Shifting Sands: How Change-Point and Community Detection Can Enrich Our Understanding of International Politics

Abstract (118 words)

When and how do international political arrangements change? International relations scholars have long examined the nature of shifts in international alliance and cooperation networks, often arguing that times of disruption in the international system are the most precarious for peace. In this research note, we rely on innovations in change-point and community detection methods to endogenously examine the timing and nature of shifts in country-to-country relationships through defense cooperative agreements. Using new methodical innovations from network science, we can see how countries move through different communities over time, changing the nature of polarity in the system. This empirical approach can help provide insights into determinants of peace, vulnerabilities in the international system, and potential aggressors in world politics.

Introduction

In many ways, international relations (IR) is the study of shifts in world power (Mansfield 1993; Winecoff 2020), although the study of these changes has been notoriously difficult (Jackson and Nexon 1999, 296).[1] Researchers have long analyzed the distribution of power across poles, often connecting changes in polarity or shifts in power dynamics to times of conflict and war (Lee 2006; Rasler and Thompson 2010; Debs and Monteiro 2014; Krainin 2017). While much work in this area looked at shifts in power between dyads or across poles, more recently, scholars have examined how states form distinct clusters or communities of increased interactions (Beardsley et al. 2020; Olivella et al. 2022) and how the dynamics of these clusters can change over time (Greenhill and Lupu 2017). In both the traditional studies of polarity and more recent studies of communities or clusters, scholars acknowledge that certain countries shift their position in the system. However, despite all the attention to structures or centers of power, IR has focused less on *when* and *how* shifts occur. Why does a particular country decide to shift its position in world politics? And how do we even know that a systemic shift in world power has occurred?

This research note illustrates the potential of a new network approach to the study of power distributions and shifting structures in world politics. Drawing on previous advances, we contend that the world system is comprised of distinct and evolving *communities*, where a community is defined as an endogenous group of countries that are more tightly connected to each other than the rest of the network (Mucha et al. 2010, 876; Maoz 2017). Shifts in the community structure within the overall network occur at different *change-points* over time, an idea and eventual empirical method that we import from cross-disciplinary network science research (Zhang and Cao 2017; Beaulieu and Killicks 2018). Examining change-points in the overall community structure allows us to see structural shifts as "routine, almost normal, ongoing" processes, letting us move past prior studies of power distribution that focused primarily on the distinction between bipolarity, multipolarity, and unipolarity and were often preoccupied with the end of the Cold War (Rasler and Thomson 2010, 6).

Once we understand the world system as a structure of communities where there are punctuated change-points over time, we can observe which countries within the system are responsible for the shift: those countries that change communities between change-points. To our knowledge, despite our preoccupation with power shifts, no existing work has focused specifically on the "shifters" that drive the changing power structures we observe over time. Our core research question is thus: what factors increase the likelihood that a country will shift communities across change-points? Using a predictive modeling approach, we identify the push and pull factors that explain over 85% of the countries that shift communities across change-points. Our research thus provides a new research avenue to a perennial question in IR, combining country-, community-, and system-levels of analysis to better understand how shifts occur in world politics.

[1] We define power as the ability to get an actor to do something they would otherwise not do (Dahl 1957). In our examination, we are looking at how defense agreements provide military power across countries. The distribution of these dyadic relationships can create fragmentation or polarity in the overall system of world power.

Through this research note, we hope to illustrate the usefulness of endogenous community detection and change-point analysis to IR. The method has many potential applications and could help us understand how communities of countries develop and shift in their economic relations, international treaty behavior, or alliances, for example. Further, communities and change-points could be useful explanatory variables in studies of development or systemic democratic peace. A short research note does not allow us to fully develop all of these possible applications of the method. Instead, in what follows, we present our network-based conceptualization of communities and change-points and outline and validate the methodology we adopt from network science.

A Network- and Community-Based Argument for Conceptualizing Systemic Change in International Relations

Our theory is based on a simple premise that is consistent with recent literature in IR: discussions of polarity in international relations can be better conceptualized as discussions of *communities* of countries (Greenhill and Lupu 2017; Beardsley et al. 2020; Edgerton 2021). In network science terms, a community is a group of nodes (or subjects of analysis, like countries) that are more closely tied to each other than to others in the overall network (or system) (Mucha et al. 2010). Importantly, for network scientists, communities are something that can be detected and are evolving or emerging over time. We do not have to begin our analysis with pre-conceived ideas about the nature of polarity; there is no need to pigeonhole the world into either unipolarity, bipolarity, or multipolarity, as was often done in earlier studies of the international system (Waltz 1979). Instead, the number of communities and the overall community structure can develop and change over time.

We assume that countries are likely attracted to certain communities because of their shared or complementary characteristics with other countries in these communities (Adler and Barnett 1998; Maoz 2010). Communities may have similar ideas about trade and security, for example, or have a long legacy of relations within a geographic sphere. Communities may also be built around complementary interests; for example, countries may seek out partners and relationships that build their weapons capacity or provide new markets (Kinne and Bunte 2020). Communities provide a space or avenue for increased socialization, building shared understandings and characteristics that can strengthen the community structure over time (Maoz 2017; Edgerton 2021).

Some democratic and Kantian peace scholarship dovetails nicely with community ideas and shows the potential value of using community-based measures in models of conflict. For example, Russett, Oneal, and Davis (1998) theorize that a community institutional structure helps to build a "mutual identity" between countries, limiting violent disputes (446-447). Similarly, Mitchell (2002) draws on community ideas from Russett (1993) and Risse-Kappen (1995) and norm emergence ideas from Finnemore and Sikkink (1998) in building an argument for how dispute-settlement behavior may permeate outside of democratic communities and affect the system as a whole. This research sees community structures not as a simmering conflict between poles, but as structures that could induce norm socialization and peace. Nonetheless, recent IR literature still acknowledges that communities of countries are hierarchical. The power

differences between and across communities can both reinforce and complicate the nature of community socialization (MacDonald 2018; Beardsley et al. 2020).

