Distance	-0.142***	-0.139***	-0.144***
	(0.028)	(0.028)	(0.027)
Major Power	1.298***	1.321***	1.276***
	(0.194)	(0.198)	(0.193)
Alliance	-0.242	-0.225	-0.192
	(0.137)	(0.132)	(0.132)
Relative Military Power	-0.124**	-0.129**	-0.121**
	(0.042)	(0.042)	(0.043)
Time	-0.050***	-0.049***	-0.050***
	(0.011)	(0.011)	(0.011)
$Time^2$	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)
$Time^3$	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-7.847***	-7.902***	-7.934***
	(0.311)	(0.359)	(0.312)
Observations	430,477	430,477	430,477
χ^2	2983***	3007***	2957***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Robustness Tests

This section sets forth the results of several robustness tests. Table 2 reports the results of models that add the Maxflow measure. Table 3 reports the results of models that include only politically relevant dyads. Table 4 reports the results of models that include dyads with ongoing MIDs. Table 5 reports the results of models that include regional dummies. These variables are coded "1" if both dyad members belong to the applicable region, and "0" otherwise.[1] Table 6 reports the results of a model based on an IGO network that excludes security IGOs. Table 7 reports the results of a Temporal Exponential Random Graph Model (TERGM). The model includes a GWESP (geometrically weighted edgewise shared partners) statistic, which captures whether there is an inherent tendency to form clusters of states while controlling for determinants of cluster existence in the network. This allows us to estimate the relationship between Same IGO Cluster and hostile MID onset while controlling for the general propensity toward clustering in the network.

[1]The dyadic nature of this coding does not result in a dummy variable trip, as a monadic coding would. Most dyads are coded "0" for all of the regional variables because most dyads do not belong the same region.

Table 2: Conflict Models - Maxflow Control

	(1) All IGOs	(2) Structured IGOs	(3) Non-Regional IGOs
Same IGO Cluster	-0.402***	-0.362***	-0.242*
	(0.121)	(0.105)	(0.111)
Joint IGO Membership	0.003	0.006	-0.012
	(0.007)	(0.011)	(0.015)
Maxflow	0.014*	0.013	0.022**
	(0.006)	(0.007)	(0.007)
Embassy	0.528***	0.502**	0.515**
	(0.157)	(0.158)	(0.162)
Diplomatic Mission	0.292	0.349	0.263
	(0.200)	(0.199)	(0.207)
Openness (Low)	0.025	0.025	0.023
	(0.021)	(0.020)	(0.020)
Trade Dependence (Low)	-12.914	-13.012	-12.445
	(7.719)	(7.327)	(7.550)
Polity (Low)	-0.047***	-0.044***	-0.049***
	(0.010)	(0.010)	(0.009)
Contiguity	2.751***	2.748***	2.729***
	(0.256)	(0.254)	(0.249)
Distance	-0.131***	-0.131***	-0.127***
	(0.028)	(0.027)	(0.027)
Major Power	1.255***	1.242***	1.296***
	(0.195)	(0.196)	(0.197)
Alliance	-0.043	-0.020	-0.119
	(0.147)	(0.138)	(0.133)
Relative Military Power	-0.111*	-0.110*	-0.124**
	(0.044)	(0.044)	(0.045)
Time	-0.059***	-0.056***	-0.058***
	(0.011)	(0.011)	(0.011)
Time^2	0.005***	0.005***	0.006***
	(0.000)	(0.000)	(0.000)
Time^3	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-7.914***	-7.897***	-7.922***
	(0.315)	(0.335)	(0.320)
Observations	398,191	398,191	398,191
χ^2	3373***	3174***	3226***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Conflict Models - Politically Relevant Dyads

	(1) All IGOs	(2) Structured IGOs	(3) Non-Regional IGOs
Same IGO Cluster	-0.580***	-0.387**	-0.363**
	(0.129)	(0.127)	(0.119)
Joint IGO Membership	0.008	0.009	0.013
	(0.005)	(0.009)	(0.007)
Embassy	0.480**	0.473**	0.454**
	(0.164)	(0.169)	(0.168)
Diplomatic Mission	0.037	0.071	0.012
	(0.195)	(0.200)	(0.199)
Openness (Low)	0.036**	0.037**	0.032*
	(0.014)	(0.014)	(0.014)
Trade Dependence (Low)	-10.659	-11.543	-11.031
	(6.122)	(6.108)	(6.259)
Polity (Low)	-0.032***	-0.031**	-0.036***
	(0.010)	(0.010)	(0.010)
Contiguity	1.984***	1.962***	1.948***
	(0.328)	(0.323)	(0.324)
Distance	0.001	-0.002	0.005
	(0.039)	(0.037)	(0.039)
Major Power	0.047	0.060	0.095
	(0.226)	(0.230)	(0.226)
Alliance	-0.162	-0.200	-0.252*
	(0.136)	(0.129)	(0.128)
Relative Military Power	-0.183***	-0.167***	-0.180***
	(0.043)	(0.043)	(0.047)
Time	-0.056***	-0.053***	-0.053***
	(0.013)	(0.013)	(0.013)
Time^2	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)
Time^3	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-5.972***	-6.069***	-6.177***
	(0.367)	(0.410)	(0.393)
Observations	37,647	37,647	37,647
χ^2	1034***	1056***	1032***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Conflict Models Including Ongoing MIDs

