Network Ties, Social Capital, and Multilateral Cooperation*

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Abstract

What enables states to act collectively in the multilateral fora? We argue that dense institutional ties generate social capital, trust and reciprocity that help groups of states to coordinate. While social capital is unobservable, we construct networks of defense alliances and intergovernmental organization (IGO) co-memberships from 1961 to 2014 and apply a dynamic blockmodel to identify latent groups of states with similar tie-formation profiles. These groups capture the social roles states occupy in cooperation networks, after accounting for their shared interests. We then test how group membership affects voting in the United Nations General Assembly (UNGA). Those states embedded in dense communities characteristic of high social capital vote with greater cohesion on controversial resolutions. By contrast, isolated states fail to coordinate. Defense alliances and IGO co-memberships, which rely on trust and repeated interactions, promote solidarity that extends to other issues in world affairs, unlike trade networks. Comparisons with Cold War alliance blocs, regional organizations such as the EU and AU, and the OECD show that dense latent groups consistently display cohesion. By demonstrating how cooperation networks embed social capital that diffuses across issue areas, the paper highlights the social foundations of multilateralism.

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1 Introduction

Terms like "the West" or "the Global South" classify states by more than geography. The West extends beyond NATO to include states linked by capitalism, globalization, or democracy, while the South combines non-alignment with developing country interests. These groups have no clear borders or membership rules, but they illustrate the multi-dimensional ways states coordinate. Few act alone, and their partners extend beyond their nearest neighbors. Taking on problems from nuclear proliferation to economic development, groups of states work together to advance their interests.

What shapes the structure of international society? While anarchy makes cooperation difficult, states nonetheless coordinate extensively through information exchange and international institutions (Keohane, 1984; Axelrod and Keohane, 1986). Existing scholarship often emphasizes state-level conditions that drive cooperation, but network approaches show how ties formed through international organizations create broader patterns of interdependence (Cao, 2009; Hafner-Burton and Montgomery, 2006; Kinne, 2013a). Building on these insights, we examine how states' choices to join agreements foster trust and create groups that can more easily form coalitions in multilateral forums.

We draw on the concept of social capital, defined as networks and norms of reciprocity that enable collective action (Putnam, 2000; Coleman, 1988). Although social capital originates at the individual level, it can aggregate into community-level behavior. Repeated interactions among officials within international institutions has been shown to socialize states (Johnston, 2007). Diplomatic exchanges shape perceptions and create opportunities for bargaining. We contend that just as local communities with higher social capital act collectively, communities of nations embedded in dense networks develop trust and reinforce cooperation at the international level.

Our analysis focuses on defense alliances and international organization memberships as key forms of cooperation. Using a dynamic mixed membership blockmodel (Olivella et al., 2022), we identify the social roles of states within these networks and then assess their influence on collective action in UN voting (Voeten, 2000a). We show that states embedded in denser networks vote with greater cohesion on controversial issues, while isolated states fail to coordinate despite similar preferences. The effect is strongest in defense alliances and IGO co-memberships, which map more closely to underlying social capital. We then benchmark our results against conventional geopolitical and institutional categories, showing that dense network groups exert a substantive effect. Finally, we differentiate social roles from alternative explanations based on interests, information, and power.

2 Social Capital and Collective Action

What leads governments to agree on how to address critical problems in world affairs? In domestic politics, parties organize competing views and advance legislative agendas, but there is no equivalent structure at the international level. Voeten (2021) shows that states hold ideological preferences that shape their behavior in multilateral institutions. Governments position themselves along identifiable policy dimensions, yet these alignments do not generate formal parties. We argue that, in the absence of such organizations, coordination emerges instead through trust and social ties among states. These ties create communities that function as informal counterparts to political parties, providing structure for international cooperation.

The challenge of collective action is central to understanding political organization. From local villages to global governance, actors struggle to establish rules for behavior that will provide public goods beneficial to the community. Some research emphasizes information and incentives, while others highlight the role of trust in shaping cooperation (Ostrom, 2000). This opens a broader agenda: the key question is not only whether cooperation is possible in a given environment, but also why some actors or communities succeed more than others.

This variation is explained by the concept of social capital, defined as the networks, norms, and trust that enable cooperation (Putnam, 1995; Ostrom, 1998). Where social capital is strong, voluntary coordination becomes possible. As Putnam notes, social capital "improves the efficiency of society by facilitating coordinated actions" (Putnam et al., 1994). He gives the example of rotating credit associations: members contribute to a common pool that is distributed to one participant on a rotating basis. The puzzle is why individuals choose to participate rather than take the money and run. Putnam argues that the "underlying stock of social capital" facilitates the cooperation because it makes people trust that others will not defect. Various studies suggest that by fostering collective action, high levels of social capital are associated with greater voter turnout and stronger economic performance (Putnam et al., 1994; Fukuyama, 1996; Abrams et al., 2011; Atkinson and Fowler, 2014; Whiteley, 2000; Knack and Keefer, 1997; Lins et al., 2017).

Similarly, policies from environmental protection to collective security rely upon collective action among states to provide global public goods. The problem of cooperation between states has been characterized by the classic Prisoner's Dilemma, where iterated interaction and common expectations support cooperation (Keohane, 1984; Axelrod and Keohane, 1986). The willingness of states to undertake multilateral cooperation also may depend upon trust (Rathbun, 2011). Through frequent interactions, it is possible that states could form networks, norms, and trust as the basis for social capital.

3 Social Capital in Dense Cooperation Network Communities

Despite its importance, social capital remains an unobservable and ambiguous concept. It refers to the intangible features of individuals and communities that support cooperation, which makes it difficult to measure and inherently endogenous in its formulation (Paldam, 2000). We address this challenge by using densely connected communities in international cooperation networks as a proxy for social capital.

This approach builds on research that measures variation in social capital at the individual level through the density of interpersonal networks and voluntary associations. In his classic study, Putnam et al. (1994) illustrates regional differences in Italy by comparing the prevalence of voluntary organizations, such as choral groups, in the North and South.

Scholars identify multiple pathways through which trust underpins international cooperation. Rationalist accounts emphasize that states signal trustworthiness through costly actions such as military restraint and international agreements (Kydd, 2005). Diplomacy also builds confidence at the leader level where direct meetings shape perception of trustworthiness (Yarhi-Milo, 2013). Constructivist work highlights how repeated interaction within international organizations can socialize states into cooperative norms and shared expectations (Johnston, 2001). A dispositional perspective argues that generalized trust precedes institutional design, with high-trust leaders and societies acting as catalysts for multilateral cooperation (Rathbun, 2011). Survey evidence supports this view, showing that publics with higher levels of generalized trust are more likely to back multilateral security institutions (Rathbun, 2012). Together, these approaches suggest that trust not only facilitates entry into multilateral agreements but can also deepen as states participate in them.

When a group of states is densely connected, it forms a community of trust based on willingness to undertake voluntary cooperation. These communities resemble societies made up of individuals. We attribute social capital arising from the density of institutionalized ties, and expect it will lead to greater ability to coordinate for collective action in multilateral fora. Figure 1 illustrates our theoretical framework.

Our approach takes a network perspective on international relations. This recognizes the interdependence of decisions among states. Network relationships among states have been found to influence conflict levels (Hafner-Burton and Montgomery, 2006; Greenhill and Lupu, 2017; Olivella et al., 2022).

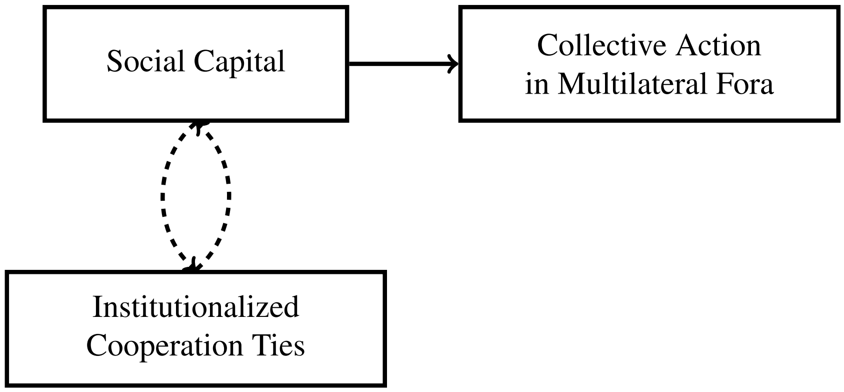

Figure 1: Theoretical Framework

In particular, we are interested in how the institutional ties binding states together are based on and further strengthen relationships with a broad significance for cooperation. Kinne (2013b) writes, “international cooperation is governed by endogenous network influences; the creation of international agreements and institutions directly affects the cooperative efforts of others.” Building on this insight and applying a newly developed network model, we map the network of ties among states.[1]

Among the various types of ties between states, which better captures social capital? There are layers of ties that bind states together. The first is recognition. In the international system, the most basic rights of sovereignty are often contested and compromised (Krasner, 1999; Buzan, 2017; Greenhouse and Davis, 2020; Barkin, 2021). The establishment of diplomatic relations represents a formal agreement with legal standing and rights. Through the exchange of embassies governments open channels of communication that can support subsequent cooperation. We conceive of this as a baseline dyadic measure of a tie that increases the possibility of other institutional relationships.

In a second level, states form ties that serve specific goals to deepen cooperation. Defense pacts and joint membership in IGOs are widespread and will be the focus of our study. One could expand the range of institutional ties to include investment treaties, environmental cooperation, and other integration

[1] Where Kinne focuses on bilateral agreements we allow both bilateral and multilateral agreements to enter our network. He applies a stochastic actor-oriented model, we apply the dynamic mixed membership blockmodel regression. We explain more detailed differences between the two methods in the Research Design and Methods section.

agreements. Through the separate analysis of networks within each type of agreement, we allow their community structure to differ and can model the interests that promote the formation of institutional ties. Then we analyze how institutional ties form a network of states that are connected to each other.

Defense treaty allies share a commitment to cooperate over the most important goal of protecting national security. Joint security production requires a high level of trust and close social ties between partner states. Otherwise, security cooperation would be too risky. A state only joins defense alliances when it believes it faces very low risks of opportunism (Leeds, 2003; Lake, 1999). Defense alliances not only build on trust and social networks but also reinforce them. Social capital and voluntary associations are mutually reinforcing in nature, and social capital increases the more it is utilized (Coleman, 1988; Putnam et al., 1994). In the case of defense alliances, the agreement to defend another country against an attack creates interest in mutual strength and solidarity. Allies frequently participate in routine meetings, joint military exercises, and demonstrations of unity, which credibly signal resolve (Kertzer, 2016). Leaders from allied countries often appear publicly together and endorse interest groups within each other's societies (Beckley, 2015). These social interactions go beyond reinforcing shared security interests to create a more general "moral convention that promises should be kept." (Snyder, 2007)

Similarly, joining the same IGO requires high levels of trust between states. States membership choices are based upon selection on affinity that allows for criteria beyond simple compliance (Davis, 2023). According to Rathbun (2011), "Generalized trust precedes institution building and serves as a form of anarchical social capital, facilitating diffuse reciprocity and allowing state leaders to commit to multilateralism even in cases that rationalists deem inhospitable to cooperation and without the institutional protections that rationalists expect." After joining, regular meetings and the expectation of future iteration of cooperation further strengthen trust among states.

The network of institutional ties expands the connections among states beyond those directly signing agreements or sharing IGO co-membership ties. As a group of states having dense ties with each other form a community, they share trust together. The community then becomes one with overlapping commitments. An institutional tie represents a forum for interaction (akin to a bowling club according to Putnam), and a densely connected community resembles a society with dense associations and high social capital. All states within the community can easily cooperate with each other, and collective action among them becomes easier.

High levels of underlying social capital make it easier for states to form institutional ties, producing the densely connected communities we observe. Once established, norms of trust and reciprocity spread throughout the network. Shared ties carry signaling value, as association with one state conveys assurance about another's type. Much like in a small village, states can vouch for one another through their own acts of acceptance. Peer effects appear across diverse cooperation outcomes, including diplomatic recognition and membership in international organizations (Kinne, 2014). Markets also recognize the value of association, as shown by Gray (2009), while Kinne (2013b) finds that third-party ties encourage trust and thereby increase cooperation. States use the information embedded in others' partnerships to gain confidence that a prospective partner is a reliable ally. Over time, trust and reciprocity become embedded norms within densely connected communities. Socialization further reinforces cooperation: agreements diffuse practices and expectations, shaping state behavior (Wendt, 1992; Johnston, 2001). Dense connections thus foster shared attitudes and make collective action more likely.

Frequent cooperative ties among states generate dense networks of interaction. States that already share trust and social connections are more likely to establish institutionalized agreements, drawing on an existing stock of social capital. These agreements, in turn, reinforce and expand that stock by fostering more trust and reciprocity. Through this self-reinforcing process, dense communities accumulate high levels of social capital that support collective action. We expect such communities to exhibit greater unity in their positions on critical issues.

Hypothesis: *State groups with dense within-group ties will achieve higher levels of collective action on critical issues.*

Dense communities in networks that correlate more with social capital should facilitate cooperation more effectively. Which types of institutional ties correlate more with social capital? If two states cooperate on a given issue and the same game is played for multiple periods, cooperation may arise because states expect reciprocity over time (Axelrod and Keohane, 1986). However, when the issue under cooperation is less certain and reciprocity cannot be achieved immediately, states need to believe that the other party will not exploit the institutional tie. Once such ties are formed, cooperative behavior also provides a stronger signal of trustworthiness for the same reason. Security cooperation is particularly difficult without trust. When states guarantee to defend each other, the gains and losses in future scenarios are uncertain at the stage of signing agreements, and states cannot expect continuous exchanges of aid (Rathbun, 2011). The sensitivity of national security issues and nontransparent information about defense policies further restrain defense cooperation. Instead, states must trust that their counterparts will not take advantage of the defense agreement for their own benefits (Kinne, 2018).

Similarly, IGO co-membership correlates strongly with social capital. Membership often entails long-term commitments under uncertainty, where reciprocity is diffuse and delayed rather than immediate. Participation requires states to trust that partners will not defect on institutional rules or norms, and sustained interaction within IGOs further reinforces that trust (Rathbun, 2011). Prior work shows that IGOs provide arenas for information exchange, monitoring, and socialization that strengthen shared expectations of cooperation (Keohane, 1984; Johnston, 2001). Thus, like defense alliances, densely connected groups in the IGO co-membership network are highly indicative of underlying social capital.

In contrast, exchanges of benefits occur frequently and continuously in trade, with shorter time horizons. Compared to security cooperation, it is also easier to have tit-for-tat enforcement with lower stakes. Additionally, trade agreements open private exchange with businesses carrying transactions, but defense pacts and IGO cooperation operate at the level of military and state leadership. Therefore, between the two types of cooperation networks we consider, defense ties have a higher correlation with trust compared to trade agreements. Dense communities in the defense alliance network then provide a better mapping of the underlying social capital among states, which supports collective action. We argue that there will be a stronger effect on collective action in the defense alliance network.

We consider voting at the United Nations General Assembly (UNGA) as a central form of collective action. UNGA voting is "the only forum in which a large number of states meet and vote on a regular basis on issues concerning the international community."(Voeten, 2000b) UNGA resolutions reflect and strengthen international norms, serve as principles for other treaties (Mesquita and Pires, 2023), and shape public attitudes (Shelef and Zeira, 2017). Voting in the UNGA, especially on important and controversial resolutions, can therefore have real-world consequences. Each vote represents an opportunity for states to cooperate when taking the same position – either in favor or against the resolution. Forming voting blocs in the UNGA then reflects the ability of states to act together on critical issues.

We differentiate our hypothesis from two alternative explanations. First, it is possible that dense in-group ties correlate with multilateral cooperation because states share interests that define these ties. For example, states that sign defense pacts share common defense interests, allowing them to act together. We test the diffusion of group dynamics across issue areas. If the cohesion of states in a community reflects their shared interests, it will vary by issue. Social capital, however, supports general cooperation across a range of topics. Second, we distinguish the effect of social capital from a purely informational mechanism that supports bargaining. Both defense alliances and trade agreements facilitate the exchange of information. However, defense alliances correlate more with social capital, and we argue they will be more likely to facilitate multilateral cooperation.

Another challenge is that the cohesion within dense communities could be attributed to states having similar underlying preferences and broad shared interests. We address this issue by controlling for shared interests and ensuring that the similarity of state characteristics is comparable across communities. If we still observe higher levels of multilateral cooperation in dense communities, it supports our hypothesis.

4 Research Design and Methods

Our empirical analysis consists of two parts. First, we analyze the structure of defense alliance and IGO co-membership networks, identifying the social role of each state in these two networks each year. Statistically, this social role means a state's probability of connection with different states in a year. We achieve this by estimating the latent groups in the two networks using a mixed membership blockmodel regression. The latent group categorizes states with similar patterns of tie formation. Therefore, this allows us to measure the social role as an estimate of states' mixed membership across latent groups. Second, we employ logit regressions with two-way fixed effects to examine the impact of membership probability on UNGA key votes.

4.1 Cooperation Network and UNGA Key Votes Data

We analyze the defense alliance network and the IGO co-membership network formed by 200 countries from 1961 to 2014.[2] The nodes in the network represent states, and the ties between them capture the existence of defense alliance pacts or a high level of shared IGO co-memberships. For IGO co-membership, a tie is coded between two states in a given year if the number of IGOs they jointly belong to

[2]This choice is based on the availability of state-level covariates *MIDS* and *log(CINC)*.

is greater than the median number of shared IGO memberships across all state pairs in that year. We allow the networks to change every year. We use defense alliance data from the Alliance Treaty Obligations and Provisions Project (ATOP), which codes all defense pacts signed during this period (Leeds et al., 2002). For IGO membership, we use data from Davis and Pratt (2021) based on the Correlates of War (COW) International Organizations Dataset (Pevehouse et al., 2004). Both the defense alliance network and the IGO co-membership networks are undirected and unweighted, so *Defense Alliance*$_{ijt}$ takes 1 if there is a defense pact between state i and j in year t and takes 0 otherwise. Similarly, *IGO Co-membership*$_{ijt}$ equals 0 or 1. From 1961 to 2014, there are 747,123 state dyads. 51,159 alliance ties and 337,374 IGO co-membership ties were observed in total.

We incorporate both monadic and dyadic covariates to explain the formation of cooperation networks. Using the same set of monadic covariates across groups allows us to test whether states in some groups are more similar than others. The size and significance of these coefficients indicate whether group membership reflects homophily on observable characteristics, which is an important concern when analyzing the independent effect of group membership on voting. Comparing the explanatory power of monadic covariates across groups also helps us assess whether in-group similarity varies across groups. Dyadic covariates control directly for factors that make pairs of states more likely to cooperate, capturing shared interests that could otherwise drive tie formation. By incorporating both types of covariates, we account for potential similarities at both the state and dyadic level. The resulting tie-formation probabilities therefore reflect states' bonds net of these observable factors, which we interpret as latent social capital.