Despite long-term relationships and socialization practices that may reinforce certain community structures, change is inevitable in international politics (Nexon 2009; Winecoff 2020). At times, changes at both the domestic and international levels can upset an international system that was previously stable. As Rasler and Thompson (2010) summarize, much international relations scholarship often assumed that systemic shifts were somewhat rare and problematic for peace, despite more recent theorizing that systemic shifts in the international system may be more routine in nature (6).[2] Countries are constantly revising their relationships to each other. Sometimes, the totality of these changing relationships will be large enough to equate to shifts in the underlying structure.

How do we know when country-level changes are broad enough to create a systemic shift in the underlying community structure? Network science and statistics have recently established new methods for detecting *change-points* in the community structure within a network over time (Zhang and Cao 2017; Beaulieu and Killick 2018). To our knowledge, while recent international relations scholarship has examined communities of countries over time, the focus has been predominately on communities as identified in each time snapshot as static networks (Greenhill and Lupu 2017) or associated with temporal change of every sample (node) (Beardsley et al. 2020), instead of the whole community structure. Instead, new network science methods allow us to identify particularly important, endogenously determined change-points in the nature of the community system. At these change-points, we can conclude that the community structure is fundamentally different than it was in a previous span of time.

An Illustration of Communities and Change-Points

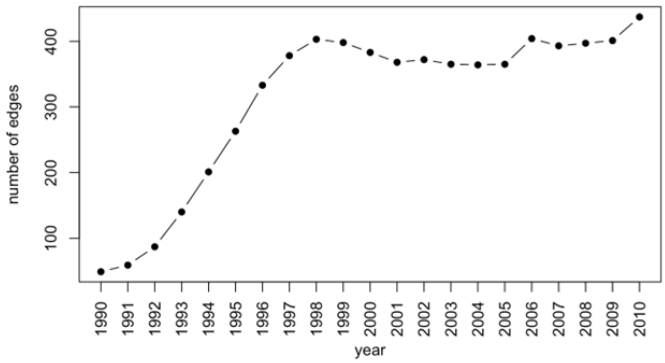
Methods and Procedure

Let us illustrate our key concepts thus far. We use Kinne (2020)'s data on defense cooperative agreements (DCAs) as our network connection between countries. While there are many potential network connections that could be useful avenues for examining communities or polarity generally, DCAs are a particularly useful network connection to focus on in that DCAs "facilitate routine interactions that comprise day-to-day defense cooperation" (Kinne 2020, 730). Unlike alliance connections, which often concentrate on what could occur between armed actors in the rare instance of conflict, the focus on DCAs is on routine cooperation between countries. As Kinne (2020) discusses, most DCA partnerships are between countries that lack formal alliances; despite this, agreements are associated with a reduced likelihood of militarized disputes and increased bilateral arms trade. Consistent with our conceptualization of communities, Kinne and Bunte (2020) contend that "governments use DCAs to build clubs of like-minded defense collaborators or 'security communities'" (1067).

[2] Greenhill and Lupu (2017) recently examined changes in polarity or fragmentation in the IGO network, finding that shifts are frequent, and fragmentation generally decreases over time.

Kinne (2020)'s DCA data is available for twenty-one years, between 1990 to 2010. A tie between two countries is recorded whenever there is a DCA that has been signed between two countries in the current year or in the prior four years. Figure 1 provides an overview of the number of ties in the DCA network over time.

Figure 1: Defense Cooperative Agreements (DCAs): Numbers of Network Ties Over Time



To detect the change-point when the community structure of DCA network changes over time, we propose a time-varying modularity change point detection method (TMCPD). Before we present the details of TMCPD, we herein introduce some notations. Let t_1 represent the year 1990, and t_{21} represent the year 2010. Let $G(t_k)$ denote the kth DCA network, $k = 1, \dots, 21$. Let $A(t_k)$ denote the adjacency matrix of $G(t_k)$, where $A_{ij}(t_k) = 1$ if there is a tie between country i and country j at time t_k, and $A_{ij}(t_k) = 0$ otherwise. Let $\mathcal{G}_{s_2}^{s_1} = \{G(t_{s_1}), G(t_{s_1+1}) \dots, G(t_{s_2})\}$ be a set of time-varying networks starting from time t_{s_1} to t_{s_2}, where $s_1, s_2 \in \{1, \dots, 21\}$ and $s_1 \leq s_2$.

TMCPD works in the following procedure:

Step 1: We let $s_1 = 1$, and vary $s_2 = 1, \dots, 21$, and construct $\mathcal{G}_1^1, \dots, \mathcal{G}_{21}^1$. For each $\mathcal{G}_k^1$, $k = 1, \dots, 21$, we employ a time-varying network modularity maximization method (Zhao and Cao 2017), to find common modules in $\mathcal{G}_k^1$. In particular, Zhao and Cao (2017) proposed a modularity function for the time-varying networks across consecutive snapshots $t_{s_1}, \dots, t_{s_2}$, i.e.