	(1) All IGOs	(2) Structured IGOs	(3) Non-Regional IGOs
Same IGO Cluster	-0.595***	-0.435***	-0.503***
	(0.116)	(0.109)	(0.105)
Joint IGO Membership	0.018**	0.025*	0.025***
	(0.006)	(0.010)	(0.008)
Embassy	0.583***	0.551***	0.562***
	(0.162)	(0.161)	(0.163)
Diplomatic Mission	0.204	0.266	0.157
	(0.199)	(0.201)	(0.200)
Openness (Low)	0.025	0.029	0.022
	(0.024)	(0.023)	(0.023)
Trade Dependence (Low)	-17.650	-18.295	-16.726
	(9.739)	(9.571)	(9.401)
Polity (Low)	-0.050***	-0.047***	-0.052***
	(0.010)	(0.011)	(0.010)
Contiguity	2.636***	2.674***	2.629***
	(0.268)	(0.266)	(0.260)
Distance	-0.154***	-0.151***	-0.151***
	(0.030)	(0.030)	(0.029)
Major Power	1.376***	1.390***	1.412***
	(0.217)	(0.222)	(0.216)
Alliance	-0.123	-0.150	-0.164
	(0.143)	(0.134)	(0.133)
Relative Military Power	-0.160***	-0.154***	-0.176***
	(0.043)	(0.043)	(0.045)
Time	-0.055***	-0.051***	-0.053***
	(0.011)	(0.011)	(0.011)
Time^2	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)
Time^3	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-7.555***	-7.679***	-7.634***
	(0.325)	(0.368)	(0.341)
Observations	431,044	431,044	431,044
χ^2	3104***	3080***	3061***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Conflict Models Including Regional Dummies

	(1) All IGOs	(2) Structured IGOs	(3) Non-Regional IGOs
Same IGO Cluster	-0.446***	-0.310*	-0.434***
	(0.135)	(0.133)	(0.117)
Joint IGO Membership	0.017**	0.019	0.029***
	(0.005)	(0.010)	(0.008)
Embassy	0.545***	0.549***	0.507***
	(0.155)	(0.154)	(0.152)
Diplomatic Mission	0.350	0.397*	0.287
	(0.184)	(0.185)	(0.187)
Openness (Low)	0.016	0.019	0.008
	(0.023)	(0.022)	(0.022)
Trade Dependence (Low)	-9.205	-9.534	-8.356
	(6.399)	(6.032)	(5.608)
Polity (Low)	-0.026*	-0.022*	-0.028**
	(0.010)	(0.011)	(0.010)
Contiguity	2.373***	2.387***	2.382***
	(0.285)	(0.281)	(0.278)
Distance	-0.140***	-0.138***	-0.137***
	(0.027)	(0.027)	(0.027)
Major Power	1.634***	1.638***	1.695***
	(0.206)	(0.213)	(0.205)
Alliance	-0.412**	-0.429**	-0.446**
	(0.160)	(0.160)	(0.151)
Relative Military Power	-0.159***	-0.162***	-0.173***
	(0.043)	(0.043)	(0.044)
Europe	-0.371	-0.292	-0.494
	(0.323)	(0.318)	(0.303)
Middle East	0.979***	1.066***	0.930***
	(0.258)	(0.265)	(0.255)
Africa	0.685*	0.640*	0.719**
	(0.268)	(0.275)	(0.250)
Asia	0.551*	0.605*	0.591*
	(0.256)	(0.263)	(0.248)
America	0.710*	0.757*	0.766*
	(0.309)	(0.324)	(0.299)
Time	-0.053***	-0.049***	-0.053***
	(0.011)	(0.011)	(0.011)
Time^2	0.005***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)
Time^3	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Constant	-7.765***	-7.781***	-7.908***
	(0.300)	(0.329)	(0.312)
Observations	430,477	430,477	430,477
χ^2	3978***	3952***	3973***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Conflict Model Excluding Security IGOs