At the state level, we use variables *log(GDP)* and *log(GDP per capita)* to measure their economic development.[3] We incorporate the variable *log(CINC)*, which is the logged Composite Index of National

[3]GDP and GDP per capita data are from the World Bank's World Development Indicators (WDI), retrieved from `https://databank.worldbank.org/source/world-development-indicators`.

Capability, to measure power and national capability.[4] The conflict propensity of a state may also affect its likelihood of signing cooperative agreements. We create a variable to measure militarized interstate disputes *MIDS*, the number of military conflicts a state engages in each year.[5] The variable *polity2* is the Polity score that measures regime type.[6] Finally, in the defense alliance network, we account for whether a state is a UN member and add a dichotomous variable *UN*.

We also consider factors at the dyad level that could affect the likelihood for any pair of states to sign an agreement. First, we account for whether two states have a *trade agreement*. We use data from the Design of Trade Agreements (DESTA) Database (Dür et al., 2014).[7] Second, we consider whether two states have formal diplomatic representation. The dichotomous variable *diplomatic representation* indicates whether two states have diplomatic representation ties at the level of charge d'affaires, minister, or ambassador in a given year.[8] In the IGO co-membership network model, we also control whether two states are in the same *defense alliance*. Additionally, we account for the *distance* between two states, and the variable *contiguity* measures whether two states are contiguous. *colonial dependence* captures whether two states have ever had colonial dependence relationships (one state being a colony of the other). The variable *log total trade* is the logged total trade flows between two states each year.[9] Finally, the dyadic variable *MIDS* measures whether two states are in a military conflict with each other.[10]

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[4]CINC data are from the Correlates of War (COW) Composite Index of National Material Capabilities (v6.0) dataset and measure a state's share in the world across the following components of power: total population, urban population, iron and steel production, energy consumption, military expenditure, and military personnel (Singer et al., 1972).

[5]MIDS data are from the monadic version of the Correlates of War (COW) Militarized Interstate Disputes (MIDs) dataset (Palmer et al., 2022)

[6]The Polity scores are from the Polity5 Project, retrieved from `https://www.systemicpeace.org/polityproject.html`.

[7]The DESTA Database includes all agreements that have the potential to liberalize trade. Partial scope agreements thus are included as soon as they liberalize at least some trade, whereas framework agreements (with very few exceptions), trade and co-operation agreements, etc. are excluded. See `https://www.designoftradeagreements.org/media/filer_public/e2/46/e246b1d6-0992-4bdc-905d-26cb93a9f7fe/desta_codebook_02_00.pdf`. The DESTA database documents the new trade agreements signed as well as states' withdrawal from them. We check whether each state dyad still has any trade agreements between them each year.

[8]Data on diplomatic representation are from the Diplomatic Representation Database (DDR) (Moyer et al., 2021, 2022).

[9]Distance, contiguity, colonial dependence, and total trade data are from the CEPII Gravity Database (Conte et al., 2022).

[10]MIDS data are from the dyadic version of the Correlates of War (COW) Militarized Interstate Disputes (MIDs) dataset (Palmer et al., 2022)

The second part of our empirical analysis focuses on how latent group memberships in the two cooperation networks correlate with collective action. According to our hypothesis, we expect to see more alignment in latent groups with denser in-group ties. We will explain the latent group memberships in the Model section. We use cohesion on key votes in the UNGA to measure collective action.[11] These votes are on the most controversial resolutions where there was not a clear majority decision.[12] We also conduct robustness checks using those identified as important votes by the US.[13] We classify votes as "Approval" and "Non-Approval," the latter including voting "No," "Abstain," or "Absent." There are 4956 votes in total, with 2643 controversial votes and 381 important votes according to the US in our analysis.

4.2 Modeling Network Structures and the Formation of Latent Groups

We begin by estimating network models for the defense alliance and IGO co-membership networks to explore their structures and recover the latent group memberships of states. In these networks, each defense pact or high level of IGO membership overlap between two states is treated as a tie. States that belong to the same latent group share similar patterns of tie formation, so group membership captures the social roles states occupy within these networks over time. We then link these memberships to states' behavior in the UNGA by estimating a logit model with two-way fixed effects.

Several network models have been applied in international relations, each suited to different purposes. Exponential Random Graph Models (ERGMs) (Robins, 2014; Cranmer and Desmarais, 2011) capture how local structural dependencies like reciprocity and transitivity shape tie formation. Similarly, Stochastic Actor-Oriented Models (SAOMs) models how ties evolve as a function of actor attributes

[11] UNGA voting data is from Voeten (2013).

[12] A vote is controversial if both the proportion of Approval/Non-approval is below the median for a vote type in the dataset.

[13] Votes important to the US are those identified as important by US State Department report Voting Practices in the United Nations. The data is also from Voeten (2013).

and structural positions (Kinne, 2013b, 2016; Chyzh, 2016; Kinne and Bunte, 2020). These two models are particularly valuable for studying micro-level processes like tie diffusion, but they are less suited to uncovering the latent group structures that characterize cooperation at the system level.[14] Latent space models similarly explain tie-formation based on affinity between state dyads (Ward et al., 2013). Community detection summarizes connection patterns in the network, and has been used to identify blocs in diplomatic exchange networks (Renshon, 2016), UNGA voting (Macon et al., 2012), and trade (Beardsley et al., 2020). This approach partitions states into groups with denser in-group than out-group ties, which is useful for describing camps in the international system. However, they do not distinguish between cohesive, isolated, and mixed-role states (which can all appear in one group), nor can they incorporate covariates to test whether groups simply reflect observable similarities.

Our approach is suited for precisely identifying the social roles of states while controlling for shared interests. We estimate a dynamic mixed-membership stochastic blockmodel with covariates (dynMMSBM) (Olivella et al., 2022), a dynamic extension of the MMSBM (Airoldi et al., 2008). The dynMMSBM groups states according to their tie-formation profiles: each latent group is characterized by a set of probabilities of forming ties with members of each group (including itself), and all states in that group share the same profile. This allows us to identify not only bloc-like dense communities but also isolated or mixed-role groups. Whereas community detection assigns states to the group with which they have the most observed connections, dynMMSBM differentiates between groups of states that are densely interconnected and those that are only loosely linked to each group.[15] Furthermore, by incorporating monadic and dyadic covariates, the model assesses observable sources of homophily (e.g., regime type, GDP) and controls for dyadic-level reasons for connection. In this way, our method moves beyond de-

[14] Chaudoin et al. (2015) uses spatial models to capture interdependence between states' actions. However, such models do not summarize connection patterns at the network level.

[15] Besides models, summary statistics like centrality have been widely applied in international relations. However, centrality only captures how connected a state is in general, not to whom it is connected, and does not separate factions.

scribing camps or modeling dyadic tie changes to uncovering the cooperation roles that states play in international networks and allows us to link those roles to collective action in the UNGA.

Formally, the outcome variable $Y_{pqt} = 1$ if state p has a defense alliance pact or IGO co-membership tie with q in year t, and $Y_{pqt} = 0$ otherwise. Intuitively, the model assumes that each state at each point in time has a mixed membership over several latent groups. These membership probabilities evolve dynamically, allowing states to shift their social roles over time. Monadic covariates (e.g., regime type, GDP) show how state-level characteristics explain group membership, while dyadic covariates (e.g., geographic distance, trade volume) account for observable factors that affect tie formation between pairs of states. When two states interact, the probability of a tie depends on their latent group memberships as well as on dyadic covariates. The blockmodel component then captures the patterns of interaction unexplained by dyadic covariates, and we interpret the higher probability of forming ties within a group as evidence of latent social capital.

In short, the dynMMSBM enables us to: (1) identify dense, mutually connected groups of states, isolated states, and states with mixed types; (2) track how these memberships evolve over time; (3) account for dyadic covariates that might otherwise confound the relationship between group membership and UNGA voting; and (4) assess whether state-level characteristics explain group membership, allowing us to rule out simple homophily. A full technical specification of the model is provided in Section A.1.

We use the model to identify three latent groups. The choice of group number here is mainly for the purpose of interpretation and a better fit of the data.[16] The vector of monadic covariates includes *log(GDP)*, *log(GDP per capita)*, *log(CINC)*, *polity2*, *MIDS* in the IGO co-membership model and and *UN* as an additional covariate in the defense alliance model. Dyadic covariates includes *trade agreement*,

[16]We incorporate two Markov states in the model, which allows the relationship between monadic covariates and group membership to evolve over time. In both the defense alliance and IGO co-membership network models, the majority of observations are in the first Markov state. We have also run models with one latent state, and the results remain robust.

diplomatic representation, *distance*, *contiguity*, *colonial dependence*, *log total trade*, and *MIDS*. *defense alliance* is another dyadic covariate in the IGO co-membership model. All monadic and dyadic covariates are lagged for one year.

5 The structure of International Cooperation Networks

In this section, we first introduce the network model results on the defense alliance network, and then we turn to the IGO co-membership network. The goal of this model is to estimate the mixed membership of each state over time, which implies its social roles.

5.1 The Defense Alliance Network

Figure 2 illustrates the estimated structure of the defense alliance network. Figure 2(a) shows the estimated blockmodel. Group 3 is the largest group, including 52.3% of all state-year observations. It is followed by Group 1 (28.6%) and Group 2 (19.1%). Figure 2 plots the dynamic change in aggregate membership in the latent groups. Over time, the aggregate membership probabilities for Groups 1, 2, and 3 remain relatively stable.

In the global defense alliance network, states within Group 1 are most likely to sign defense pacts with each other after accounting for dyadic covariates (any two states in Group 1 have a 98.5% probability of forming a tie with each other). These are mostly the US and its closest allies in Latin America and Europe. Table A1 shows the list of countries that are most likely to be in the three groups.[17] For example, the US, the UK, Chile, and Argentina often instantiate Group 1. The US and the UK are NATO members, while Chile and Argentina are both non-NATO allies of the US. Importantly, states like the UK and Argentina are identified as being in the same group because they share dense defense ties with

[17]For interpretation purposes, we only list countries that have an average population larger than 5 million.

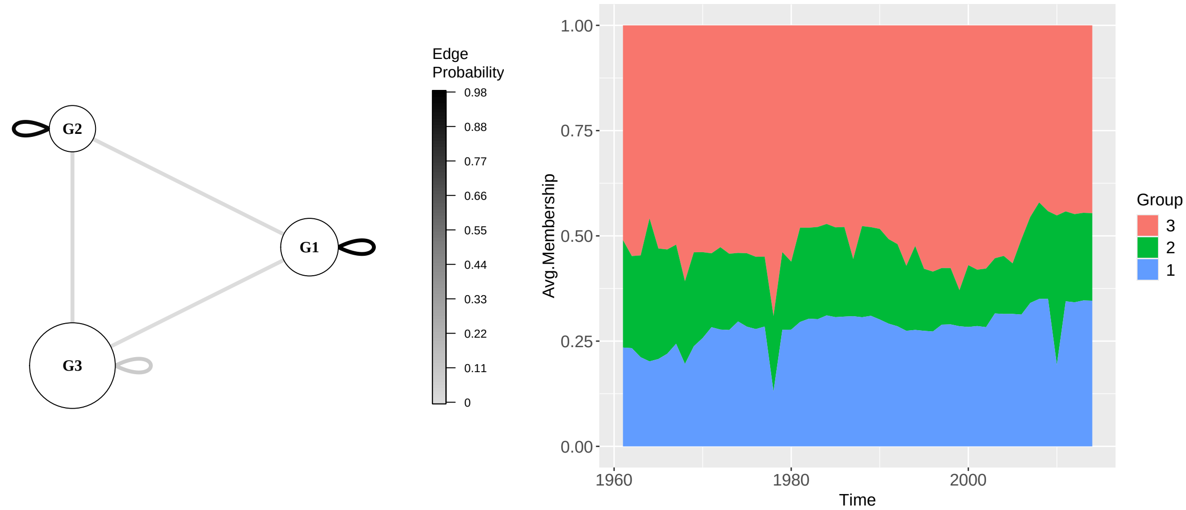
common partners, even if they do not have direct defense ties. This helps us detect a community of states cooperating in the network. Group 2 states have a slightly lower probability (94.5%) of signing defense pacts within the group.[18] States that are also active in signing defense pacts but are outside of the small circle of US allies, such as Saudi Arabia, Egypt, Russia, and Algeria, are often in Group 2. Finally, Group 3 identifies a group of isolated states in the defense alliance network. Their probability of having defense ties with others in the group is only 9.2%, and they are also very unlikely to establish defense ties with states in the other two groups. Ukraine, Switzerland, China, and India are examples of Group 3 members.[19] The overall structure of the global defense alliance network is highly segregated. Groups 1 and 2 are closed clubs, and the probability for states to share defense ties between the two groups is extremely low (0.4%).

Therefore, we identify three distinct social roles in the defense alliance network. Group 1 states primarily connect with other Group 1 members, forming one dense and internally cohesive cluster. Group 2 states primarily connect with other Group 2 members, forming a separate dense cluster that is largely disconnected from Group 1. These two roles represent distinct alliance communities, each characterized by strong in-group ties but few or no links across groups. In contrast, Group 3 states remain largely isolated, forming few alliances at all.

The monadic covariates show the characteristics of states in the same latent group. Table 1 presents the effect of monadic covariates on group membership. The estimates are from a Dirichlet regression, where the coefficients represent the changes in the probabilities of being in a group relative to other groups as the covariates change. Therefore, each coefficient should be interpreted relative to estimates of the same predictor of the other two groups. The most powerful predictor of group membership is the logged CINC score. Comparing three coefficients for the CINC score across groups, we find states

[18] Note this probability is after accounting for dyadic covariates.

[19] We show the mixed membership of eight states over time as examples in Figure A1 in the Appendix.



(a) Blockmodel (b) Aggregate membership

Figure 2: Network Structure and Latent Memberships in the Defense Alliance Network

Note: In Panel (a), the nodes (circles) represent the three latent groups. The size of the nodes indicates the groups' membership size. The edges between the nodes represent the estimated probability a state from one group forms a defense pact with nodes from the other group. Panel (b) shows the average membership proportion in the three latent groups from 1961 to 2014.

with high national capability are the most likely to be in Group 1 and least likely to be in Group 3. UN membership is also a strong predictor. UN members are most likely to be in Group 1 and least likely to be in Group 3. However, when taking into account all covariates, the effect of CINC and UN membership on predicted mixed membership probability is indistinguishable from zero. We visualize the marginal effect of them on group membership in Figure A2 in the Appendix. The other covariates are even less strong to predict group membership with large standard errors for the estimates. This confirms that the similarity of states within the same latent group is comparable. Social roles in dense groups are not proxies for similar underlying characteristics.

Finally, the dyadic covariates control for other reasons that two states sign a defense pact besides their latent memberships. Figure A3 shows the effect of dyadic covariates.

Predictor	Group1	Group2	Group3
(Intercept)	4.027 (1.017)	5.025 (1.017)	7.040 (1.017)
log(GDP)	-0.014 (1.017)	-0.017 (1.017)	0.050 (1.017)
log(GDP per capita)	0.018 (1.017)	-0.042 (1.018)	-0.258 (1.017)
log(CINC)	7.578 (1.017)	5.853 (1.017)	4.137 (1.017)
polity2	0.032 (1.017)	-0.028 (1.017)	-0.010 (1.017)
MIDS	-0.036 (1.017)	0.022 (1.017)	-0.027 (1.017)
UN	-5.231 (1.017)	-5.788 (1.018)	-7.300 (1.018)

Table 1: Monadic Covariates in the Defense Alliance Network

Note: The model was in the first latent state for over 98% of the time, so we report coefficient estimates in this state. The estimates are coefficients of a Dirichlet regression, and standard errors are in parentheses.

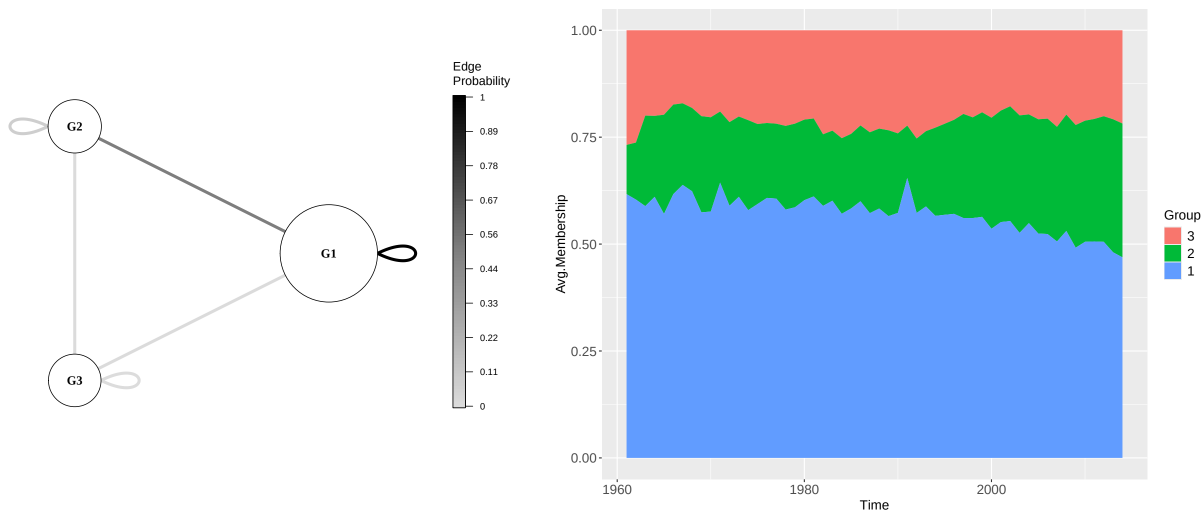
5.2 The IGO Co-membership Network

Figure 3 shows the estimated structure of the IGO Co-membership network. Figure 3(a) shows the estimated blockmodel. Group 1 is the largest group, while groups 2 and 3 have similar proportions of membership. Figure 3(b) plots the dynamic change in aggregate membership in the latent groups. The proportion of membership in the three groups remains relatively stable over time.

In the IGO co-membership network, states within Group 1 are most likely to have strong IGO ties with each other (with a 99.9% probability) after accounting for dyadic covariates. Similarly, Table A2 shows the list of countries that are most likely to be in the three groups.[20] Group 1 includes states like Australia, Japan, Canada, Argentina, and Morocco. Group 2 states have a low probability (7.16%) of joining many IGOs with others in the group after considering the dyadic covariates. However, they have a moderate probability to join IGOs with Group 1 states (50.4%). Countries including Ukraine, Russia, Azerbaijan, Kazakhstan, and Nepal often instantiate in Group 2. Finally, Group 3 identifies a group of the most isolated states in the IGO co-membership network. Their probability of having IGO ties with others in the group is only 0.01%. They also have a nearly zero probability of connecting with the two other groups. Countries like North Korea, South Sudan, and Tajikistan are often in this group.