$$M_{s_2}^{s_1} = \frac{\sum_{l=s_1}^{s_2} m(t_l)\, M(t_l)}{\sum_{l=s_1}^{s_2} m(t_l)},$$

where $m(t_l)$ is the total number of edges in network $G(t_l)$ and $M(t_l)$ denotes the modularity of the network $G(t_l)$ according to the definition of modularity introduced by Newman and Girvan (2004). The algorithm iteratively builds new communities until the modularity $M_{s_2}^{s_1}$ reaches its maximum, i.e. $\hat{M}_{s_2}^{s_1}$. Thus, the algorithm automatically provides us with a rationale for the

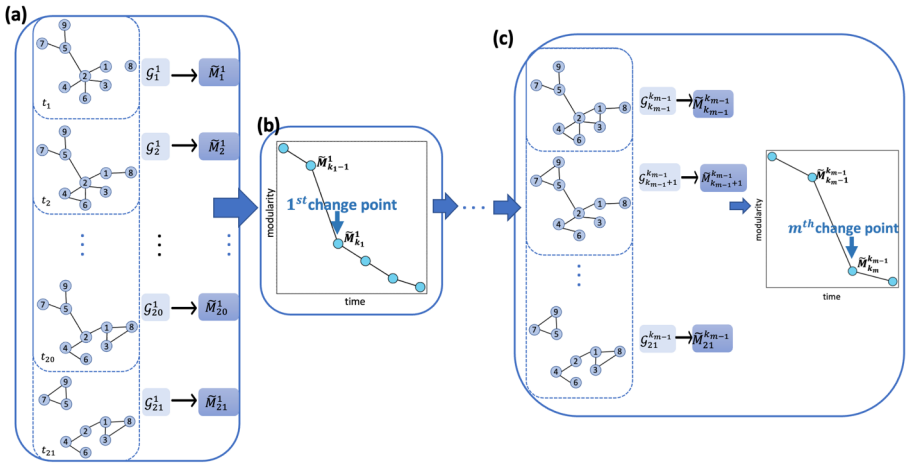
number of communities identified and the maximized modularity $\tilde{M}_{s_2}^{s_1}$ can represent the common community structure in the network series $\mathcal{G}_k^1$. In this step, we get the maximized modularity values $\tilde{M}_1^1, \tilde{M}_2^1, \ldots, \tilde{M}_{21}^1$.

Step 2: We apply the change-point detection method proposed by Beaulieu and Killick (2018) to detect the first change point of the series $\{\tilde{M}_1^1, \tilde{M}_2^1, \ldots, \tilde{M}_{21}^1\}$, denoted as $\tilde{M}_{k_1}^1$. Thus t_{k_1} is the first change point of the community structure over time.

Based on k_1, we then repeat step 1 and 2, except for that we let $s_1 = k_1$, vary $s_2 = k_1, \ldots, 21$, and have $\mathcal{G}_{k_1}^{k_1}, \ldots, \mathcal{G}_{21}^{k_1}$. In a similar way, we get the second change point at time t_{k_2}. This procedure is iteratively conducted until a stopping rule is satisfied, as we show below in Figure 2. Let m denotes the mth iteration, k_m is the mth chang point we detected. If no change point is detected in the modularity series $\{\tilde{M}_{k_m}^{k_m}, \tilde{M}_{k_m+1}^{k_m}, \ldots, \tilde{M}_{21}^{k_m}\}$, the iteration stops. We thus have m change points, i.e., $t_{k_1}, \ldots, t_{k_m}$.

Figure 2: Overview of the Workflow of TMCPD

(a) Construct 21 sets of time-varying networks $\{G_s^1, s=1,..,21\}$, Then find common modules for each set of time-varying networks and record the maximized modularity values. (b) Detect the first change point based on the series of modularity. (c) Build sets of time-varying networks starting at the last "change-point" snapshot. Iterate steps (a)&(b) until no change-point. Our source code for TMCPD is available at [redacted – available when/if paper accepted].



Description of the Change-Points and Communities

Using this method, we identify three change-points in the community structure: 1994, 1999, and 2006. These change points divide the overall time period into four stages: Stage 1 (1990-1993), Stage 2 (1994-1998), Stage 3 (1999-2005), and Stage 4 (2006-2010). Figure 3 provides year-by-year plots of the network, with nodes (countries) of the same color belonging to the same community.