	(1)
Same IGO Cluster	-0.529***
	(0.117)
Joint IGO Membership	0.015**
	(0.005)
Embassy	0.621***
	(0.157)
Diplomatic Mission	0.315
	(0.188)
Openness (Low)	0.022
	(0.021)
Trade Dependence (Low)	-14.400
	(8.352)
Polity (Low)	-0.044***
	(0.010)
Contiguity	2.677***
	(0.256)
Distance	-0.150***
	(0.028)
Major Power	1.297***
	(0.192)
Alliance	-0.156
	(0.141)
Relative Military Power	-0.142***
	(0.042)
Time	-0.054***
	(0.011)
$Time^2$	0.006***
	(0.000)
$Time^3$	-0.000***
	(0.000)
Constant	-7.631***
	(0.315)
Observations	430,477
χ^2	3131***

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Conflict - TERGM

	(1) All IGOs
Same IGO Cluster	-5.568***
	(0.060)
Joint IGO Membership	0.036***
	(0.003)
Maxflow	-0.001
	(0.003)
Openness (Low)	0.139***
	(0.005)
Trade Dependence (Low)	-14.950***
	(3.078)
Polity (Low)	-0.121***
	(0.005)
Distance	-0.477***
	(0.007)
Relative Military Power	0.261***
	(0.015)
GWESP	0.594***
	(0.044)
AIC	129354

Robust standard errors in parentheses.
Coefficients for Embassy, Diplomatic Mission, Contiguity, Major Power, and Alliances could not be estimated because of singularities in the data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Models of Preferences

To further test the importance of IGO clusters, we replicate the analysis by Bearce and Bondanella (2007) of the relationship between structured IGO membership and states' interests. We replicate their analysis while adding a measure of joint membership in IGO clusters. As our main measure of interest similarity, we follow Bearce and Bondanella (2007) by using the Affinity scores developed by Gartzke (1998). This measure captures the similarity of dyadic voting decisions in the United Nations General Assembly (UNGA). The Affinity scores are coded from 1 to -1, with similarly voting dyads receiving positive scores. Following Bearce and Bondanella (2007), we test the robustness of our results by also estimating a model that uses the similarity of alliance portfolios as the dependent variable (Altfeld and Bueno de Mesquita, 1979).

Key Independent Variable. Our key independent variable is a binary indicator of whether both members of the dyad are members of the same IGO cluster. Following Bearce and Bondanella (2007), we focus here only on structured and interventionist IGOs—i.e, those that have more substantial organizational structure and greater authority to intervene in the affairs of their member-states. As Bearce and Bondanella (2007) argue, there is little reason to expect the social interaction to have effects in minimalist IGOs, so they are excluded from the analysis. Following Bearce and Bondanella (2007), we lag this variable by 5 years because states' interests are likely to converge slowly.

Control Variables. To ensure comparability, we control for the same variables used by Bearce and Bondanella (2007). First, we include a measure of joint structured IGO memberships, also lagged by 5 years (Joint Structured IGO Membership). In order to distinguish the effects of IGOs from the effects of other contacts between states, we control for other state-to-state contacts by using a measure of the lower numbers of diplomatic missions in the dyad-year (Extra-IGO Contact), as coded by Bearce and Bondanella (2007).

Both UNGA voting decisions and the structure of the IGO network may be influenced by regime type, so we include a measure of the absolute difference between the dyad's Polity IV scores (Domestic Political Difference) (Marshall and Jaggers, 2009). To address the effects of economic interactions, we include a measure of the lower of the dyad's two bilateral trade to GDP ratios, calculated as is often done in the trade-and-conflict literature (Trade Dependence Low)(Oneal and Russett, 1997).[2] We address the effects of economic development by including the ratio of the natural log of the richer dyad member's GDP per capita to the natural log of the poorer dyad member's GDP per capita (Relative Economic Development).

We include a measure of the ratio of the natural log of the states' GDP (Relative Economic Size) as well as the natural log of the ratio of the dyad members' military power, as provided by the Correlates of War (COW) capabilities index (Relative Military Power). Allied states may be more likely to join IGOs and more likely to have similar preferences, so we include a dichotomous variable (Alliance) coded "1" for dyads that have concluded an entente, neutrality pact, or defense pact based on the COW Alliance Data Set (Small and Singer, 1990). UNGA voting patterns have changed significantly since the end of the Cold War, so we include an indicator for all dyad-years since 1991 (Cold War). We include a measure of the logged distance between the dyad members' national capitals (Distance). Dyads with a former colonial relationship may have similar interests based on this history, so we control for this using an indicator variable (Colonial Relationship). To address temporal dependence, we include a lagged dependent variable.