[20]For interpretation purposes, we only list countries that have an average population larger than 5 million.

States in Group 1 share a role characterized by dense interconnections, as they actively form ties with one another. States in Group 2 occupy a different role: they establish some links with Group 1 but remain too weakly connected to be part of it, and they rarely connect with others in their own group. Group 1 thus constitutes a cohesive community associated with high levels of social capital, whereas membership in Groups 2 and 3 reflects more isolated positions with relatively low social capital.



(a) Blockmodel (b) Aggregate membership

Figure 3: Network Structure and Latent Memberships in the IGO Co-membership Network

Note: In Panel (a), the nodes (circles) represent the three latent groups. The size of the nodes indicates the groups' membership size. The edges between the nodes represent the estimated probability a state from one group forms an IGO co-membership tie with nodes from the other group. Panel (b) shows the average membership proportion in the three latent groups from 1961 to 2014.

The monadic covariates still have a limited effect in sorting states into latent groups. Table 2 presents the effect of monadic covariates on group membership. The most powerful predictor is the logged CINC score. States with high national capability are most likely to be in Group 2, while least likely to be in Group 1. However, we also visualize the marginal effect of the logged CINC score on group membership in Figure A2 in the Appendix. Its effect on the predicted mixed membership probability is negligible. Therefore, similar to the defense alliance network, the level of similarity of states within each latent group is comparable.

Predictor	Group1	Group2	Group3
(Intercept)	-6.691 (2.425)	0.025 (2.435)	2.976 (2.435)
log(GDP)	0.305 (2.388)	-0.105 (2.436)	-0.275 (2.435)
log(GDP per capita)	-0.109 (1.761)	0.131 (2.435)	0.193 (2.435)
log(CINC)	-4.220 (2.524)	7.196 (2.435)	6.114 (2.435)
polity2	0.044 (2.439)	-0.006 (2.435)	-0.008 (2.435)
MIDS	-0.093 (2.439)	-0.002 (2.435)	0.033 (2.435)

Table 2: Monadic Covariates in the IGO Co-membership Network

Note: The model was in the first latent state for over 98% of the time, so we report coefficient estimates in this state. The estimates are coefficients of a Dirichlet regression, and standard errors are in parenthesis.

Finally, Figure A5 shows the effect of dyadic covariates.

6 Latent Group Memberships Explaining Collective Action

Now that we have estimated the mixed membership probability of each state in each year, which represents the social role of states over time. Latent groups with dense ties correspond to communities with high social capital. Then, we analyze how differences in the stock of underlying social capital lead to different abilities of states to act collectively in the multilateral fora. Specifically, we examine key votes in the UNGA.

6.1 Model Explaining UNGA Voting

After estimating the network models, we will obtain a state's mixed membership vector in each year for the two networks separately. To understand how membership in the latent groups affects voting in the UNGA, we estimate the correlation between the estimated probability of a state being in a latent group and whether it votes with the majority of group members in the following year.

We examine whether being in the same group influences countries' voting patterns on controversial issues. Our goal is to analyze (1) whether latent group membership makes states vote with their group and (2) how the effect of group membership depends on the density of ties within the group. Therefore, the unit of analysis is country-vote-group. The dependent variable is whether a state voted with the group majority in a vote. We define the group majority vote as the majority vote of states with the highest probability of being in this group (compared to the two other groups). For example, if a state has a probability 60% of being in group 1, 10% in group 2, and 30% in group 3, then we count its dichotomous group membership as group 1 and take its vote into account when calculating group 1's majority vote. For each country-vote observation, we exclude this country when calculating the majority vote. The dependent variable is a dichotomous variable that takes 1 when a state's vote is the same as the majority of a group and 0 otherwise.

The independent variable is a state's estimated probability of being in each group, lagged by one year. Since each state's probability of being in Groups 1, 2, and 3 sums to 1, we exclude group 3 from the model to avoid perfect collinearity, and it serves as the baseline. Using different groups as the baseline does not affect the interpretation of the results. We interact membership probabilities with the corresponding group indicators to explore how latent groups moderate their effects. In this way, the model allows group-specific effects of the membership probability variable.

Since the dependent variable is dichotomous, we run a logit model with country and vote level fixed effects, as shown in equation (1). Here, i denotes country, j denotes latent groups, and v denotes vote. Each country-vote observation is expanded into three country-vote-latent group observations. $P(G1)$and $P(G2)$ are the membership probabilities of state i in the year before vote v in Groups 1 and 2. $G1$ and $G2$ are indicators of whether this country-vote observation is for Group 1 or Group 2. Both of them take 0 when the observation is for Group 3.

$$\begin{aligned} \mathrm{Y}_{ivj} = {} & \beta_0 + \beta_1 \cdot \mathrm{P(G1)}_{iv} + \beta_2 \cdot \mathrm{G1} + \beta_3 \cdot \mathrm{P(G1)}_{iv} \times \mathrm{G1} \\ & + \beta_4 \cdot \mathrm{P(G2)}_{iv} + \beta_5 \cdot \mathrm{G2} + \beta_6 \cdot \mathrm{P(G2)}_{iv} \times \mathrm{G2} \\ & + \alpha_i + \gamma_v + \epsilon_{ivj} \end{aligned} \tag{1}$$

6.2 Key UNGA Votes

We begin by examining how membership probability influences states' propensity to vote with their group's majority in the UNGA. To understand what shapes states position-taking for issues that lack consensus or high levels of agreement among members, we restrict the analysis to controversial votes, defined as those with divided outcomes. Figure 4 reports the estimated marginal effects for each latent group.[21]

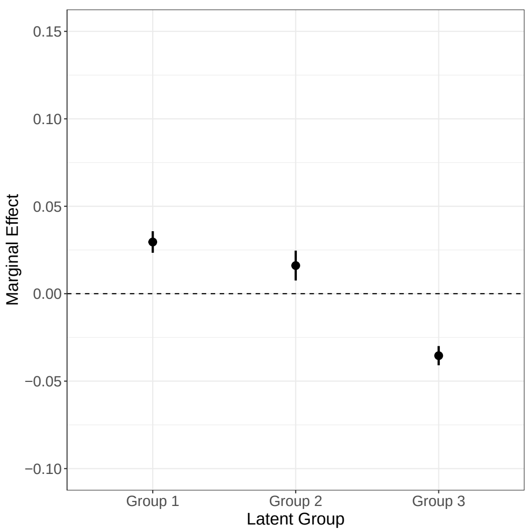
Figure 4(a) demonstrates that a higher probability of belonging to Group 1 in the defense alliance network significantly increases the likelihood of voting with the majority of Group 1 members. The magnitude of the effect is nontrivial: moving a state's membership probability in Group 1 from 0 to 1 increases its probability of voting with the group majority by approximately 3%. While this may appear modest, the effect is substantively meaningful in the context of controversial votes. For instance, among 33 controversial votes, this translates into a group member shifting its vote on an issue to align with the majority. Membership in Group 2 also raises the probability of alignment, though the effect size is smaller than that for Group 1. By contrast, membership in Group 3 decreases the likelihood of voting with the majority.

Figure 4(b) presents the effects of latent group memberships in the IGO co-membership network on UNGA voting. Membership in Group 1 exerts a significant positive influence on the probability of voting with the group majority, with an effect size even larger than that observed for Group 1 in the defense alliance network. This is likely because cooperation in IGOs requires trust across a broader range of issue areas than defense alliances. Moreover, IGO co-membership is a more institutionalized form of cooperation, which strengthens the social capital embedded in dense groups and amplifies their effect on voting alignment. By contrast, higher membership probabilities in Groups 2 and 3 reduce the likelihood of alignment with their respective group majorities. This divergence reflects structural differences between the two networks: whereas the defense alliance network contains two densely connected communities, the IGO co-membership network has only one. Nonetheless, the relatively higher level of interconnection in Group 2 makes it slightly more cohesive than Group 3. We also consider important

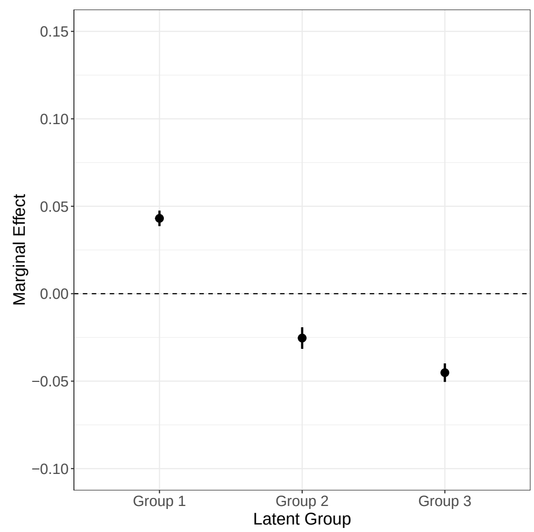
[21] Because the model is logistic and thus non-linear, we compute average marginal effects across all observations in the dataset.

votes identified by the US as an alternative set of key votes, and the results remain the same.[22].

Therefore, more connected communities in both the defense alliance and IGO co-membership networks exhibit greater solidarity in the UNGA by voting together. This finding supports our hypothesis that a high level of social capital promotes collective action. Importantly, we interpret dense ties as a proxy for underlying social capital, as we control for dyadic covariates and demonstrate that state-level characteristics do not explain group membership. Group 3 (and Group 2 in the IGO co-membership network) fail to act cohesively not because they lack shared interests, but because they lack the social capital necessary to translate common preferences into coordinated behavior.



(a) Defense alliance network



(b) IGO co-membership network

Figure 4: Latent Membership Probabilities and 2643 UNGA Controversial Votes

Note: The y-axis is the effect of latent group membership probabilities on a state's probability of voting with the majority in that group. The x-axis is the three latent groups.

Next, we analyze whether network effects diffuse across different issues. This will reveal whether common interests are driving voting coherence among members of a latent group, as one would expect such interests to differ by issue. For example, based on narrowly defined interests, the defense network latent groups should exhibit higher alignment when voting on security issues than on economic issues,

[22]See Figure B1.

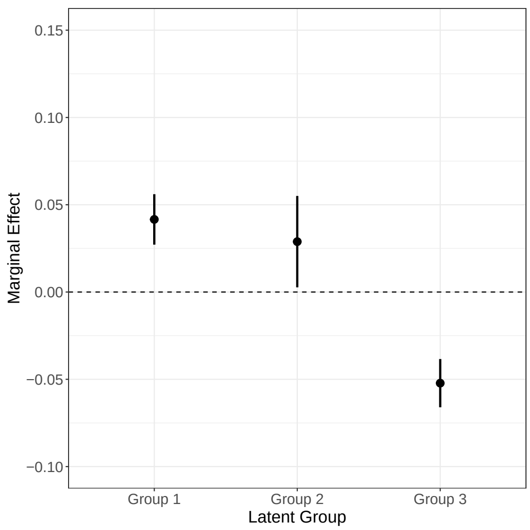
while the IGO co-membership network latent groups should show higher alignment for economic issues over security issues, as the majority of IGOs have an economic agenda. It is important to root out this possibility because if the effect is driven by agreement-defined shared interests, then it may have little to do with the underlying social capital. In contrast, evidence that latent groups act similarly across issues would suggest that trust and social capital underlie voting cohesion. Such network diffusion across issues might arise when trust shared throughout a community is general and supports cooperation on a broad set of issues.

To perform this test, we subset the controversial UNGA votes by their issue areas. The issue area classifications are also from Voeten (2013) and are coded based on vote descriptions. Voeten (2013) classify six types of votes: Votes related to the Palestinian conflict, nuclear weapons and nuclear material, arms control and disarmament, colonialism, human rights, and (economic) development. For all issue areas, the votes span our entire analysis window (1962 to 2015). However, 34% of the controversial votes do not have coded issues, and collective security is missing from the categories. We therefore create another category, collective security, by searching keywords "security" and "aggression" in the vote descriptions. Figure 5 plots the effect of defense alliance network group memberships across issues.[23] The pattern we described above in the pooled controversial votes is consistent across almost all issue areas. The effect size is also highly consistent. Although the latent groups are based on defense cooperation, they have similar effects on human rights and economic development. States in the isolated Group 3, in contrast, are divided on all issues.

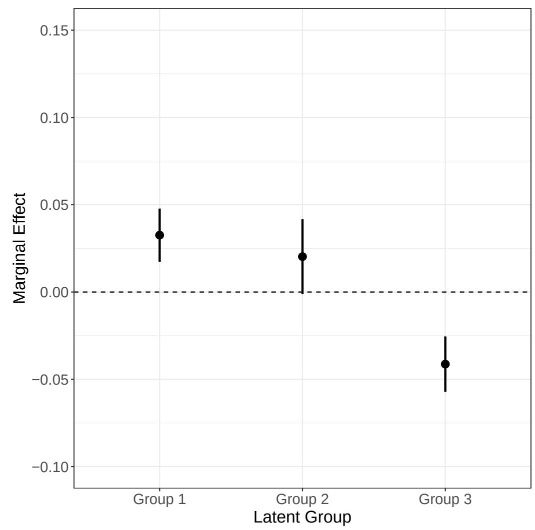
Similarly, Figure 6 demonstrates that the effect of group membership in the IGO co-membership network extends across issue areas. In all cases, only membership in Group 1-the densely connected

[23] To ensure that the results are not driven by the Palestinian conflict alone, we exclude votes on this issue from other categories. The results for colonialism-related votes are reported in Figure B2 in the Appendix, because colonialism votes are highly concentrated in the early decades and therefore not representative of broader cooperation.

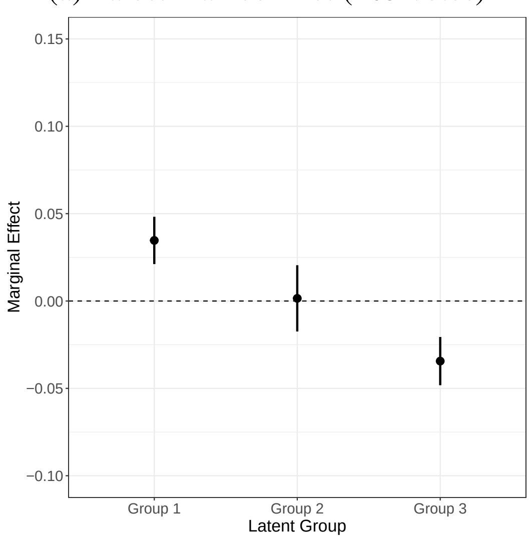
community-consistently increases the likelihood of voting with the majority. This evidence of diffusion across issues supports the role of social capital as the underlying driving force of state behavior.



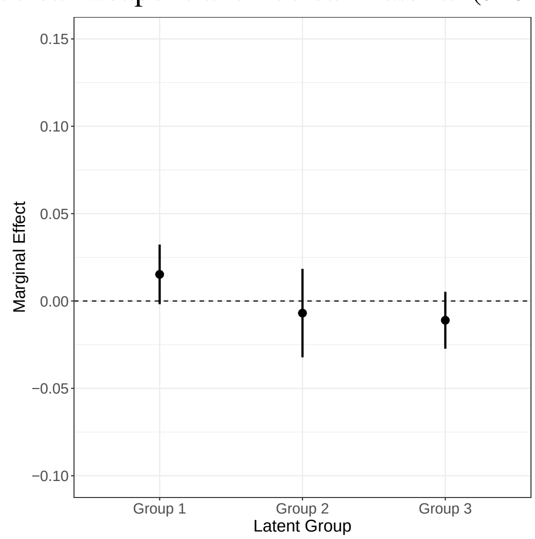
(a) Palestinian conflict (403 votes)



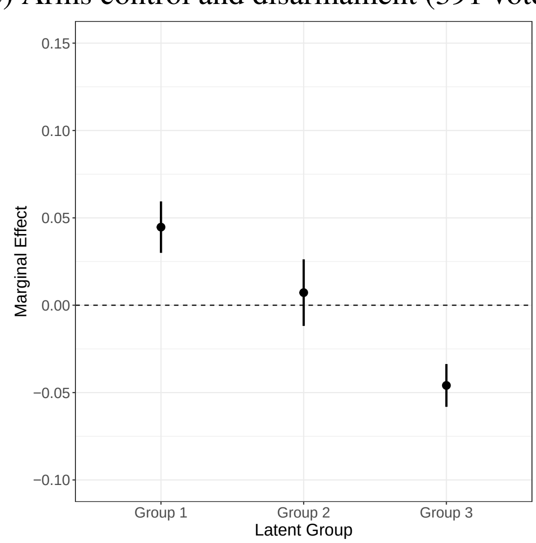
(b) Nuclear weapons and nuclear material (325 votes)



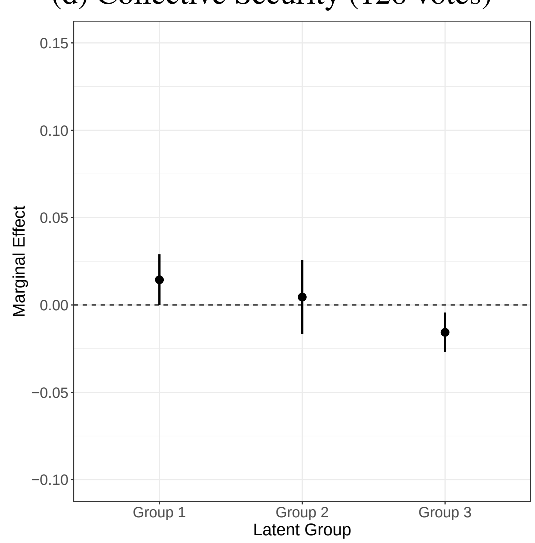
(c) Arms control and disarmament (391 votes)



(d) Collective Security (126 votes)

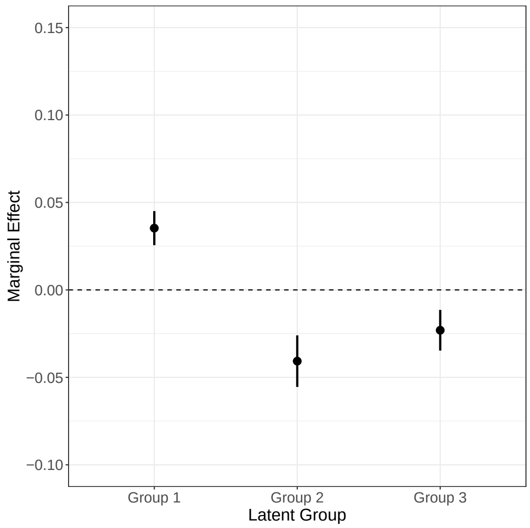


(e) Human rights (421 votes)