Figure 3: Communities and Change-Points, 1990 to 2010

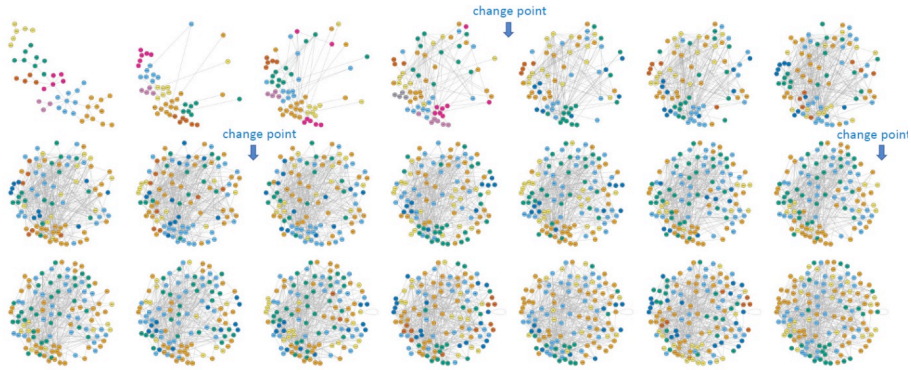
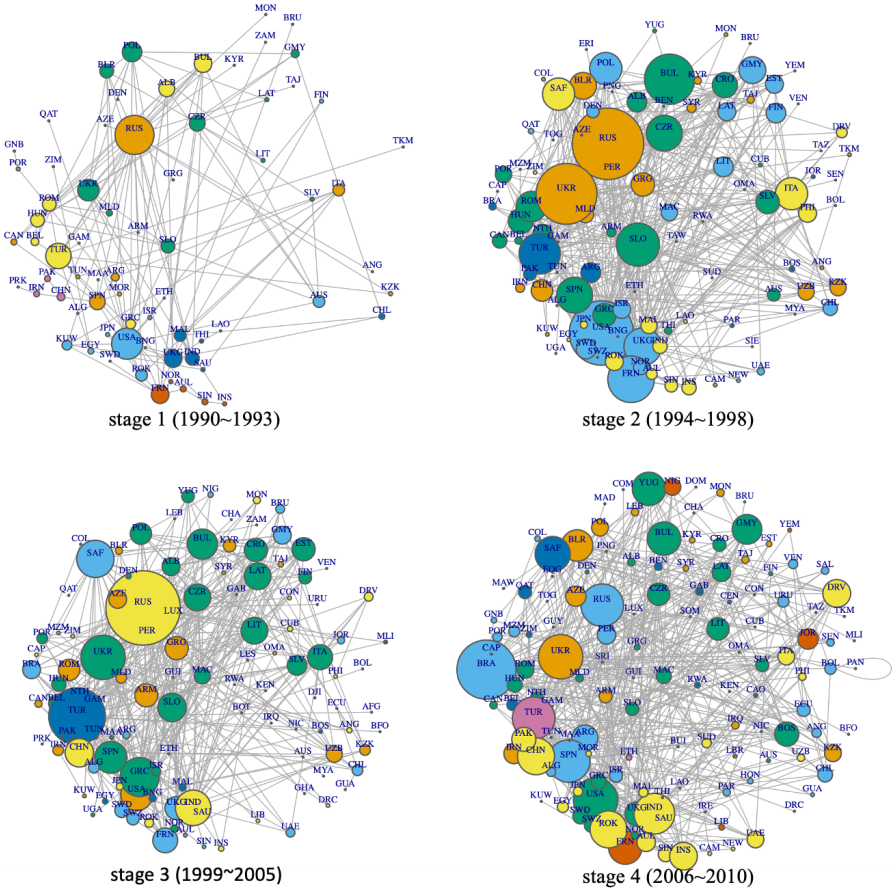


Figure 4 provides similar information but focuses on the communities identified in each stage; Correlates of War three-letter abbreviations are used to identify countries. We do not find any strong changes in the number of communities identified over time, indicating that the nature of fragmentation does not change dramatically in this network, something slightly different than what was found in Greenhill and Lupu (2017)'s investigation of the IGO network over time. Stage 1 has eight identified communities, Stages 2 and 3 have five communities each, and Stage 4 has seven identified communities. A small number of countries are not included in any community due to the nature of the connections at that stage.

Figure 4: Communities Identified at Each Stage



stage 1 (1990~1993) stage 2 (1994~2005)

stage 3 (1999~2005) stage 4 (2006~2010)

A descriptive look at the communities and stages identified using this approach provides some valuable insights for IR. Figure 5 illustrates each country's subgraph centrality in each community at each stage. [3] We use closeness centrality to measure how central a node is all other nodes in one graph. Nodes(countries) with high closeness centrality are more "central" in the sense that they can communicate or influence other nodes more efficiently. Mathematically, the

[3] Our appendix provides descriptive figures to illustrate changes over time and differences in country-level subgroup centrality.

closeness centrality of a node v, i.e. $C(v)$, in a graph is defined as $C(v) = 1/\Sigma_{u \neq v}(d(v,u))$, where $d(v,u)$ is the shortest path distance from node v to node u.

As shown, some communities are dominated by one or two central countries, while other communities are full of countries of more roughly equal centrality. For example, in the eight communities identified in Stage 1 of the sample, from 1990 to 1993, there are three communities that have one country that has much greater centrality than the rest of the countries in their community: Community 1 with Russia, Community 2 with the United States, and Community 3 with Ukraine. Although there is some variation in centrality scores in the remaining communities, there is not as drastic a difference across countries. In line with Beardsley et al. (2020), we could see differences in centrality scores as indicative of different hierarchical patterns within each community. When hierarchical differences are more pronounced, we could expect less conflict in the community, as pacifying socialization processes within the community could be reinforced by power differences.