We estimate our models using ordinary least squares (OLS) with robust standard errors clustered by dyad. Our results are reported in Table 8. The first model includes all dyads, while the next several models follow Bearce and Bondanella (2007) by testing our hypothesis within several regional sub-samples. These present more conservative tests of the hypothesis

[2]We use the trade and GDP data provided by Gleditsch (2002).

because of the much smaller sample sizes. These tests also allow us to analyze whether these effects occur in different regions or whether they may be limited to Europe, the region the literature has examined in more detail. In these models, we do not include Colonial Relationship because of the infrequency of within-region colonialism. Finally, we include a model that uses alliance portfolio similarity as the dependent variable. In this model, the dyadic indicator Alliance is excluded because it is reflected in the dependent variable. The data cover the years 1960 to 1991.

Table 8 reports the results of our interest convergence models. We find that the interests of states that belong to the same IGO cluster are significantly more likely to converge. The first model indicates that this is the case with respect to similarity of UNGA voting. We know there is a significant amount of regionalism in IGO joining, so also test whether the effect is driven by this regionalism and whether the effect is consistent within various geographic regions. Our results are consistent in each major region. When we change our measure of interests from UNGA voting to alliance portfolios, we continue to find that the interests of joint members of IGO clusters are significantly more likely to converge. These results are independent of the number of IGOs to which the dyad jointly belongs.

The number of joint IGO memberships in the dyad—the key treatment variable in Bearce and Bondanella (2007)—is significant and positive in several of our models. This indicates that there is an additive interest convergence effect of structured IGO membership regardless of whether a dyad belongs to the same IGO cluster. In other words, while IGOs have indirect effects through the network, they can also have direct effects consistent with the arguments put forward by Bearce and Bondanella (2007) and others. Yet the substantive effect of Same IGO Cluster is consistently much larger than that of Joint Structured IGO Membership. The substantive effect of belonging to the same IGO cluster is equivalent to the effect of belonging to many of the same IGOs; in Model 1, for example, the effect of joint cluster membership is equivalent to direct dyadic joint membership in 17 IGOs. The network effects are not only statistically significant but substantively much more important than individual dyadic effects.

Table 8: Models of Interest Convergence

	Affinity Scores						Alliance Portfolio
	All Dyads	Europe	Asia	America	Africa	Middle East	All Dyads
Same IGO Cluster	0.017***	0.037**	0.010***	0.017***	0.062***	0.038***	0.008***
	(0.001)	(0.012)	(0.003)	(0.005)	(0.010)	(0.010)	(0.000)
Joint Structured	0.001***	0.002**	0.000	-0.001*	0.002***	-0.000	-0.000***
IGO Membership	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extra-IGO Contact	-0.000***	-0.000*	-0.000	-0.000***	0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Domestic Political Diff.	-0.001***	-0.004***	-0.000	-0.000	-0.000*	-0.000	0.000***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade Dependence (Low)	0.082	-0.050	0.064	-0.471**	-0.214	0.885*	0.054**
	(0.051)	(0.158)	(0.034)	(0.150)	(0.295)	(0.424)	(0.019)
Relative Econ. Dev.	-0.004***	0.032***	-0.011***	-0.022***	-0.010***	-0.003	-0.001***
	(0.000)	(0.008)	(0.002)	(0.004)	(0.002)	(0.002)	(0.000)
Relative Economic Size	-0.007***	-0.005**	-0.004***	-0.003**	-0.005***	-0.000	-0.001***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Relative Military Power	0.001	-0.003	0.003**	-0.005***	0.004**	0.004*	0.000
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)
Alliance	-0.001	0.020***	-0.009	-0.009**	-0.007***	-0.002	
	(0.001)	(0.005)	(0.007)	(0.003)	(0.002)	(0.005)	
Cold War	0.024***	-0.062***	0.012*	0.009**	0.000	0.015***	-0.021***
	(0.001)	(0.008)	(0.005)	(0.003)	(0.001)	(0.003)	(0.001)
Distance	0.000***	-0.000	-0.000***	-0.000	-0.000*	0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Colonial Relationship	-0.044***	.					-0.002
	(0.006)	.					(0.001)
Lagged DV	0.863***	0.772***	0.803***	0.916***	0.772***	0.953***	0.978***
	(0.003)	(0.016)	(0.015)	(0.009)	(0.015)	(0.010)	(0.001)
Constant	0.136***	0.245***	0.211***	0.141***	0.168***	0.004	0.050***
	(0.003)	(0.030)	(0.018)	(0.014)	(0.009)	(0.012)	(0.001)
N	185,553	6,194	5,202	8,850	15,718	2,828	185,553

Robust standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In our main models, we lag Same IGO Cluster to account for the slowness of the interest convergence process. The five-year period is fairly arbitrary, however, so we follow Bearce and Bondanella (2007) in re-estimating the first model in Table 8 using lags ranging from one year to eight years. Figure 4 shows the results from these tests, indicating that our key result is not dependent on the arbitrary choice of lag period.