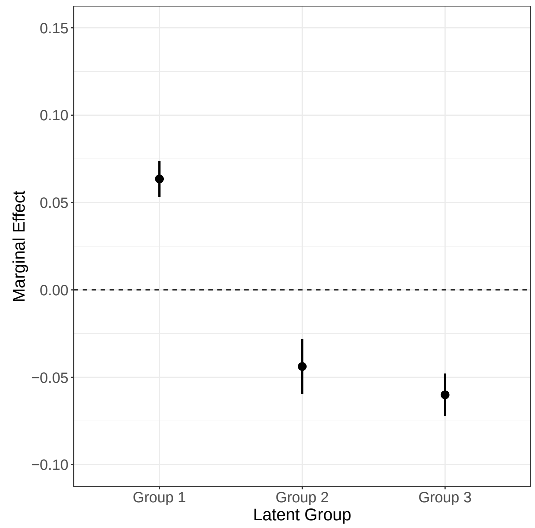


(f) Economic development (351 votes)

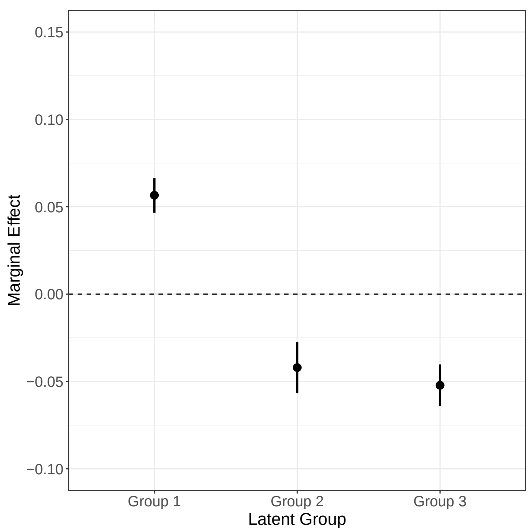
Figure 5: Defense Alliance Network: Latent Membership Probabilities and Controversial UNGA Votes



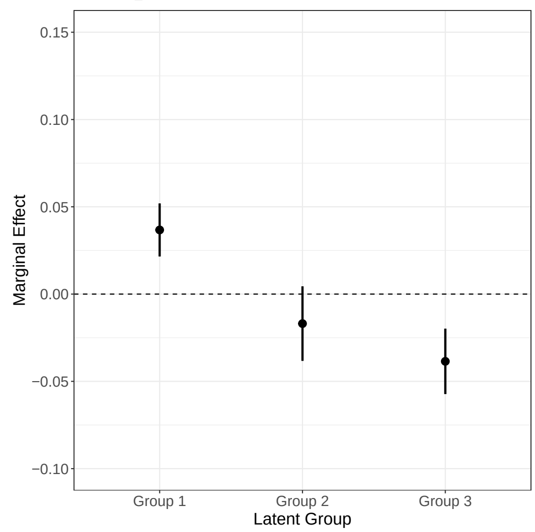
(a) Palestinian conflict (403 votes)



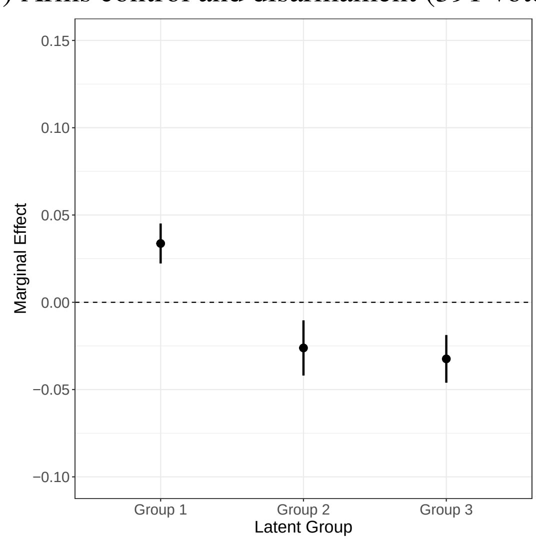
(b) Nuclear weapons and nuclear material (325 votes)



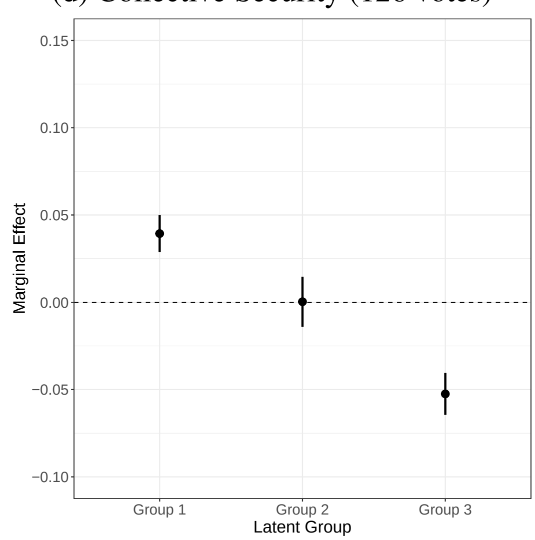
(c) Arms control and disarmament (391 votes)



(d) Collective Security (126 votes)



(e) Human rights (421 votes)



(f) Economic development (351 votes)

Figure 6: IGO Co-membership Network: Latent Membership Probabilities and Controversial UNGA Votes

6.3 Benchmarking Against Known State Categories

To benchmark our results, we compare the effect of group membership in the defense alliance network to the effect of bilateral alliances.[24] Specifically, we compare our three latent groups to US allies, USSR/Russia allies, and all other countries. The models are the same, except for the way group labels are defined. We analyze the pre-Cold War period (pre-1988) and the post-Cold War period (post-1994) separately.[25]

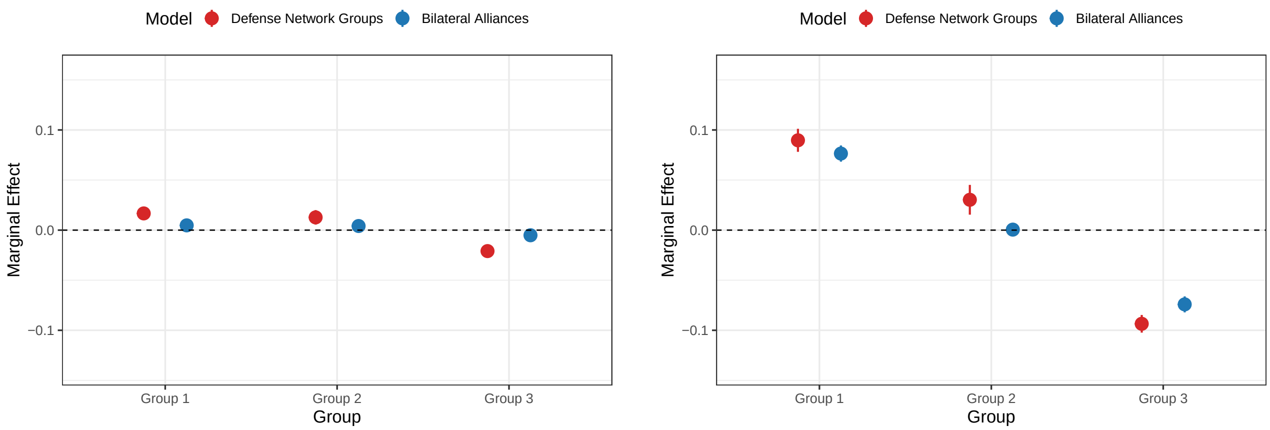
Figure 7 shows that while classifications based on bilateral defense ties do help predict voting behavior, our latent groupings perform on par with, or even outperform, these observable alliances. Moreover, our approach more effectively captures the fragmentation within the isolated group, which shows less cohesion.[26] This advantage becomes even stronger in the post–Cold War era, when the geopolitical divide between the US and Russia softened. Table 3(A) compares the Proportional Reduction in Error (PRE) between our model and classifications based on US allies vs USSR/Russia allies. PRE quantifies the improvement in prediction accuracy relative to the baseline, where all states vote with the global majority. Our model achieving a higher PRE suggests that it better predicts voting behavior.

For the IGO co-membership network, we compare the effect of group membership in our network to the effect of important single IGO membership. Specifically, we conduct two sets of comparisons: (1) We compare our three latent groups to members of the European Union (EU and EEC), members of the African Union (AU and OAU), and all other countries; and (2) We compare our three latent groups to

[24]To compare, we dichotomize group membership by assigning each country-year the group that it has the highest probability of being in. For computational reasons, we no longer exclude a state itself when calculating the majority vote of a group, but this does not affect the results.

[25]To ensure a fair comparison, we exclude the transitional period between 1988 and 1994 from our analysis. The benchmark model based on US vs USSR/Russia alliances is specifically constructed to capture Cold War alignments and their dissolution, and thus is designed to capture this transition period. In contrast, our latent group model is designed to uncover long-term structural blocs in defense cooperation, which is not comparable to the benchmark model during this period. Including this period would therefore bias the comparison in favor of the benchmark, overstating its relative performance (indeed, if we run the model for 1988-1994, the benchmark model has a much larger effect).

[26]Figure B3 and Figures B4 in the Appendix show that this advantage is consistent across issue areas.



(a) Cold War votes (1888)

(b) Post-Cold War votes (632)

Figure 7: Defense Alliance Group Membership and UNGA Controversial Votes

Note: The y-axis is the effect of dichotomous latent group membership or bilateral alliance on a state's probability of voting with the majority in that group. The x-axis is the three groups. The nodes represent point estimates, and the error bars are 95% confidence intervals. For defense alliance network groups, groups 1 to 3 are ranked according to the probability of their in-group tie formation (high to low). For US/USSR-Russia alliance classification, group 1 includes all US allies, group 2 includes USSR/Russia allies, and group 3 includes all other countries. CW refers to the Cold War period (pre-1988). Post CW refers to the post-Cold War period (post-1994).

members of the OECD, members of the SCO or BRICS, and all other countries. Figure 8 presents the results.[27] Unlike the defense alliance network, the results indicate that EU membership has a stronger effect on UNGA voting. OECD and SCO/BRICS membership also has a stronger effect than membership in a dense IGO network group. Group 1 in our network, which has a high probability of forming in-group ties, has an effect comparable to membership in the African Union. On some issues (nuclear weapons, arms control, and economic development), its effect is also comparable to the OECD.[28] It is probably unsurprising that EU membership has a strong effect. However, our latent group captures another group of states that are not clearly defined as the EU (e.g., Australia, Argentina, India, Pakistan, Sweden), while also exhibiting considerable effect on solidarity that is comparable to the AU and OECD. Additionally, while EU/AU membership is overall helpful in predicting voting behavior, Table 3(B) shows that our

[27] Note that the effect estimated here is marginal, and does not represent raw cohesion within groups. For example, the raw level of cohesion within the EU group is very high.

[28] Figure B5 in the Appendix presents results in different issue areas.

Table 3: Proportional Reduction in Error (PRE) by Grouping Strategy

Panel A: Defense Network	
Grouping	**PRE**
Defense Network Latent Groups	**0.215**
US Allies / USSR-Russia Allies / Others	0.169
Panel B: IGO Co-membership Network	
Grouping	**PRE**
EU Members / AU Members / Others	0.231
IGO Co-membership Network Latent Groups	**0.154**
OECD Members / SCO-BRICS Members / Others	0.150

Note: This table compares the predictive accuracy of different grouping strategies. Each model predicts how states vote on UNGA resolutions. The baseline assumes that states vote with the global majority on each resolution. The models improve upon this by assuming that countries in dense latent groups or predefined alliances/IGOs vote with their group's majority, while others follow the global majority. The PRE (proportional reduction in error) quantifies the improvement in prediction accuracy relative to the baseline. Higher PRE values indicate better predictive performance.

measure outperforms OECD/SCO-BRICS in reducing overall prediction error because the latter only identifies two very small blocs.

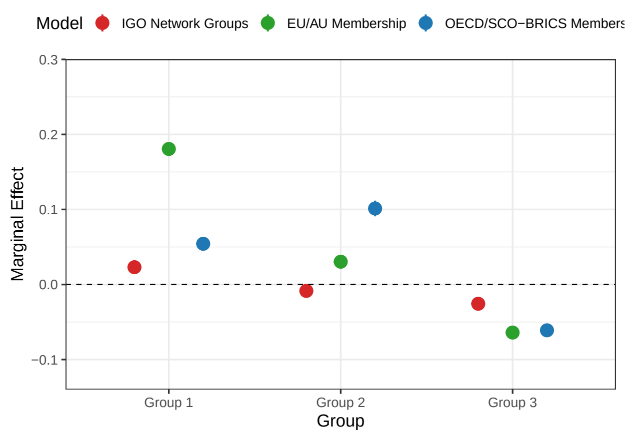


Figure 8: IO Group Membership and 2643 UNGA Controversial Votes

Note: The y-axis is the effect of IO group membership on a state's probability of voting with the majority in that group. The x-axis is the three groups. The nodes represent point estimates, and the error bars are 95% confidence intervals. For IO co-membership network groups, groups 1 to 3 are ranked according to the probability of their in-group tie formation (high to low). For classification based on EU/AU membership, group 1 includes EU members, group 2 includes AU members, and group 3 includes all other countries. For classifications based on OCED/SCO-BRICS membership, group 1 includes OCED members, group 2 includes SCO or BRICS members, and group 3 includes all other countries.

6.4 Alternative Explanations

In this section, we consider alternative explanations for our findings. By focusing on the interaction level of state behavior, we differentiate social roles from interests, information, and power. These dimensions will still be important, but here we address the concern that the social capital relationship could reflect one of these different logics of cooperation.

Institutional commitments convey information about state preferences that could lower barriers to cooperation in a more general way. One possibility is that dense ties in defense alliances and IGO co-membership networks promote information exchange that facilitates multilateral cooperation in the UN General Assembly on other issues. To assess this possibility, we compare the defense and IGO networks with the trade agreement network. Based on our earlier discussion, we consider trade agreements to have a strong basis on information to promote reciprocity while not generating the levels of trust that are associated with defense and IGO membership. If information exchange is the key mechanism to promote cohesion, we would expect to find similar cohesion in the trade network. Figure A6 displays the structure of the trade agreement network, where Groups 1 and 2 are also densely connected. However, these dense connections are insufficient to produce cohesion on other issues. Figure B6 shows that membership in these groups has no effect on key UNGA votes. This null result holds for all issue areas, including economic development (see Figure B7). The differential impact of density in trust-based networks supports our argument about social capital. The lack of explanatory power from the trade network casts doubt on the possibility that all types of agreement are equal when it comes to building cohesion among large groups of states.

Hegemonic states can lead others through bribes and coercion that may steer behavior in tie formation and then within UN voting. We consider the role of the most powerful member in each group to evaluate how power dictates where states line up in the group structure. For the defense alliance network, one potential concern is that our dense groups are simply capturing US allies and Arab states. Closer examination shows that there is variation in how defense ties form the latent groups. At a descriptive level, the groups do not completely overlap with allies of the leading state, the US in Group 1 and Saudi Arabia in Group 2.[29] In fact, 44.6% of country-year observations of US bilateral allies are not in Group 1, and more than 8% of Group 1 country-year observations are not direct US allies. For example, NATO ally Canada held partial membership in Group 2 for some years, as it did not have many defense ties with the US's major non-NATO allies (MNNA). Similarly, 51.6% of country-year observations of Saudi Arabia's bilateral allies are not in Group 2, and 55.4% of Group 2 country-year observations are not Saudi Arabia's direct allies. Figure B9 shows that the two dense groups identified by our model predict UNGA voting more effectively than the simple classification of US allies versus Arab states.

Given that the decision to form ties is based on national interest, there is also concern that the underlying economic and political characteristics of states drive the behavior we observe. There are several ways in which we address this possibility. We include common state-level characteristics such as income, democracy, and conflict involvement as monadic covariates, and find that these are not predictive of group membership. This indicates that there is no systematic homophily within groups. The states in dense groups are no more similar to each other than they are similar to states in the isolated group. Dyadic covariates likewise control for shared interests between state pairs. As an additional test, we replicate our voting analysis using two of the most common interest-based characteristics: income level and regime type. Figure B8 shows that neither characteristic produces consistent voting blocs. Among income groups, only entering the high-income state group increases the probability that states will vote together. When grouping by regime type, only autocracies and the mixed category (neither autocracy

[29] We picked the US and Saudi Arabia because many Group 1 members are allies of the US, and many Group 2 members are allies of Saudi Arabia.

nor democracy) exhibited cohesion, while democracies were divided.[30] Surprisingly, our results indicate that non-democracy may contribute to common action within the UN. This is the opposite of expectations for a domestic level of social capital supported in democracies acting to build trust among states. Further analysis should explore what contributes to the pattern. For our argument, the key point is to emphasize that the social capital formed at the international level has a stronger influence on multilateral cooperation than state characteristics.

7 Conclusion

This paper contends that states accrue social capital through their participation in networks of cooperation built around high-trust agreements. Using a dynamic blockmodel, we identify groups of states with dense in-group connections through the analysis of cooperation networks formed around defense treaties and IGO membership. Our analysis of the evolution of the global defense alliance network and the IGO co-membership network from 1961 to 2014 allows us to categorize latent groups of states that exhibit high social capital through their dense interaction. By focusing on the similarity of tie formation, we can also characterize a group of states that are isolated and lack social capital. The model incorporates monadic conditions associated with group membership and dyadic conditions that support the formation of ties.

Based on mapping the concept of social capital to latent groups, we assess the impact of social capital on multilateral cooperation. For both networks, we find two groups that exhibit high social capital and one group that has low social capital. Comparison of voting behavior in the General Assembly of the United Nations reveals distinct patterns based on group membership. In both networks, we find support for our hypothesis that states in densely connected groups are more likely to cooperate as a coalition

[30]For example, Indonesia, Bangladesh, Senegal, Comoros, and Namibia are among the democracies that least often voted with the democratic majority, whereas Ireland, Norway, Austria, Sweden, and Denmark were most likely to align with the democratic majority. We also tested alternative thresholds for dividing regime types, and the results remain unchanged. Note that this analysis does not control for other factors. It is intended only to show that our latent groups are not merely reproducing regime type clusters, and should not be interpreted as evidence about the causal effect of regime type on voting.

that votes coherently on UNGA key votes. By examining the effect on UNGA key votes in different issue areas, we demonstrate that the effect is not explained by narrow shared interests. Indeed, voting cohesion of groups generated within the defense cooperation network holds as strongly for nonsecurity issues. Moreover, the effect size is substantial compared to using conventional geopolitical or institutional categories, such as US vs Russia allies, OECD members, or the AU. However, not all agreements matter in the formation of social capital and we do not see a similar relationship arising from the network of states formed around trade agreements.