Figure 5: Communities and Country-Level Subgroup Centrality Across Change-Points

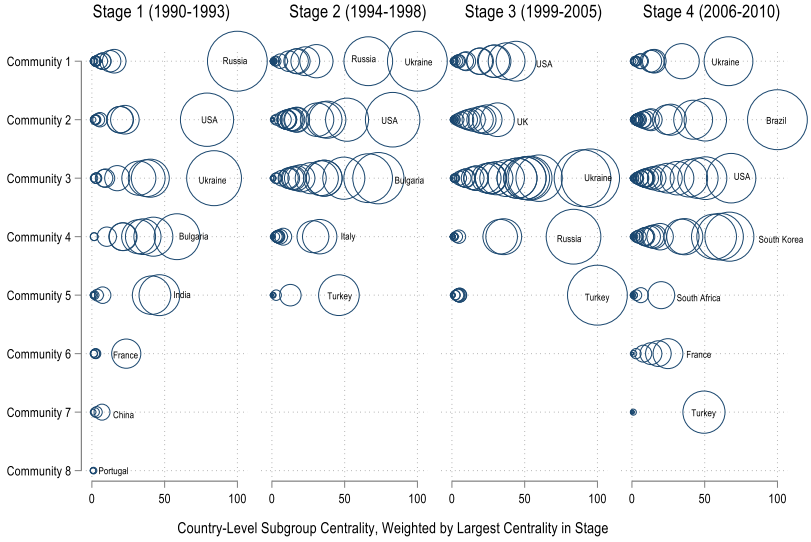
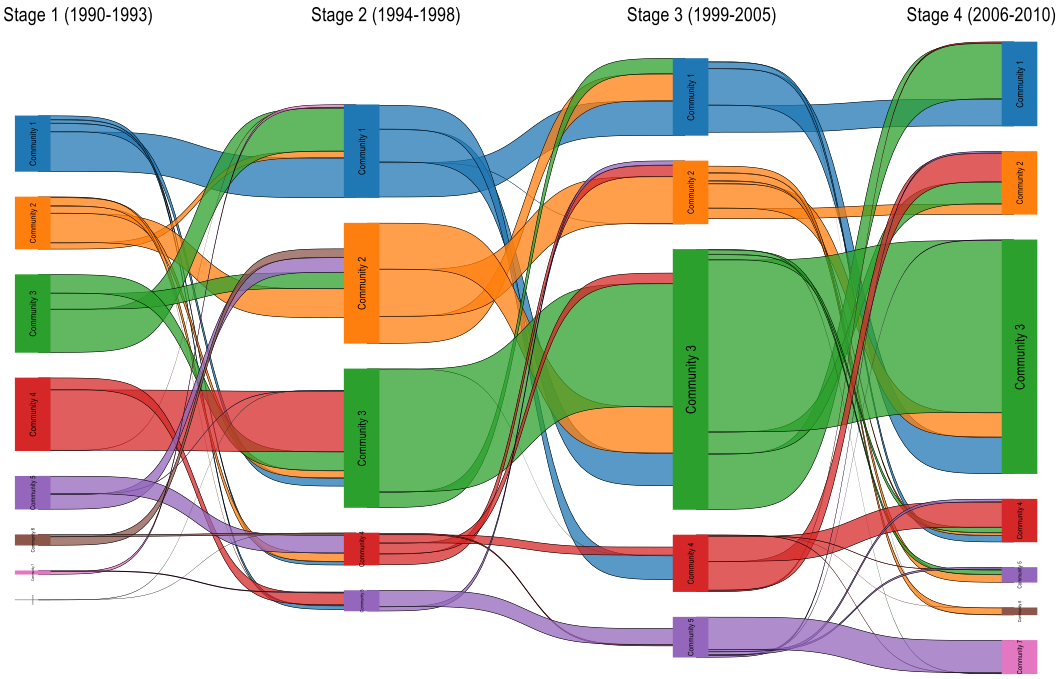


Figure 6 is a Sankey diagram of the shifts in countries across communities over time. At each stage, the bars within each community are weighted by the country-level subgroup centrality scores of the countries in the community, allowing us to see the relative power shifts across communities at each change-point. The figure helps to illustrate an interesting dynamic: while some countries stay in communities with similar partners over time, other countries shift their communities across change-points. At times, these shifts lead to differences in the relative size and power (centrality) of communities.

Figure 6: Shifts in Communities Across Change-Points, Flows Represent Country-Level Subgroup Centrality Scores, Weighted By Largest Centrality In Stage



Method Robustness and Sensitivity

Our findings concerning the community structure and change-points are robust to changes in the (a) size and (b) time span of the network. To investigate the potential impact of network size on our results, we conducted experiments by sequentially removing the top five and ten countries with the lowest average degrees across the entire time period and comparing these outcomes with the original dataset. To investigate the potential impact of variations in the time span, we applied our method to five different time spans by excluding the initial three, four, and five years, as well as the last three and four years, respectively. We then analyzed variations in three key metrics before and after the exclusion of certain countries or years: (a) change point locations, (b) the count of communities in each year, and (c) the assignment of community labels to each country for each year, as measured using the Rand (1971) index.

As shown in the appendix, the change points and community assignments are remarkably consistent when we remove the top five countries with the lowest degrees or restrict or analysis to starting in 1993 or ending in either 2006 or 2007. In the other experiments, the year of one

change-point may shift slightly but the four-stage structure remains unchanged. Similarly, across the time span and difference experiments, the number of communities identified remains consistent the majority of the time and the Rand Index is typically 1.0 or close 1.0. In all, these results help show the robustness of this method to variation in size or time span. As the availability of DCA data expands to cover more years, we could expect new change-points and communities to be detected.

Of course, there is no foolproof way to establish the ground truth or compare our results to some underlying reality.[4] Nonetheless, our analysis shows patterns consistent with well-known shifts in country preferences over time. For example, Ukraine starts out in Stage 1(1990-1993) as a dominant player in Community 3, which is a community made up of smaller Eastern European and Baltic states. In Stage 2 (1994-1998), it shifts to a community with Russia (Community 2), before moving back in Stages 3 (1999-2005) and 4 (2006-2010) to slightly more equitable communities of countries that primarily border Russia. These shifts and the large centrality score of Ukraine are consistent with it "wavering between the West and Russia" during this time period, as well as Ukraine's attempts to establish itself as a cooperative, independent country on the world stage (Sullivan 2022, np).

As another attempt to show the underlying utility and validity of our method, the appendix shows the community detection and change-point analysis applied just to Middle Eastern countries and three major powers, namely the USA, China, and Russia. As could be expected, the analysis shows the growth in Russian and Chinese influence over time, as well as the strengthening of a community between Lebanon, Iran, and Jordan. Given this descriptive analysis and the robustness of our results, we think the method has much potential in IR. In the next section, we investigate one route forward, focusing specifically on understanding why some countries shift communities over time.