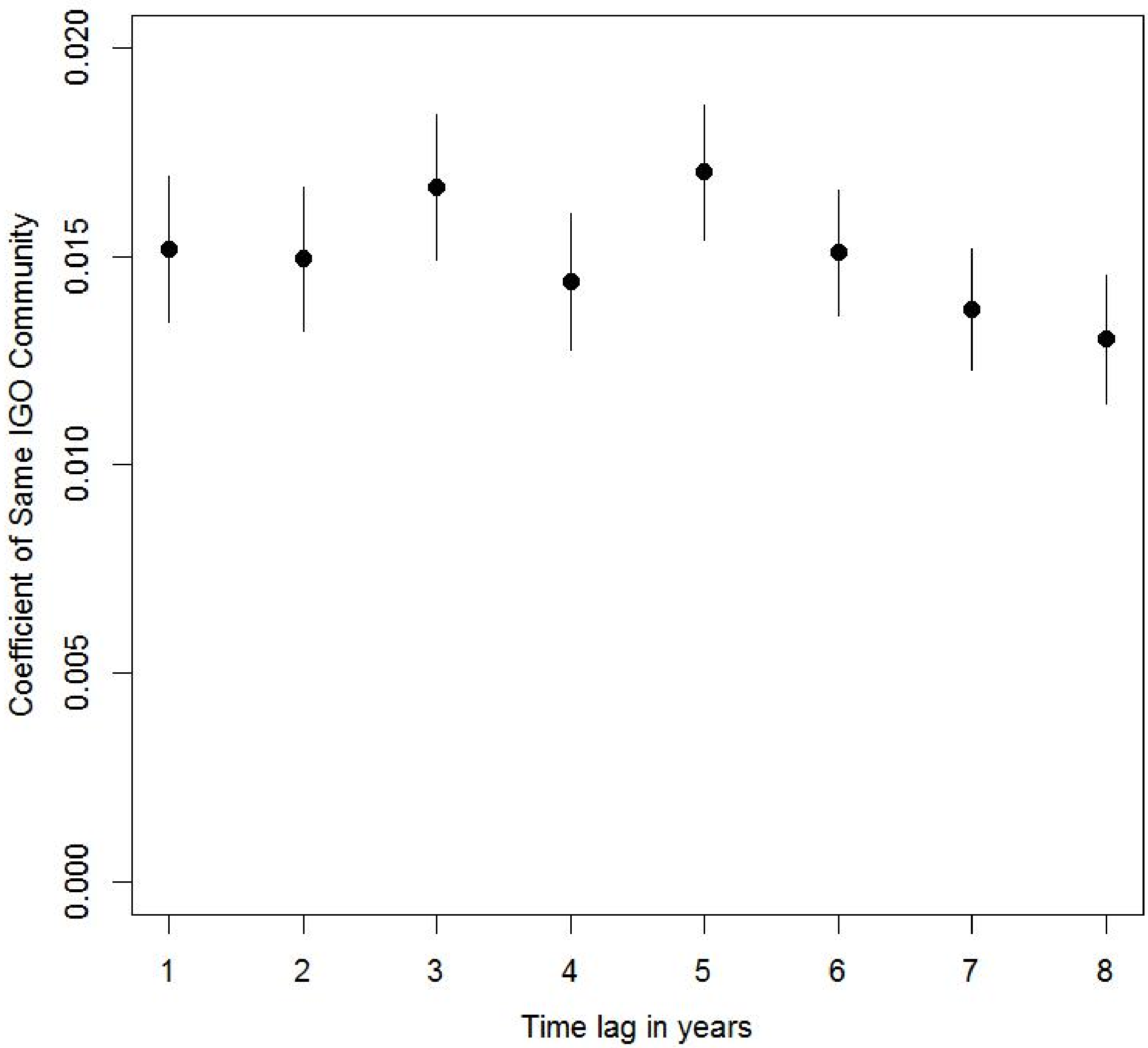

Figure 4: The coefficient of Same IGO Cluster in models of interest convergence using various lags of this variable.

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