Our research demonstrates that social capital helps to explain how states act collectively in multilateral settings. A long question within international relations has asked how states structure international society (Bull, 1977; Dunne and Reus-Smit, 2017; Davis, 2025). Research has shown that bilateral cooperation increases the probability of future bilateral tie formation (Kinne, 2013b), and exiting multilateral agreements can lower future cooperation (Schmidt, 2025). We extend on these insights to show how densely connected communities form around agreements and identify higher cohesion among the groups with dense ties. This represents a new approach to studying relationships among states. Some states are bound together, even without a formal agreement, through the trust shared within a community. This supports their collective action on a range of topics. Coalitions in multilateral forums could either advance or block an agenda, as we saw in our analysis of UN votes. More generally, this logic may contribute to understanding conditions that support effective multilateral cooperation. Gray (2018) highlights the wide variation in vitality across international institutions. Future research could explore whether shared trust binding the states that are members of the organization contributes to the vitality of the organization.

States sort into groups and categories when working together. However, the choice of who to align with is not easy given the complex interests and diverse issues. By sharing trust and social networks, states within a densely connected community can more easily adopt similar stances on international issues. Among isolated states, the lack of social capital inhibits their coordination on critical issues despite shared interests.

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Online Appendix:

The Structure of International Cooperation Networks

A Additional Tables and Figures for the Network Models

A.1 Model Details

Formally, the data generation process of dynMMSBM can be summarized as follows:

1. Node i's mixed membership in K latent groups at time t is

$$\pi_{it} \sim \sum_{m=1}^{M} \Pr(S_t = m \mid S_{t-1}) \times \text{Dirichlet}(\exp[(x_{it}^\top \beta_{km})]_{k=1}^{K})$$

   where S is the random state that the network is in at time t. $S_t \mid S_{t-1} = n \sim \text{Categorical}(A_n)$ and A is a transition matrix. x_{it} is a vector of monadic predictors, and β_{km} is a vector of monadic coefficients specific to group k in state m.

2. Given mixed memberships of p and q, for pair pq, p's group indicator when interacting with q at time t is modeled as $z_{pqt} \sim \text{Multinomial}(1, \pi_{pt})$. Similarly, $w_{qpt} \sim \text{Multinomial}(1, \pi_{qt})$

3. Given the membership of node p and q at time t when interacting with each other, the edge Y_{pqt} is modeled as:

$$Y_{pqt} \sim \text{Bernoulli}\left(\text{logistic}^{-1}\left(z_{pqt}^\top \mathbf{B} w_{pqt}^\top + \mathbf{d}_{pqt}^\top \gamma\right)\right)$$

   where $B_{K\times K}$ is the block model matrix that captures the probability of tie-formation between latent groups, and $\mathbf{d}_{pqt}$ is dyadic predictors with associated coefficients γ.

Therefore, the joint probability can be written as:

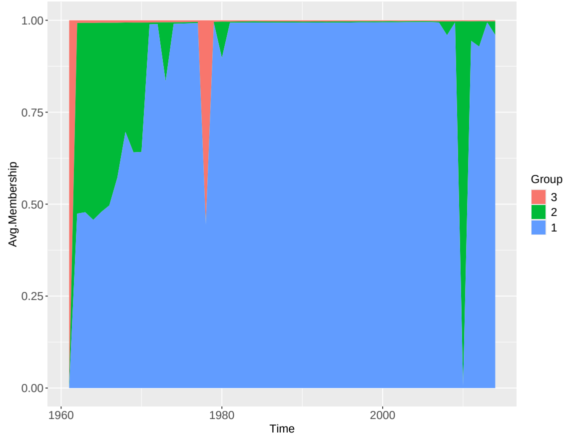
$$\begin{aligned}
&P(Y, \{Z, W, S\}, \Pi, A \mid \beta, \gamma, \mathbf{B}, \mathbf{D}, \mathbf{X}) \\
&= P(S_1)\left[\prod_{t=2}^{T} P(S_t \mid S_{t-1}, A)\right]\left[\prod_{t=1}^{T}\prod_{it\in V_t} P(\pi_{it} \mid X, \beta, S_t)\right]\prod_{m=1}^{M} P(A_m) \\
&\times \left[\prod_{t=1}^{T}\prod_{p,q\in V_t}[P(Y_{pqt} \mid z_{pqt}, w_{qpt}, \mathbf{B}, \gamma, \mathbf{D})P(z_{pqt} \mid \pi_{pt})P(w_{qpt} \mid \pi_{qt})]\right]
\end{aligned}$$

A.2 Defense Alliance Network

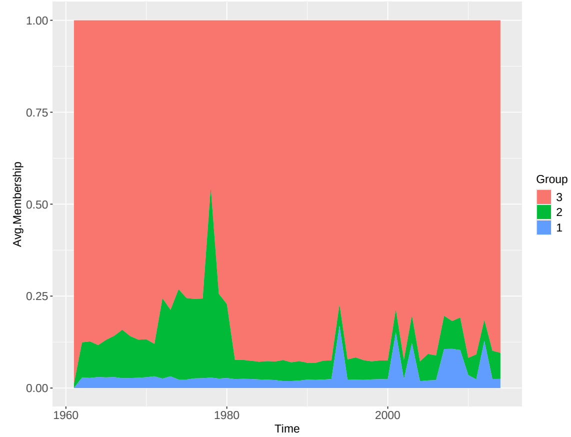
Group 1	Group 2	Group 3
Venezuela	Yemen	Ukraine
Ecuador	Saudi Arabia	India
Colombia	Iraq	Nepal
Chile	Sudan	Afghanistan
Guatemala	Algeria	Bangladesh
Honduras	Syria	Iran
Mexico	Tunisia	Uganda
Bolivia	Morocco	Sri Lanka
Haiti	Somalia	Burundi
Peru	Egypt	Myanmar (Burma)
Argentina	Senegal	Cameroon
Brazil	Burkina Faso	Vietnam
Dominican Republic	Niger	Tanzania
Belgium	Benin	Malawi
United States	Guinea	Malaysia
Netherlands	Ghana	Kenya
United Kingdom	Côte d'Ivoire	Congo - Kinshasa
Italy	Belarus	Zambia
Greece	Kazakhstan	Indonesia
Denmark	Russia	Angola
Turkey	Tajikistan	Cambodia
Czechia	Uzbekistan	Zimbabwe
Portugal	Azerbaijan	Cuba
France	Nigeria	South Sudan
Spain	Canada	Madagascar

Table A1: Defense Alliance Network: Countries with the Highest Membership Probability in Each Group

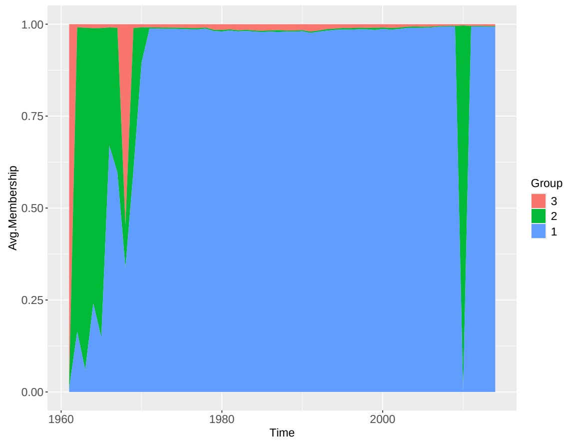
Note: This table shows the top 25 countries that most frequently instantiate membership in each latent group in the defense alliance network. We only include countries with an average population above five million.



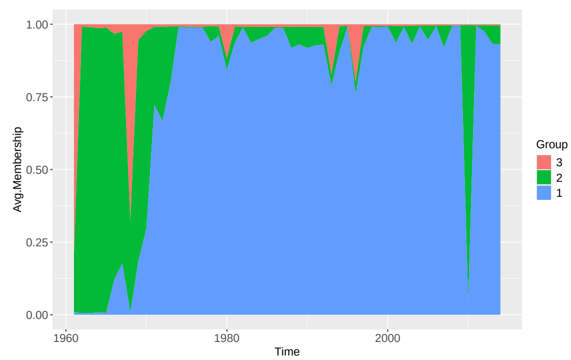
(a) US



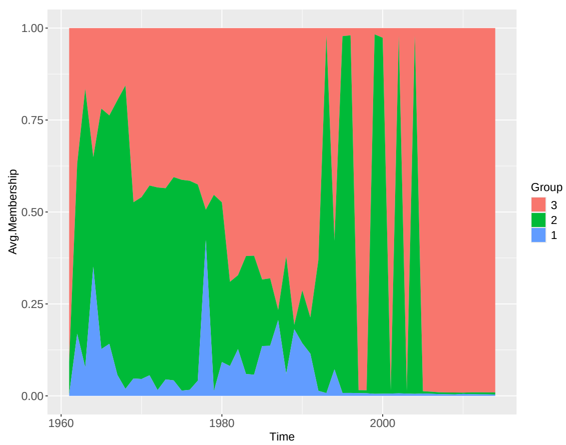
(b) China



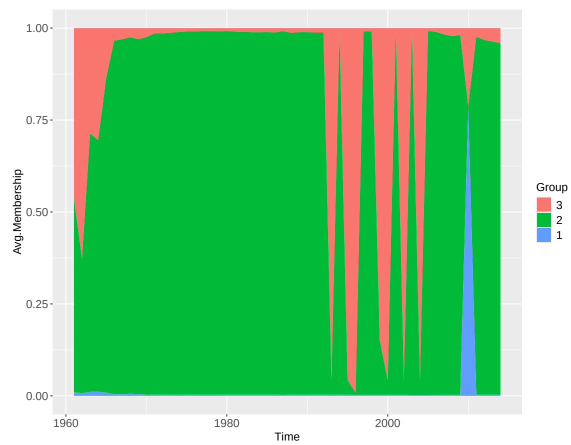
(c) UK



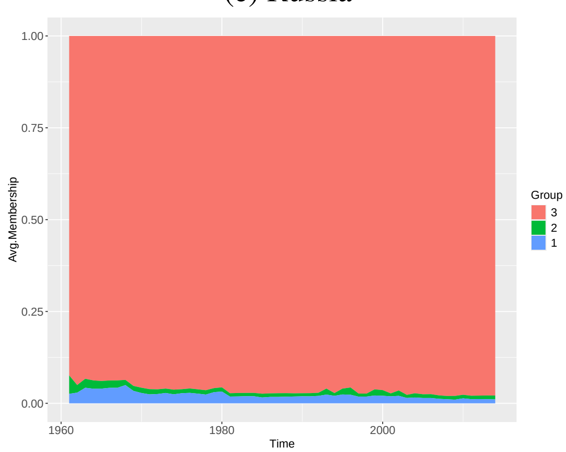
(d) France



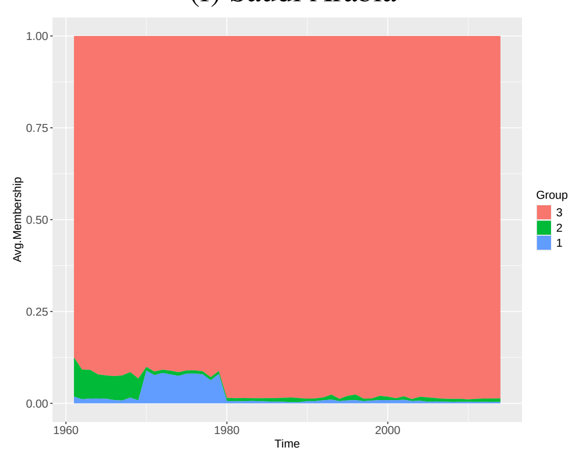
(e) Russia



(f) Saudi Arabia

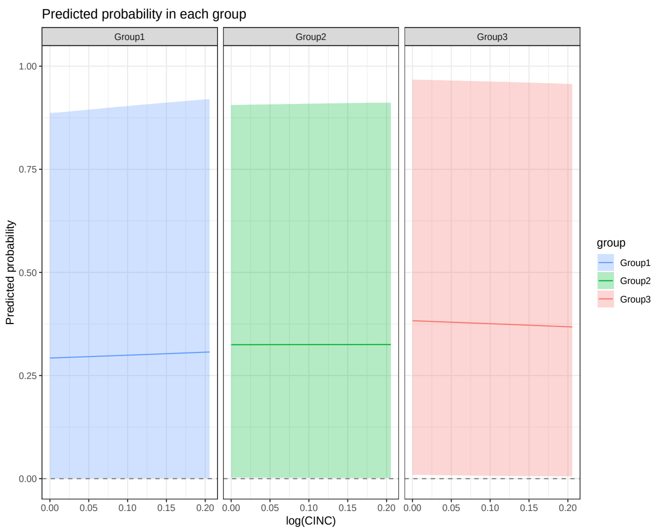


(g) India

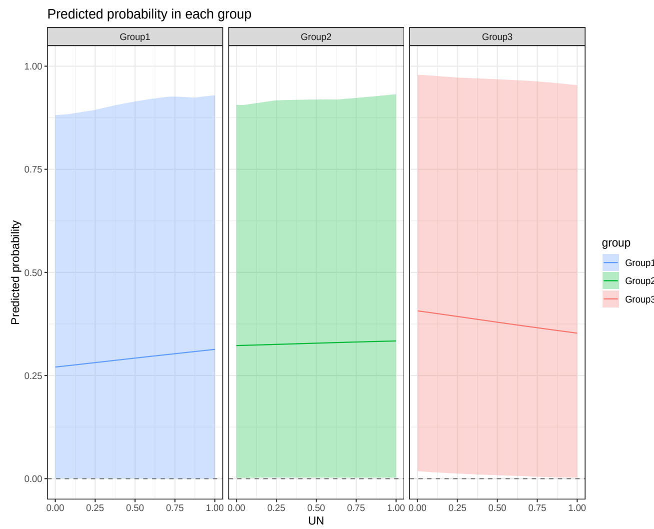


(h) Iran

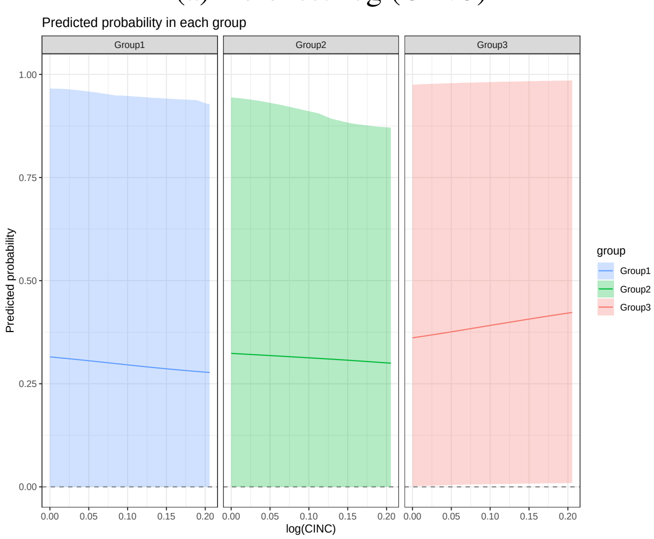
Figure A1: Example States' Membership in the Defense Alliance Network



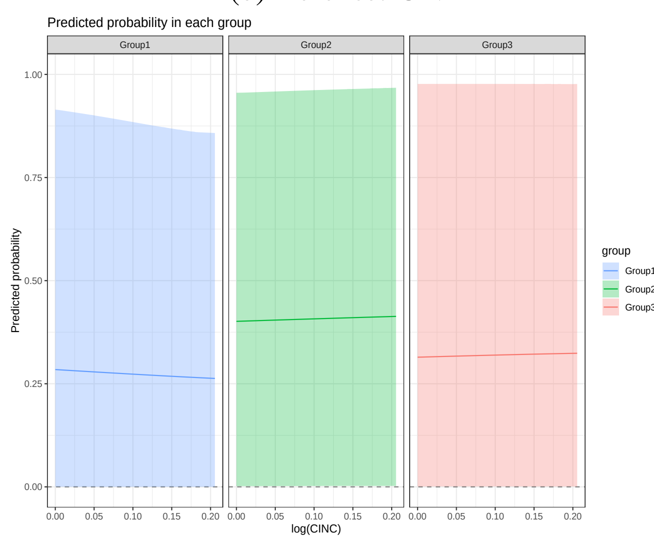
(a) Defense: log (CINC)



(b) Defense: UN



(c) Trade agreement: log (CINC)



(d) IGO co-membership: log (CINC)

Figure A2: Marginal Effects of Most Powerful Monadic Coefficients in the Three Networks

Note: The x-axis is the value of each covariate ranging from its minimum to the maximum in the data. The y-axis is the marginal effect of a one-unit covariate change on a state's membership probability in each latent group. One-unit is defined as 2% of the covariate's total range. The solid line is the average effect, and the shaded area is the 95% bootstrapped confidence interval.

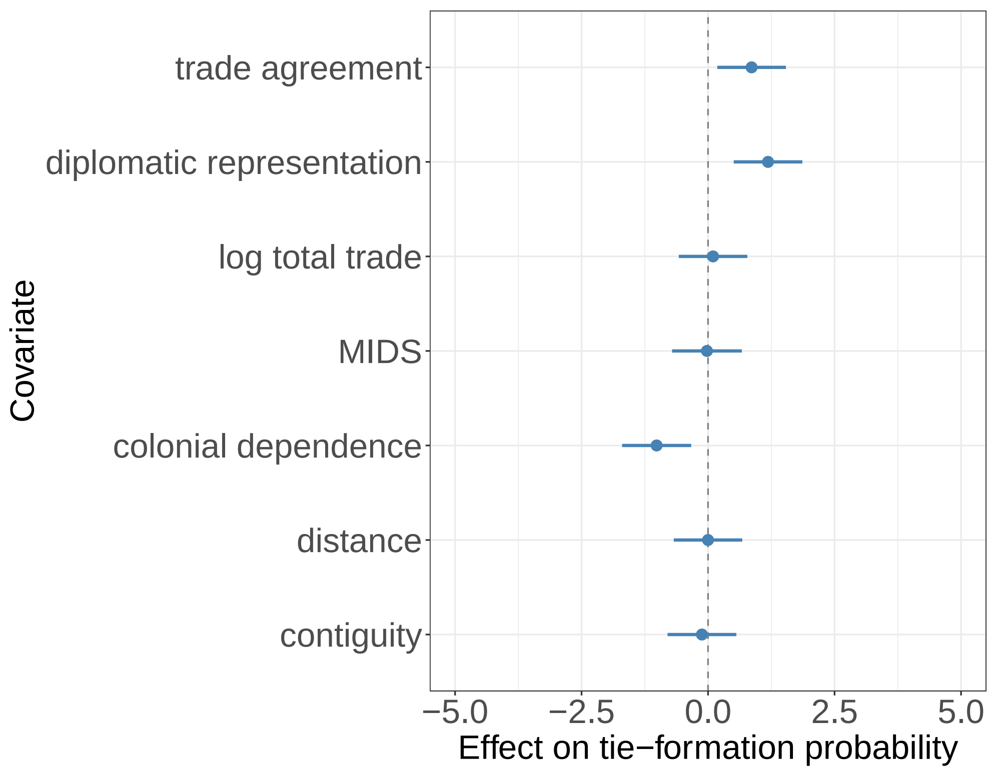


Figure A3: Dyadic Covariates in the Defense Alliance Network

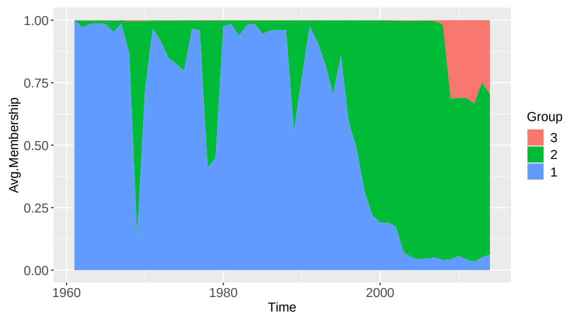
Note: This figure shows the effect of dyadic covariates on the probability of defense alliance tie formation. The solid dots are the posterior estimates, and the lines are 95% confidence intervals.