Extension: Using Network-Based Change-Points and Communities to Understand Country-Level Shifts in the International System

To our knowledge, despite all of the focus on changing polarity, the drivers of country-level shifts have received relatively little attention in international relations. This is unfortunate; if we see polarity or communities as important for conflict behavior, our field must develop a better understanding of the determinants of shifts and *shifters* in the system. In this section, we illustrate how change-points and community-detection can help us identify and predict which countries will shift in the international system. Our focus on the countries that shift communities is fundamentally distinct from existing research on the determinants network connections between countries. If community structure helps in socialization and influences behavior, as previous research has indicated (Beardsley et al. 2020; Olivella et al. 2022), we should see most new network connections form within communities and not across communities. By incorporating new ideas and methods from network science, we are thus able to isolate and examine a class of countries (the "shifters") that are fundamentally changing the structure of the world system but have been missing in traditional analyses of the determinants of network ties.

[4] We thank an anonymous reviewer for this point.

We use an inductive, prediction-based method to understand the country-level determinants of shifting across communities between change-points. We begin by dividing countries into two populations:

Shifters: those countries that shift identified communities across change-points

Stayers: those countries that stay in an identified community across change-points

Figure 7 lists the number of countries that shift across communities or stay within a community across change-points. The "NA" columns record the number of countries which are isolated (i.e. no ties with others) or are not assigned to a community in the next stage. The dark gray cells identify those that stay in a given community across change-points, and the light gray cells identify those that shift communities. For our training and conceptual-development purposes, we do not focus now on the quadrants that are not gray. The small numbers of countries in those cells are later used to help us evaluate our model success.

Figure 7: Shifters v. Stayers Across Stages

Shifters vs Stayers

From stage 1 to stage 2						
NO.	**1**	**2**	**3**	**4**	**5**	**NA**
1	8	3	0	3	1	2
2	2	3	4	1	1	1
3	3	0	5	3	0	0
4	1	0	0	6	2	0
5	0	3	3	1	0	1
6	0	3	3	0	0	0
7	2	0	0	0	1	1
8	0	1	0	1	0	0

From stage 2 to stage 3						
No.	**1**	**2**	**3**	**4**	**5**	**NA**
1	12	6	3	2	0	7
2	0	9	4	1	3	3
3	1	0	8	9	0	3
4	3	1	1	14	0	1
5	0	1	4	0	5	2

From stage 3 to stage 4								
No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**NA**
1	9	2	0	5	0	2	0	0
2	1	8	8	1	4	1	2	2
3	0	4	10	4	2	3	0	4
4	4	1	3	18	1	0	1	2
5	0	3	2	1	2	0	1	2

Note: *1. For ease of readability, the dark gray cells identify those that stay in one community across change points, and the light gray cells identify those that shift communities.*
2. In each table, the columns represent the community label in the previous stage, and the rows represent the community label in the next stage.

We start with a list of common covariates which capture a country's conflict-related characteristics, its regime type, and its economic system. We also include three variables that represent the country's position in the overall network in the year of the potential shift in community across stages: PageRank, total degree, and closeness centrality. Table 1 shows these potential covariates; to aid with replicability, all variables come from the Quality of Governance Standard Dataset (Teorell et al. 2022). Figure 8 provides the bivariate relationships between shift/stay and each potential covariate using the full network sample.

Starting with our full list of potential covariates, we select covariates that most effectively align with the data regarding a country's community transitions across stages, utilizing a logistic regression model. Let $X_1, \ldots, X_K$ be the candidate covariates and Y_i be a binary response, where $Y_i = 1$ indicates country i is a shifter and $Y_i = 0$ indicates country i is a stayer. Thus, the full

model is $Y_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_k X_{i,K} + \varepsilon$, where $X_{i,1}, \ldots, X_{i,K}$ represent the average values of each covariate for country i across the previous stage. First, we use the AIC information criteria to compare different possible models in a backward stepwise approach and determine which one is the best fit for our data. AIC for one model is calculated by the formula $\mathrm{AIC} = 2\mathrm{K} - 2\ln(\mathrm{L})$, where K is the number of independent variables used and L is the estimated log-likelihood in the model. The lower AIC is, the better the model is. Second, we use VIF (Variable Inflation Factors) to detect multicollinearity. If two or more predictors are highly correlated between them, the fit of the model will be compromised since the individual linear effect of each predictor is hard to disentangle from the rest of correlated predictors. The VIF for the j^{th} predictor, in particular, is $\mathrm{VIF_j} = \frac{1}{1-\mathrm{R_j^2}}$, where $\mathrm{R_j^2}$ is the R^2 value obtained by regressing the j^{th} predictor on the remaining predictors. Generally, when a VIF value is larger than 5, it indicates high multicollinearity between this independent variable and the others. Thus, we remove one predictor with the largest VIF value each time until none of the VIF values exceeds 5.

Finally, we build the logistic regression model with the selected collection of predictors(covariates). We combine the stayers/shifters samples in Figure 7, and randomly split them into two: 80% as the training data to infer the parameters and 20% as the testing data to get a prediction performance. We repeat it 50 times, identifying the model that provides the best prediction of shifters. Using this approach, we built a model that predicted roughly 85% of shifts by countries across communities between stages.[5]

Our final model includes just three covariates: level of democracy, number of alliances, and the military personnel index. Figure 9 shows the AUC contribution of each final predictor variable, which is the difference of AUC for the model with and without each predictor variable. Figure 10 is a bar plot to illustrate the final size and direction of the coefficients. As a country's level of democracy and number of alliances increases, it is less likely to shift communities between change-points. As a country's military force size increases, it is more likely to shift communities.