A.3 IGO Co-membership Network

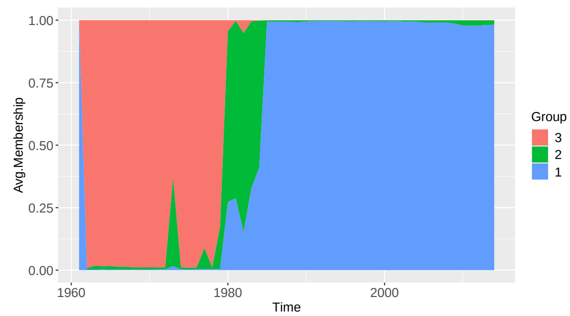
Group 1	Group 2	Group 3
Australia	Ukraine	North Korea
Japan	Russia	South Sudan
Canada	Azerbaijan	Tajikistan
Argentina	Kazakhstan	Vietnam
Morocco	Nepal	Uzbekistan
Peru	Burundi	Belarus
Philippines	Chad	Yemen
India	Rwanda	Somalia
Chile	Germany	Afghanistan
Pakistan	Myanmar (Burma)	Mozambique
Portugal	Yemen	Angola
Spain	Belarus	China
Sweden	Niger	Zimbabwe
Belgium	Hungary	Azerbaijan
Indonesia	Afghanistan	Nepal
Tunisia	Ethiopia	Kazakhstan
Denmark	Slovakia	Rwanda
Brazil	Somalia	Cambodia
Egypt	Czechia	Ethiopia
Netherlands	Angola	Burundi
Nigeria	Cambodia	Myanmar (Burma)
Mexico	Malawi	South Africa
Italy	Honduras	Iraq
Colombia	Bulgaria	Russia
United Kingdom	Uzbekistan	Czechia

Table A2: IGO Co-membership Network: Countries with the Highest Membership Probability in Each Group

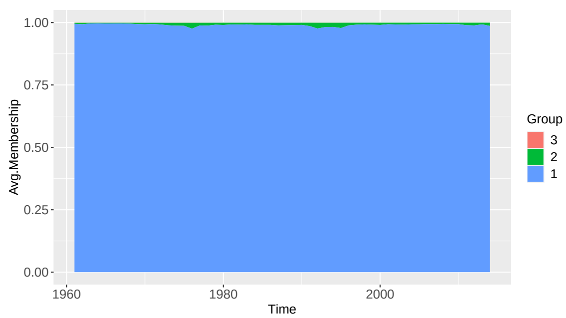
Note: This table shows the top 25 countries that most frequently instantiate membership in each latent group in the IGO co-membership network. We only include countries with an average population above five million.



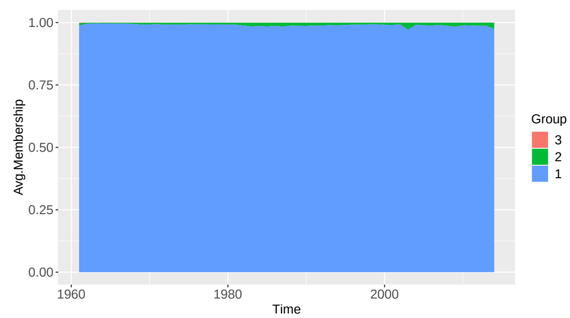
(a) US



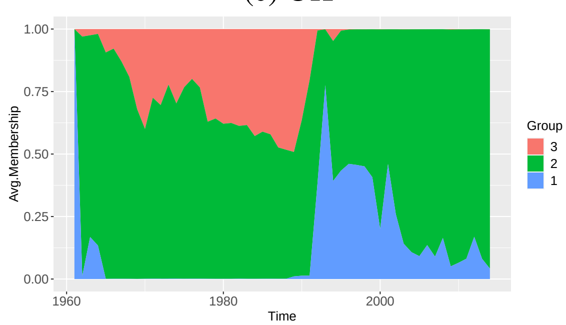
(b) China



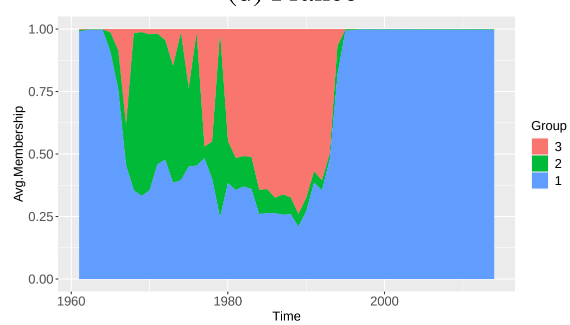
(c) UK



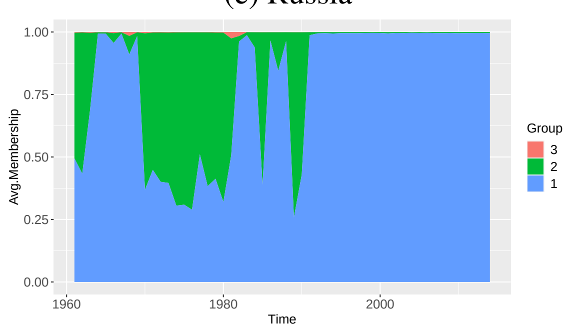
(d) France



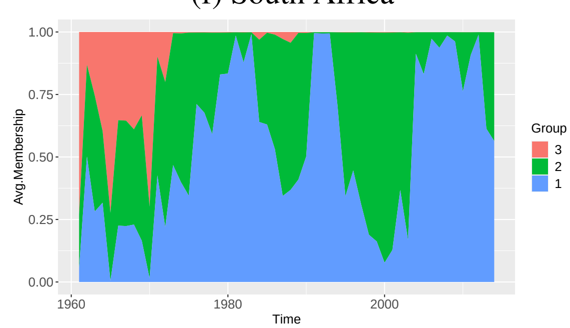
(e) Russia



(f) South Africa



(g) Switzerland



(h) Saudi Arabia

Figure A4: Example States' Membership in the IGO Co-membership Network

Note: The figure shows the mixed membership in three latent groups each year the state is present in the network for eight example states. The marked shifts in mixed membership can be explained by incidents changing states' monadic covariates (e.g., GDP) or large changes in tie-formation patterns.

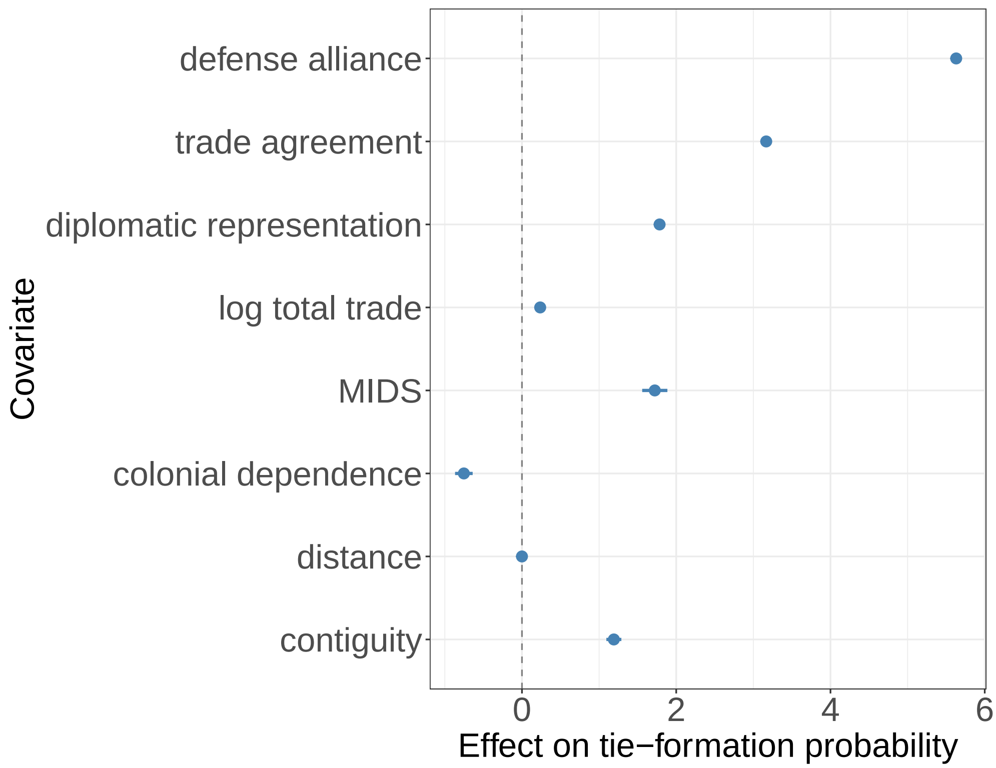
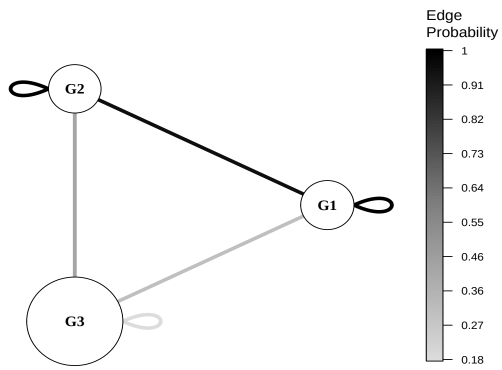


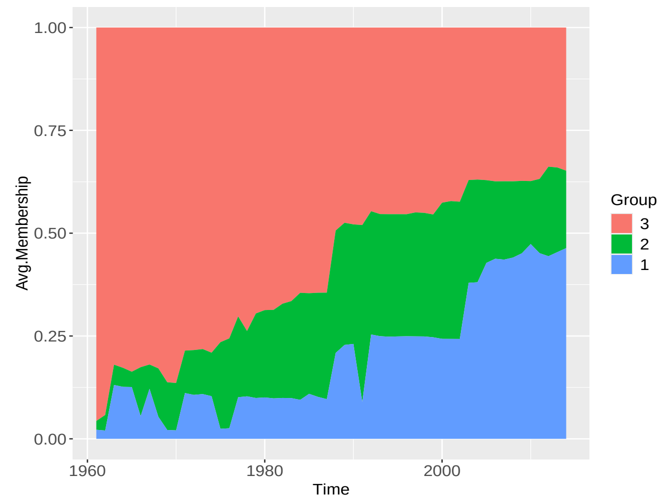
Figure A5: Dyadic Covariates in the IGO Co-membership Network

Note: This figure shows the effect of dyadic covariates on the probability of IGO co-membership tie formation. The solid dots are the posterior estimates, and the lines are 95% confidence intervals.

A.4 Trade Agreement Network



(a) Blockmodel



(b) Aggregate membership

Figure A6: Network Structure and Latent Memberships in the Trade Agreement Network

Note: In Panel (a), the nodes (circles) represent the three latent groups. The size of the nodes indicates the groups' membership size. The edges between the nodes represent the estimated probability a state from one group forms a trade agreement with nodes from the other group. Panel (b) shows the average membership proportion in the three latent groups from 1961 to 2014.

Predictor	Group1	Group2	Group3
(Intercept)	-2.622 (3.816)	0.484 (3.816)	1.716 (3.816)
log(GDP)	0.047 (3.825)	-0.146 (3.816)	-0.153 (3.816)
log(GDP per capita)	-0.024 (3.815)	0.153 (3.816)	0.129 (3.816)
log(CINC)	7.062 (3.816)	11.996 (3.816)	40.910 (3.816)
polity2	-0.009 (3.817)	-0.005 (3.816)	-0.023 (3.816)
MIDS	-0.001 (3.815)	0.005 (3.816)	0.084 (3.816)
WTO/GATT	0.080 (3.817)	0.074 (3.816)	-0.745 (3.816)

Table A3: Monadic Covariates in the Trade Agreement Network

Note: The model was in the first latent state for over 98% of the time, so we report coefficient estimates in this state. The estimates are coefficients of a Dirichlet regression, and standard errors are in parenthesis. The standard errors for Group 2 and Group 3 are different from four digits after the decimal point.

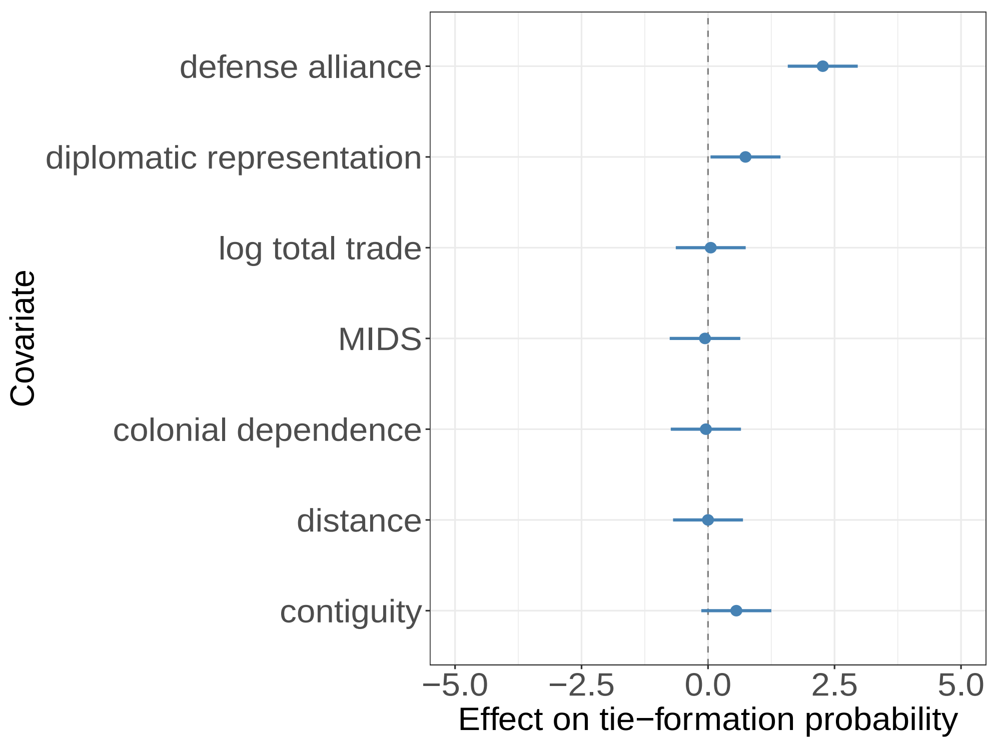


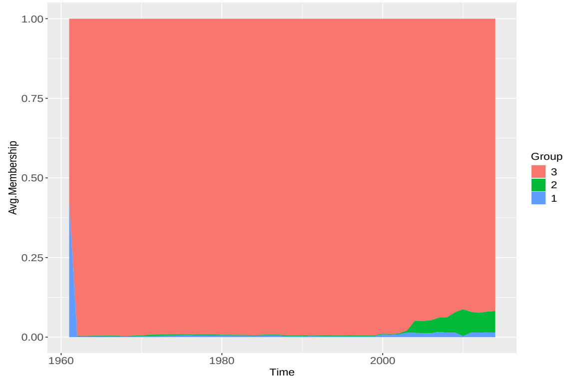
Figure A7: Dyadic Covariates in the Trade Agreement Network

Note: This figure shows the effect of dyadic covariates on the probability of trade agreement formation. The solid dots are the posterior estimates, and the lines are 95% confidence intervals.

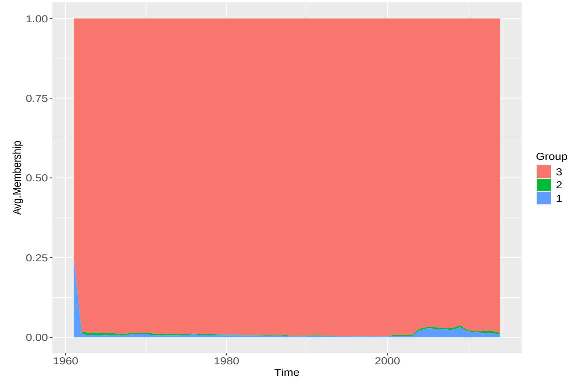
Group 1	Group 2	Group 3
Egypt	France	Belarus
Benin	Italy	Azerbaijan
Tunisia	Germany	Uzbekistan
Angola	Belgium	Tajikistan
Mexico	Netherlands	South Sudan
Chile	Denmark	Kazakhstan
South Korea	United Kingdom	Ukraine
Mozambique	Mali	Afghanistan
Pakistan	Burkina Faso	Nepal
Peru	Niger	Russia
Philippines	Greece	Saudi Arabia
Cameroon	Côte d'Ivoire	China
Congo - Kinshasa	Senegal	Japan
Nigeria	Spain	Myanmar (Burma)
Brazil	Burundi	Cambodia
Ghana	Rwanda	United States
Algeria	Benin	Canada
Morocco	Madagascar	Honduras
Zimbabwe	Malawi	Guatemala
India	Somalia	Switzerland
Mali	Uganda	Yemen
Sudan	Zambia	Syria
Senegal	Kenya	Bulgaria
Tanzania	Portugal	Australia
Burkina Faso	Ethiopia	Hungary

Table A4: Trade Agreement Network: Countries with the Highest Membership Probability in Each Group

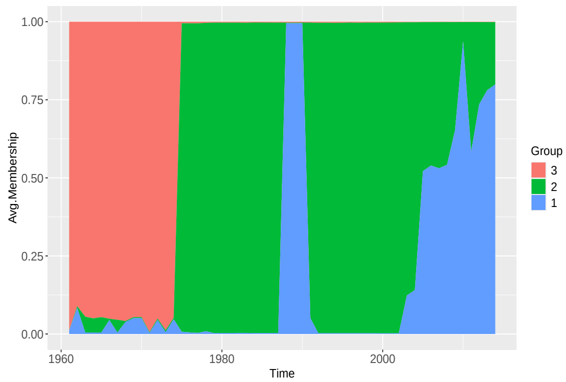
Note: This table shows the top 25 countries that most frequently instantiate membership in each latent group in the trade agreement network. We only include countries with an average population above five million.