Worth mentioning, none of our network structure variables remained in our final model. Although our descriptive analysis (Figure 8) shows that countries that shift between communities are less central to the network, these variables do not have the final predictive power as democracy, alliances, and military personnel. Building on our approach, we think future researchers could test hypotheses about whether the characteristics of the previous community make it ripe for shifting or whether the availability of potential alternative communities serves to entice potential shifters. These possible extensions may help researchers further develop theories on the nature of norms and hierarchy in the international system.

As a whole, our findings are intuitive but also potentially powerful. Democratization and actions taken to assure states that they do not necessarily have to rely on their own country's militarization are enough to induce stability in the system, lessening the need for countries to shift communities across change-points.

[5] Our appendix shows the final AUC-ROC curve for the model across our 50 replications. The final logistic regression table is also in the appendix.

Table 1: Potential Covariates – Predicting Shifters in Communities Across Stages

Covariate	Source
Conflict and Military Service	
Number of Alliances	Leeds et al. (2002)
Global Militarization Index	Mutschler and Bales (2020)
Heavy Weapons Index	Mutschler and Bales (2020)
Military Expenditure Index	Mutschler and Bales (2020)
Military Personnel Index	Mutschler and Bales (2020)
Extrasystemic armed conflict	Harbom et al. (2008); Pettersson (2020); Pettersson et al (2021)
Interstate armed conflict	Harbom et al. (2008); Pettersson (2020); Pettersson et al (2021)
Internal armed conflict	Harbom et al. (2008); Pettersson (2020); Pettersson et al (2021)
Internationalized internal armed conflict	Harbom et al. (2008); Pettersson (2020); Pettersson et al (2021)
Political and Economic System	
Did the main regime change	Bjørnskov and Rode (2020)
Level of Democracy (Freedom House/Polity)	Freedom House (2021a); Marshall and Gurr (2020)
Deliberative democracy index	Coppedge et al. (2021); Pemstein et al. (2021)
Egalitarian democracy index	Coppedge et al. (2021); Pemstein et al. (2021)
Liberal democracy index	Coppedge et al. (2021); Pemstein et al. (2021)
Public Economy	
Real GDP per Capita (2005)	Gleditsch and Ward (1999); Gleditsch (2002)
Quality of Government	
ICRG Indicator of Quality of Government	PRS Group et al. (2021)
Political corruption index	Coppedge et al. (2021); Pemstein et al. (2021)
Network Structure	
PageRank	As calculated, Kinne (2020)
Degree	As calculated, Kinne (2020)
Centrality	As calculated, Kinne (2020)

*All variables come from Teorell et al. (2022)

Figure 8: Descriptive Analysis of Covariates, Shifters (Light Gray) and Stayers (Dark Gray) in Communities Across Change-Points

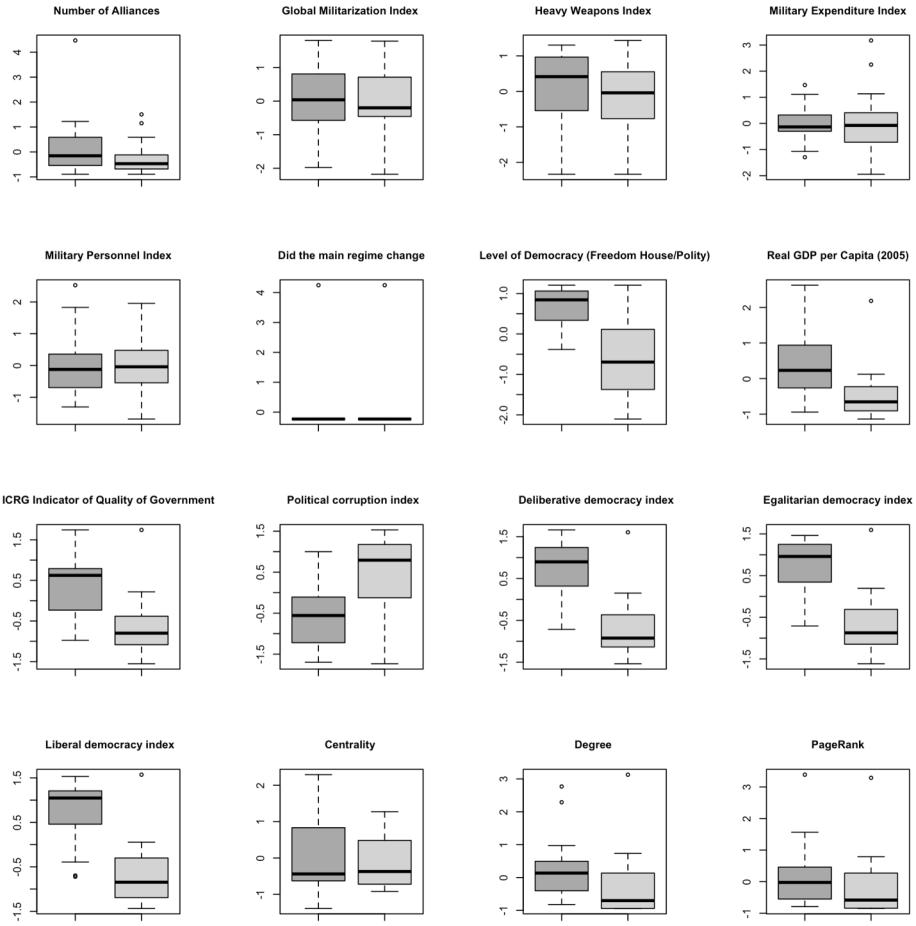


Figure 9: AUC Contribution of Final Predictors, Shifting Across Communities Between Change-Points

Commented [AM1]: AIC or AUC?

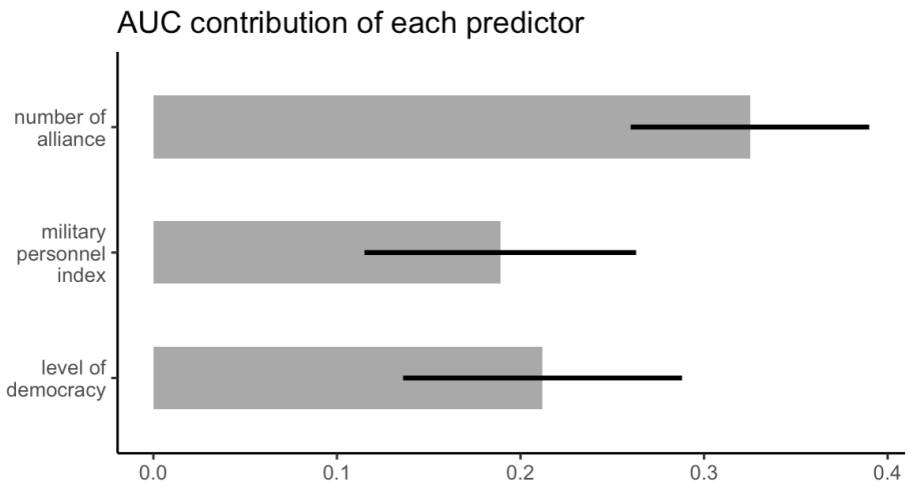
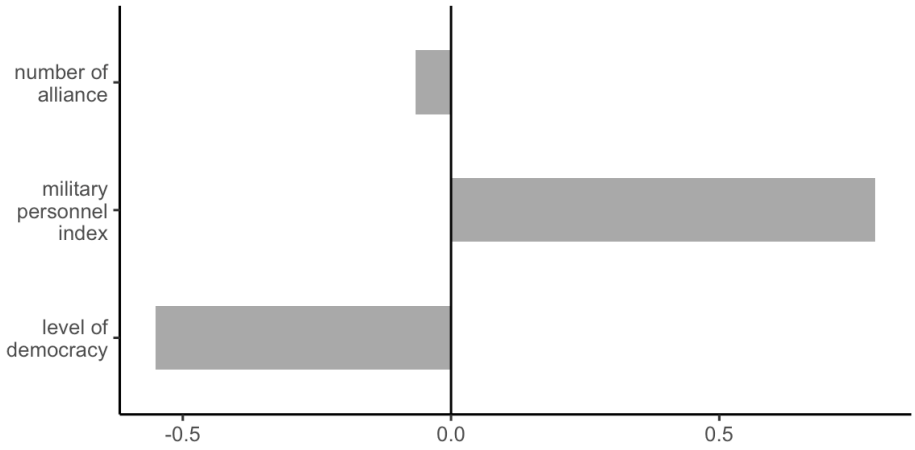


Figure 10: Coefficient Plot, Shifting Across Communities Between Change-Points



Conclusion: Communities, Change-Points, and Shifters in the World System

How do we determine change in the world system? While change in the system has been one of the predominant questions of international relations, it is notoriously difficult to explain using traditional approaches (Jackson and Nexon 1999, 296). Drawing on cross-disciplinary network science, this research note illustrated one useful way forward: better understanding countries that shift across communities between change-points. We used data on defense cooperation agreements from Kinne (2020) to show how change-points in the community structure can be detected endogenously. Further, we use a prediction-based approach to better understand what countries are at risk for shifting communities. The nature of defense (military personnel versus alliances) and the level of democracy help explain over 85% of the country-level shifters across communities at change-points.

We see our approach as a fundamental step forward in reexamining the importance of world systems and systemic shifts. By combining levels of analysis (countries, communities, systems), we are able to better understand when the system is shifting and what the shift looks like. Unlike previous attempts to ex-post understand the system as bipolar, multipolar, or unipolar, network science allows us to see communities or divisions as endogenous to the system and evolving over time. By further focusing on change-points, we are able to see when the community structure is fundamentally altered.

We see many potential avenues forward. First, country-level analyses of conflict could use community classifications or whether a country is a shifter across communities as a potentially important covariate If communities are an avenue of socialization, we should see communities develop distinct patterns of behavior towards insiders and outsiders. Further, we should see countries that do not shift communities more ingrained towards the shared behavior of their community, more likely to match the belligerent levels that dominate their community at a given time. Identity-based arguments around communities and change-points would be an important extension for democratic peace arguments based on shared ideals or norms (Russett, Oneal, and Davis 1998; Mitchell 2002). Future analysis could use information on communities and change-points as right-hand side variables in studies of conflict.

Second, future researchers could examine the communities and change-points identified in other country-based networks. For example, Greenhill and Lupu (2017)'s study of the IGO network may be extended to examine when change-points in the system occur; it could be that fragmentation matters more in the time immediately before and after a change-point. Change-point detection could also be useful in understanding shifts in world trade or finance. Instead of conceptualizing countries as core or periphery, we could examine how community-based organizational structures shift over time, leading some states to enter into the community trade system or to be left outside of any trade community at certain stages of development. We might identify multiple communities among those countries previously identified as "core" to the world trade system (Smith and Sarabi 2022).

Third, we think there is value in an inductive, prediction-based approach to understanding shifters in the system. Researchers have previously argued that predictive approaches are

potentially very useful for understanding when conflict could occur (Ward et al. 2010). By identifying which sets of factors make countries at risk for potential shifts in the world system, we can build better iterative theoretical models of how best to prevent countries from joining communities which could be potentially problematic for peace.

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