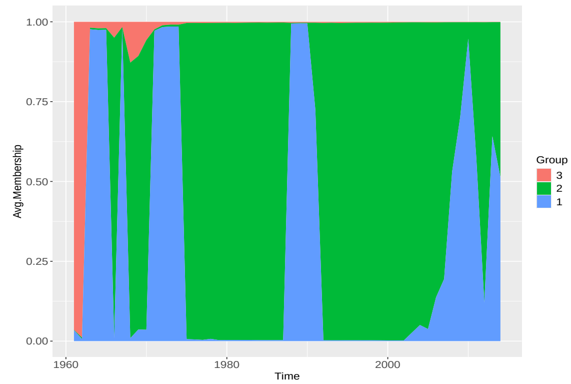
(a) US



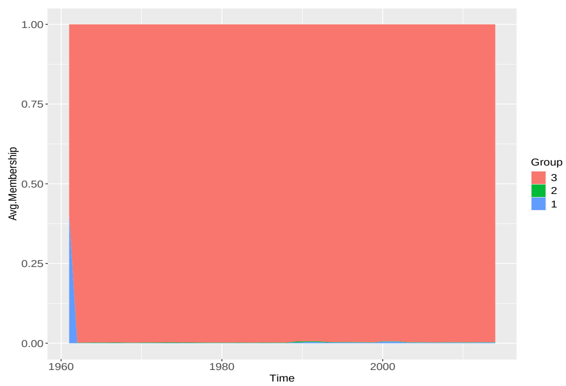
(b) China



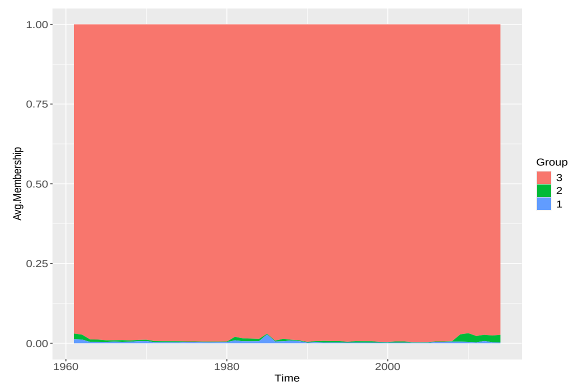
(c) UK



(d) France

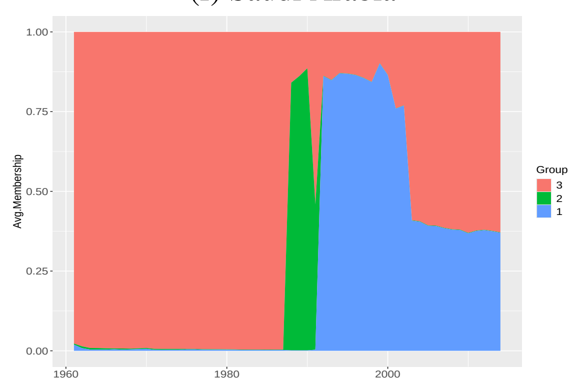


(e) Russia



(f) Saudi Arabia

(g) India

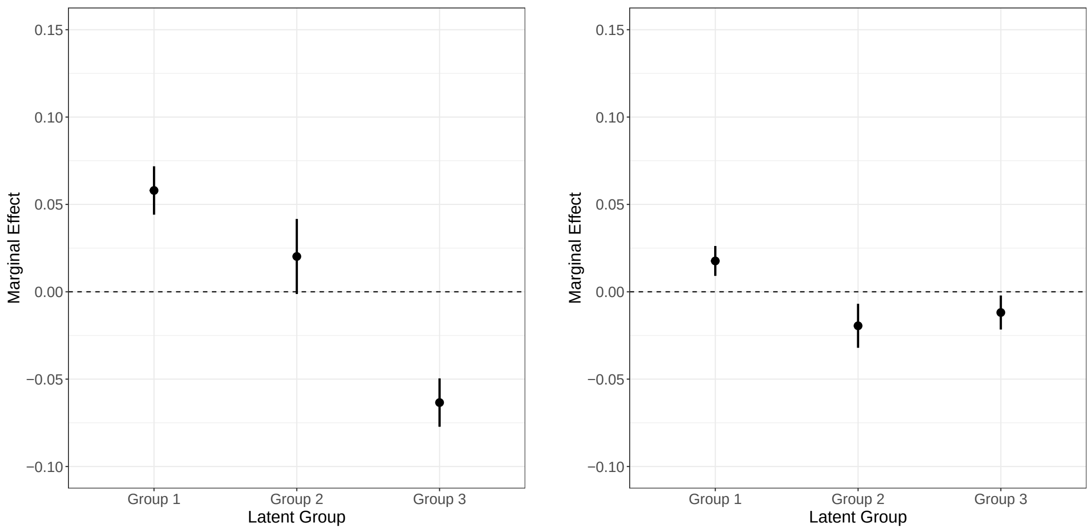


(h) Iran

Figure A8: Example States' Membership in the Trade Agreement Network

Note: The figure shows the mixed membership in three latent groups each year the state is present in the network for eight example states. The marked shifts in mixed membership can be explained by incidents changing states' monadic covariates (e.g., GDP) or large changes in tie-formation patterns.

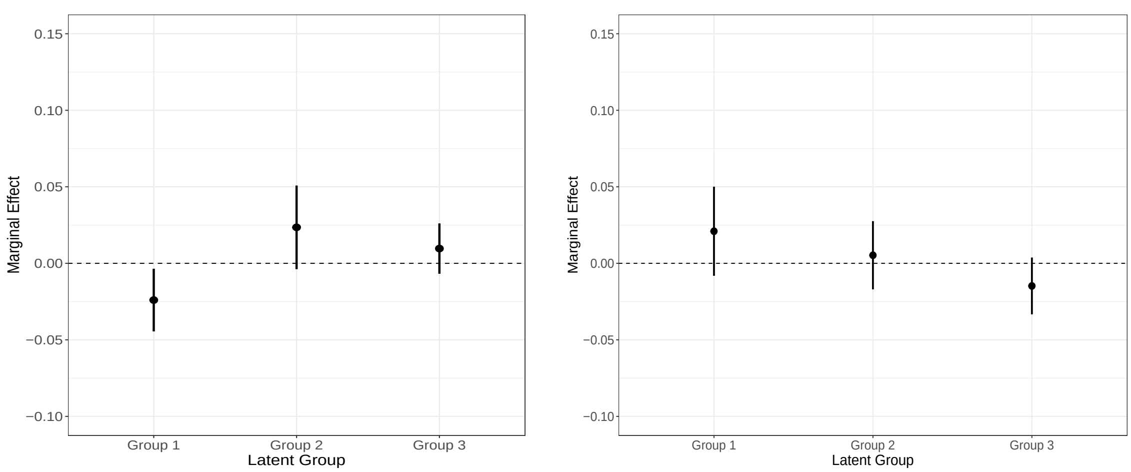
B Additional Figures on Key UNGA Votes



(a) Defense alliance network (b) IGO co-membership network

Figure B1: Latent Membership Probabilities and 381 UNGA Key Votes Identified by the US

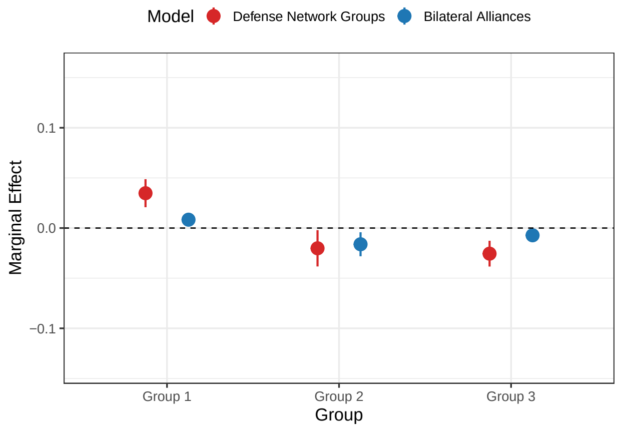
Note: The y-axis is the effect of latent group membership probabilities on a state's probability of voting with the majority in that group. The x-axis is the three latent groups.



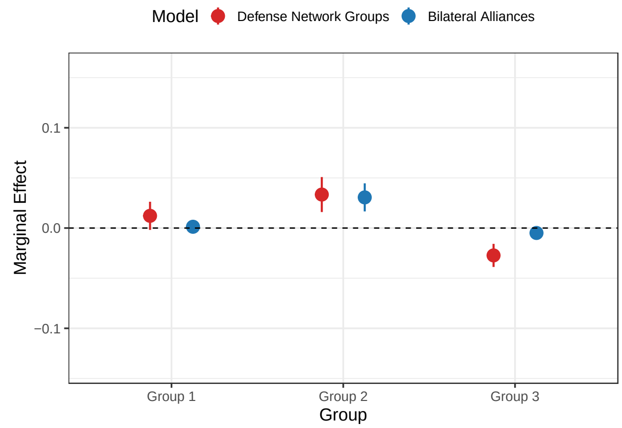
(a) Defense Alliance Network (b) Trade Agreement Network

Figure B2: Controversial Votes on Colonialism (408 votes)

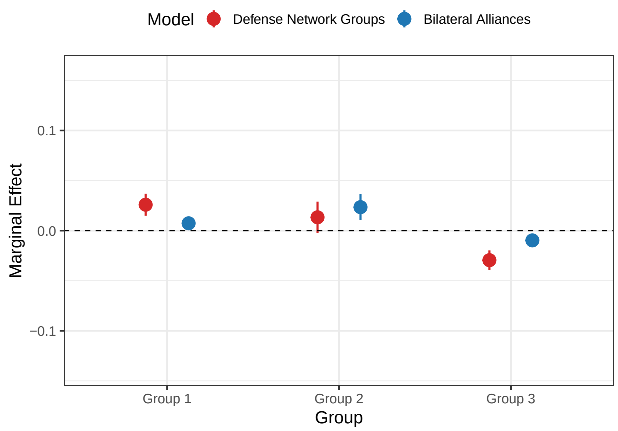
Note: The y-axis is the effect of latent group membership probabilities on a state's probability of voting with the majority in that group. The x-axis is the three latent groups.



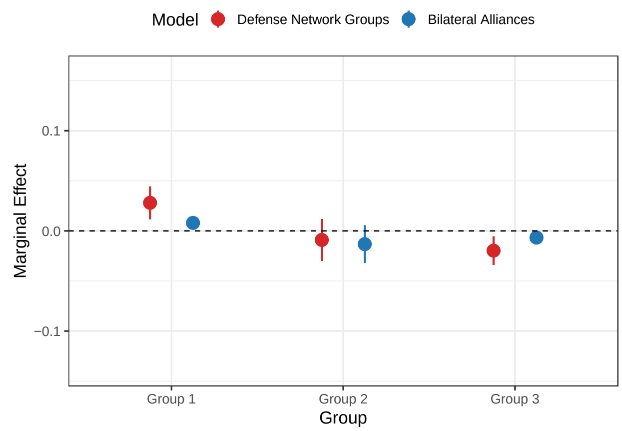
(a) Palestinian conflict (237 votes)



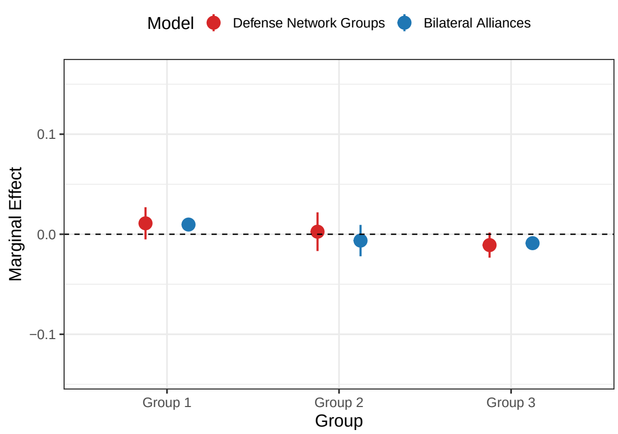
(b) Nuclear weapons and nuclear material (193 votes)



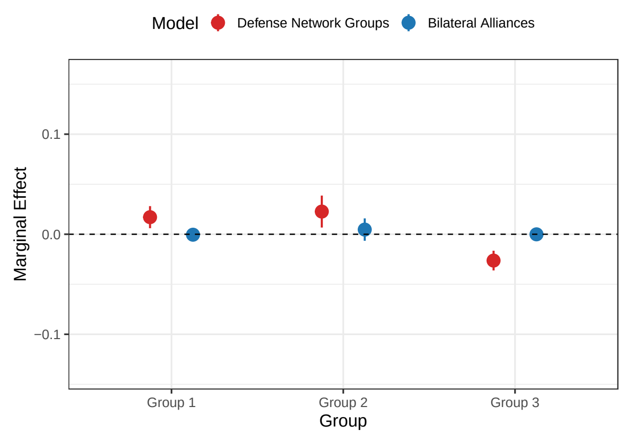
(c) Arms control and disarmament (240 votes)



(d) Collective Security (156 votes)

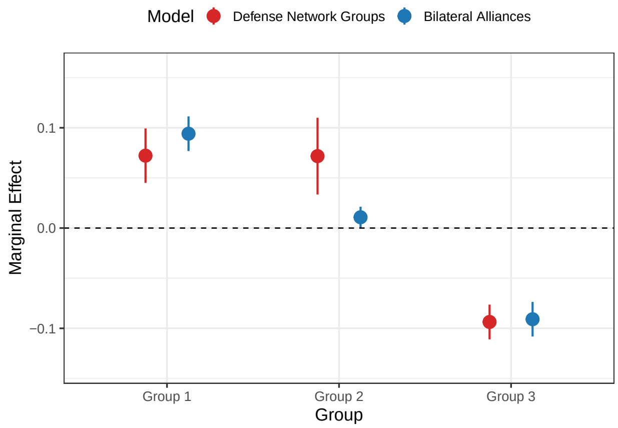


(e) Human rights (209 votes)

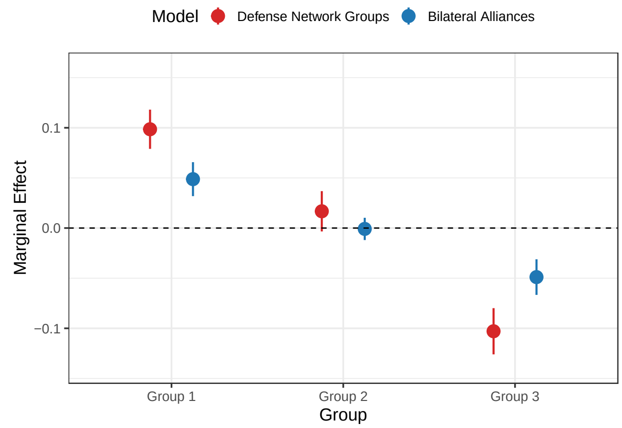


(f) Economic development (293 votes)

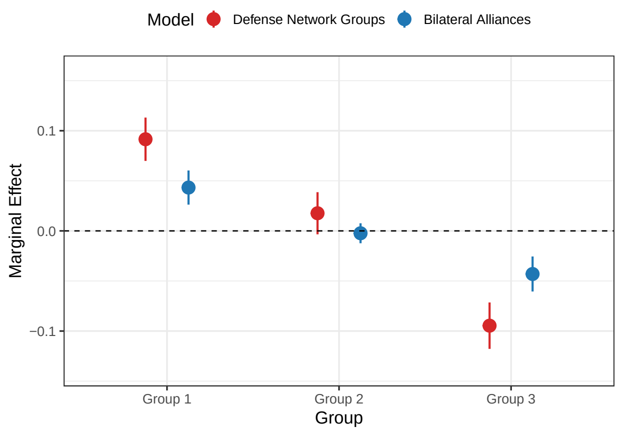
Figure B3: Defense Alliance Group Membership (versus US/Russia-USSR allies) and Controversial UNGA Votes (Cold War period: Pre-1988)



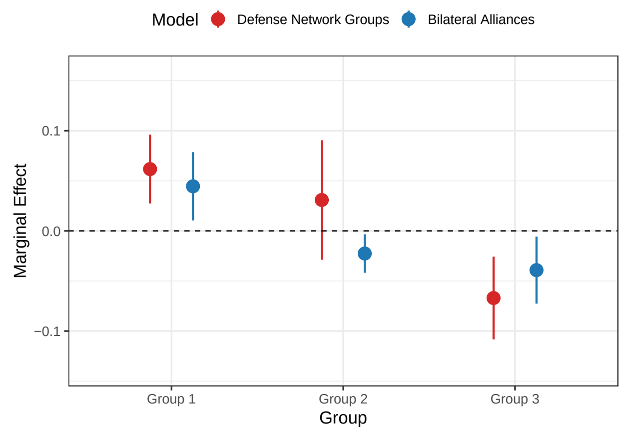
(a) Palestinian conflict (107 votes)



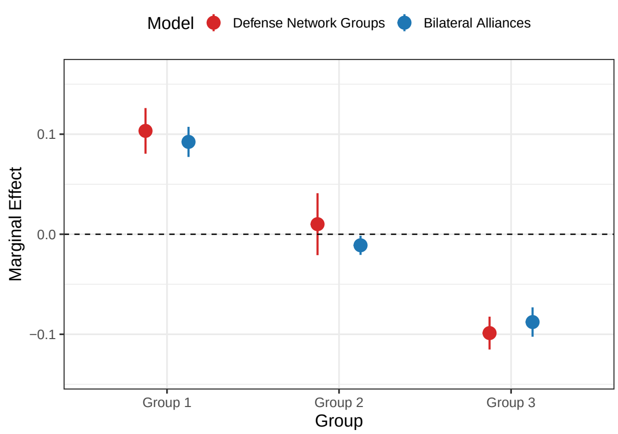
(b) Nuclear weapons and nuclear material (100 votes)



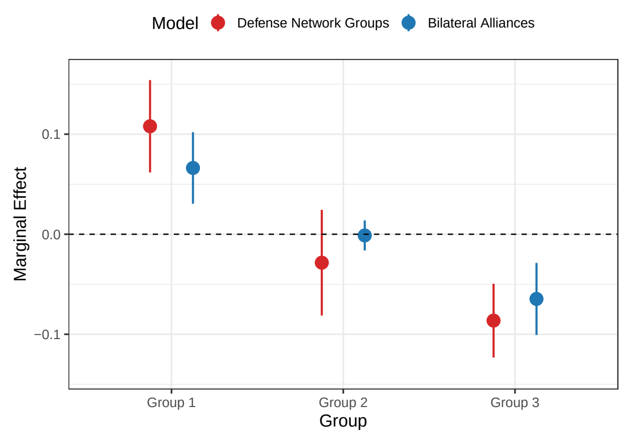
(c) Arms control and disarmament (120 votes)



(d) Collective Security (32 votes)

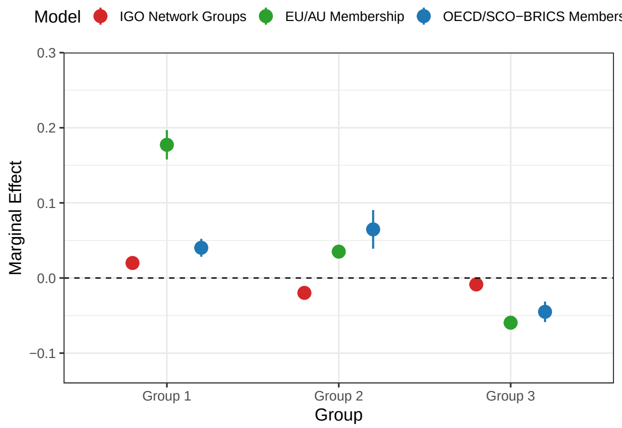


(e) Human rights (172 votes)

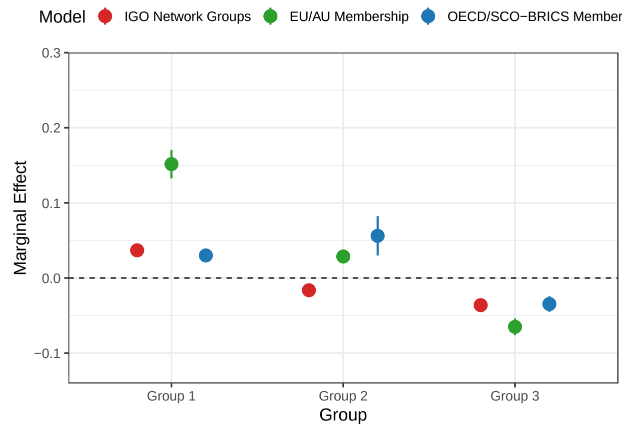


(f) Economic development (30 votes)

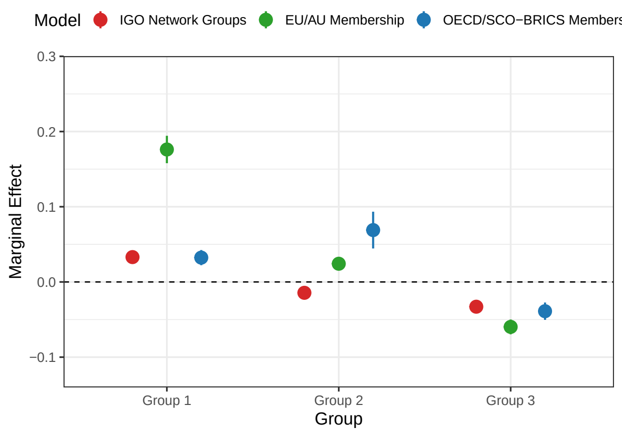
Figure B4: Defense Alliance Group Membership (versus US/Russia-USSR allies) and Controversial UNGA Votes (Post Cold War period: Post-1994)



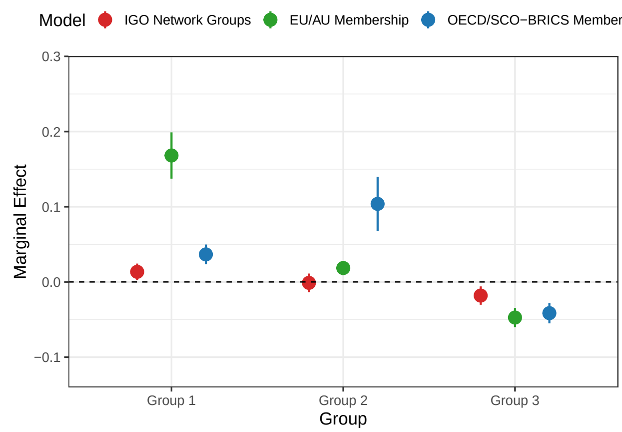
(a) Palestinian conflict (403 votes)



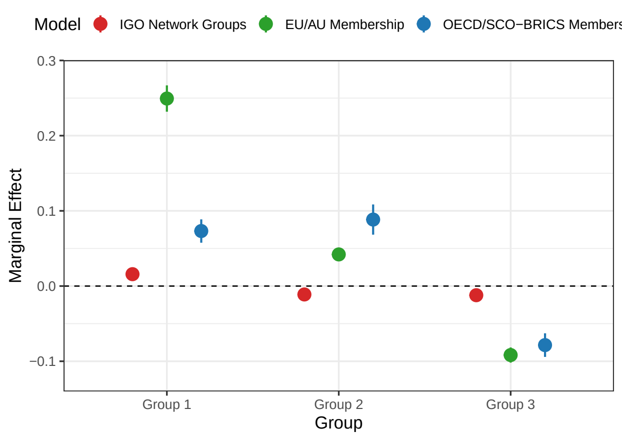
(b) Nuclear weapons and nuclear material (325 votes)



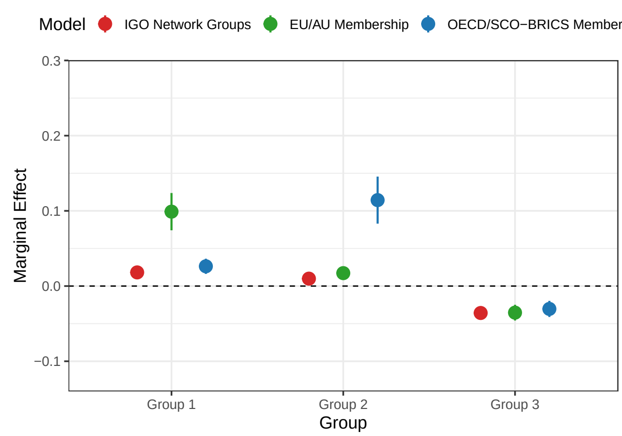
(c) Arms control and disarmament (391 votes)



(d) Collective Security (205 votes)

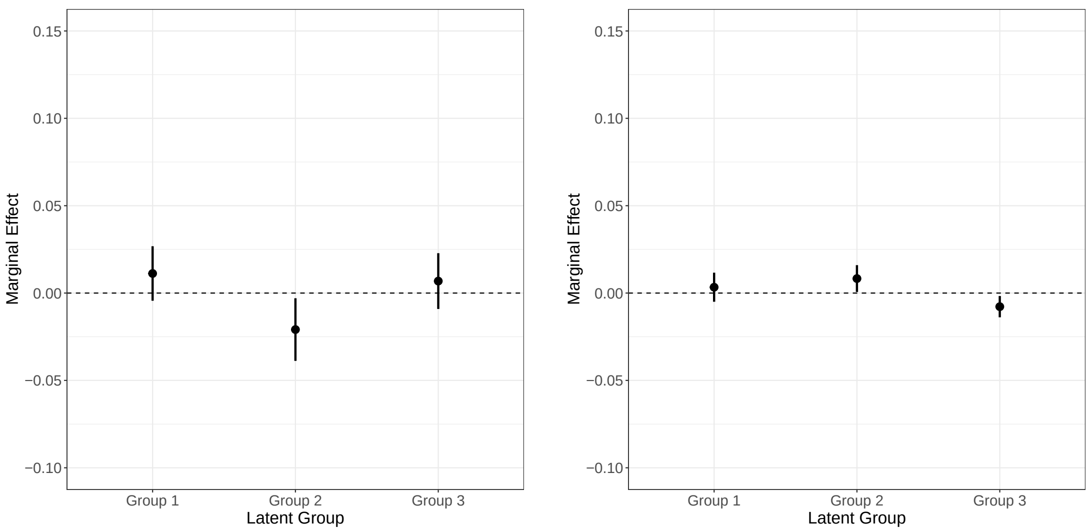


(e) Human rights (421 votes)



(f) Economic development (351 votes)

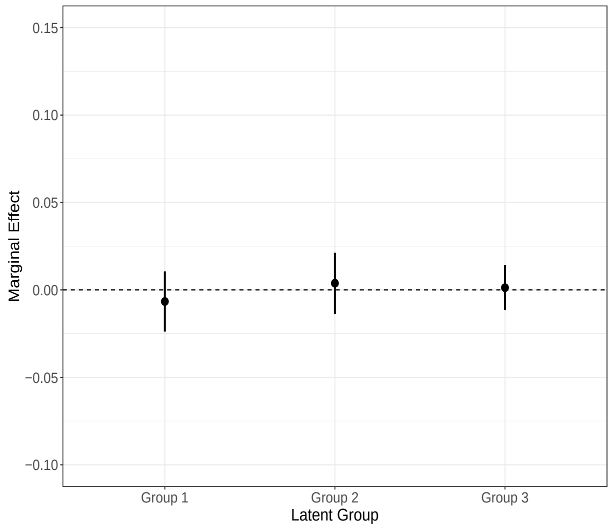
Figure B5: IO Group Membership and Controversial UNGA Votes



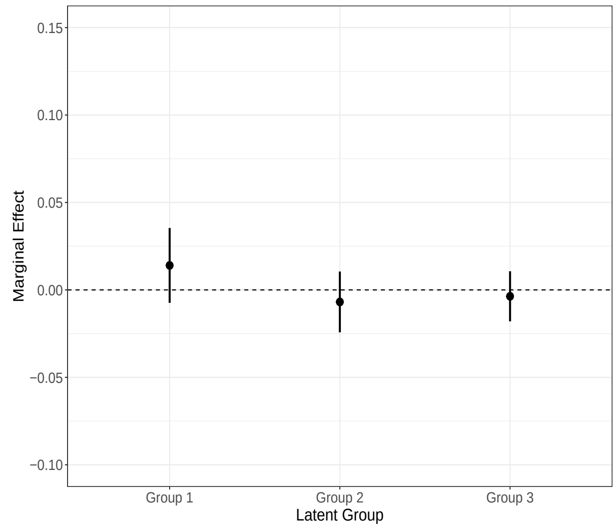
(a)381 US Important Votes (b) 2643 Controversial Votes

Figure B6: Latent Membership Probabilities in the Trade Agreement Network and UNGA Key Votes

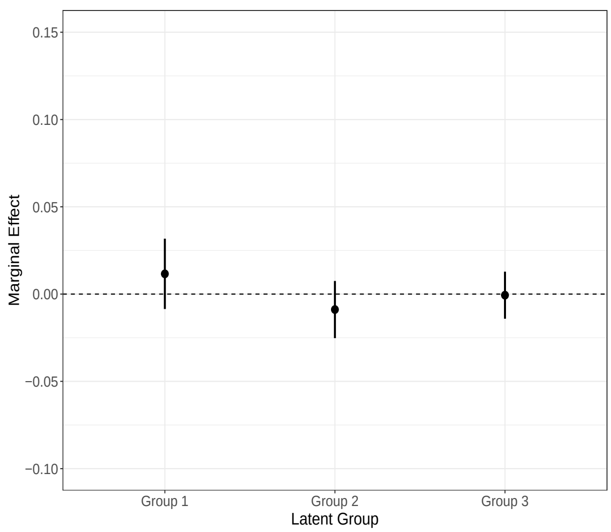
Note: The y-axis is the effect of latent group membership probabilities on a state's probability of voting with the majority in that group. The x-axis is the three latent groups.



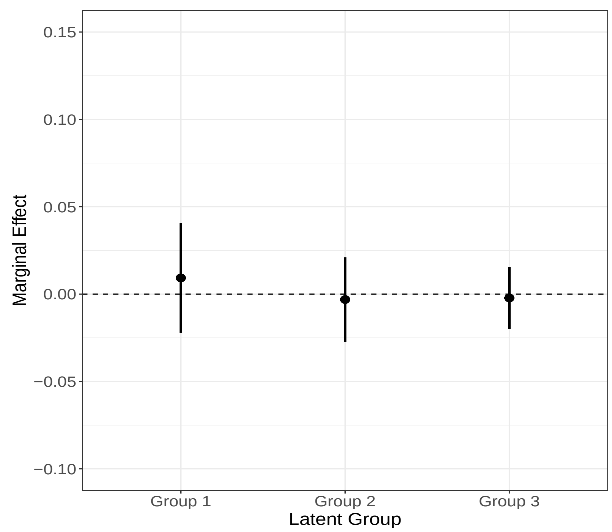
(a) Palestinian conflict (403 votes)



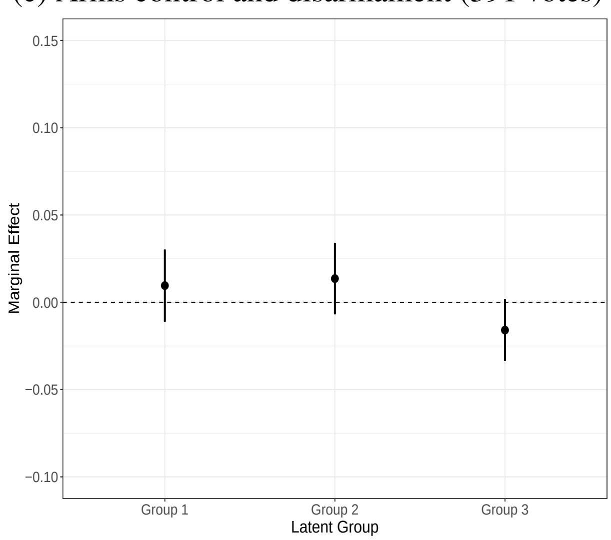
(b) Nuclear weapons and nuclear material (325 votes)



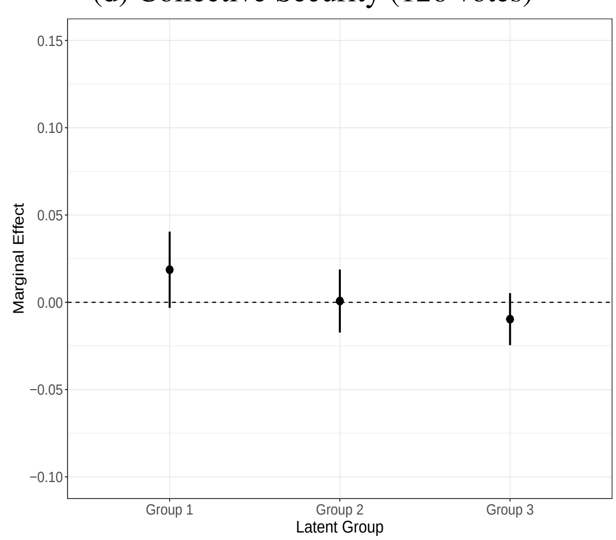
(c) Arms control and disarmament (391 votes)



(d) Collective Security (126 votes)

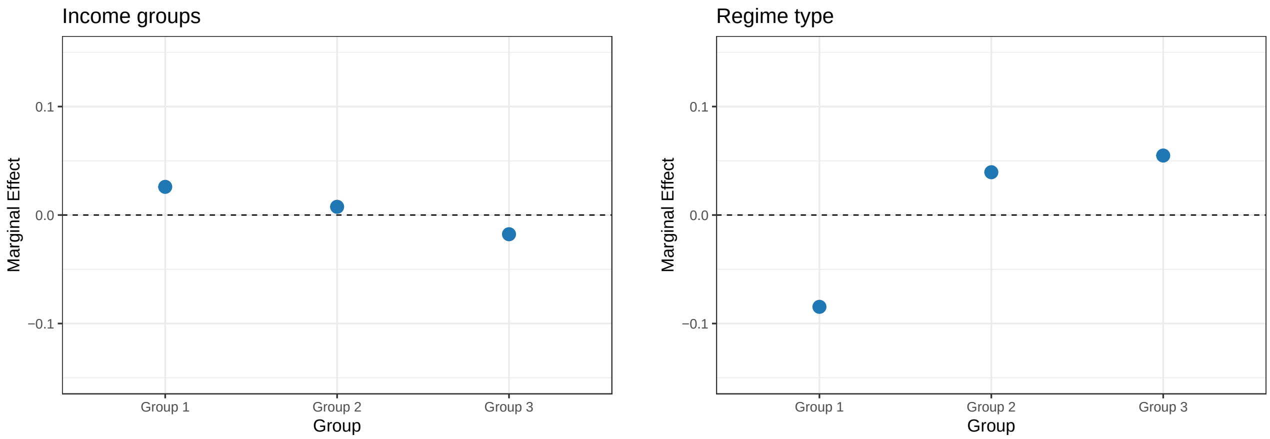


(e) Human rights (421 votes)



(f) Economic development (351 votes)

Figure B7: Trade Agreement Network: Latent Membership Probabilities and Controversial UNGA Votes



(a) Income groups (b) Regime type groups

Figure B8: Interest-based Groups and UNGA Key Votes

Note: The y-axis is the effect of income group membership on a state's probability of voting with the majority in that group. The nodes represent point estimates, and the error bars are 95% confidence intervals. The y-axis is the effect of regime-based group membership on a state's probability of voting with the majority in that group. In figure (a), the x-axis is the three World Bank income groups. Group 1 is high-income countries, group 2 is low-income countries, and group 3 includes middle-income countries. In figure (b), the x-axis represents the three regime-based groups. Group 1 is democracies (polity2 >5), group 2 is autocracies (polity2 $<$-5), and group 3 includes countries in between.

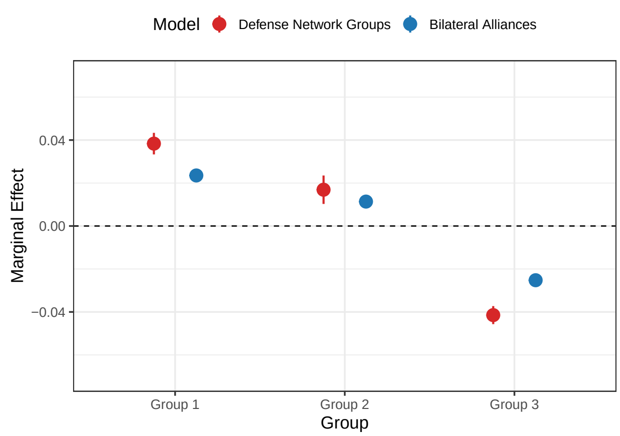


Figure B9: Defense Alliance Group Membership (versus US/Saudi Arabia allies) and UNGA Controversial Votes

Note: The y-axis is the effect of defense alliance group membership on a state's probability of voting with the majority in that group. The x-axis is the three latent groups. The nodes represent point estimates, and the error bars are 95% confidence intervals. For defense network groups, groups 1 to 3 are ranked according to the probability of their in-group tie formation (high to low). For bilateral alliances, group 1 includes all US allies, group 2 includes Saudi Arabia's allies, and group 3 includes all other countries.