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Understanding Multilateral Sanctions using a Multi-way Network Perspective

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Abstract

Countries often rely on sanctions to express discontent or disagreement with the actions of their peers in the international community. Many times, these sanctions have played a direct role in the lives of citizens and have led to course-correction by offending states. Sometimes, countries will issue joint sanctions, or sanctions sent by a coordinated group of countries. From a network perspective, multilateral sanctions add an additional layer of complexity to the representation of that sanction in the network, as well as to the assumptions made surrounding how sanctions are issued. For example, it is incorrect to assume a multilateral sanction issued by two countries is the same as two individual sanctions issued to a target state. In this thesis, we evaluate the evolution of the (multilateral) sanction network between 1945 and 2005 based on the Threat and Impositions of Sanctions dataset (Morgan, Bapat, & Kobayashi, 2014). In particular, we explore the role balance theory plays in sanction collaboration. Although the network tends to have more balanced structures than unbalanced ones, we find no evidence for all rules that constitute balance theory hold. Specifically, we do not find an effect of the "my enemy's enemy is my friend" mechanism on the formation of collaborations. At the same time, we do find evidence for the "my friend's friend is my friend" mechanism and find that country pairs where one country has sanctioned the other earlier, are less likely to collaborate on sanctions later.

Contents

1 Introduction

Sanctions have been a way countries have historically expressed political, military, social and economic disagreement against targeted states (Doxey, 1987). Sanctions do not impact only the relationships between the states imposing them (the 'sender states') and the states receiving them (the 'target states'), but also the lives of many citizens of each state. Historically, sanctions have reduced bilateral trade by as much as 90%, often delivering damage to the economies of both the sender and the target state (Hufbauer, Elliott, Cyrus, Winston, et al., 1997). Losses in operating revenue, asset values, and employees are much smaller for sanctioned firms compared to non-sanctioned peers, however, if a targeted regime chooses to "shield" strategically important firms from harm (Ahn & Ludema, 2020).

To study the use of sanctions over time, Morgan et al. (2014) composed the Threat and Impositions of Economic Sanctions (TIES) data, containing information on sanctions in the form of tariffs, export controls, embargoes, import bans, travel bans, frozen assets, foreign aid cuts, and blockades from 1945 to 2005 (Morgan et al., 2014). They documented the rise of sanction use in recent years, as well as the tendency for sanctions to be issued by a small group of states. Morgan et al. (2014) also documented that in recent years, the world saw a rise in both multilateral sanctions, and that sanctions have become increasingly successful in changing the behavior of the target state. This observation supports their earlier finding that revealed multilateral sanctions are more effective than unilateral sanctions (Bapat & Morgan, 2009).

Since sanctions always involve at least two states (a sender and a target), we can say that sanctions are inherently relational. Cranmer, Heinrich, and Desmarais (2014) conducted an analysis over dyadic relationships in the TIES data. In their study, they maintained that the complex mixture of dyadic (i.e., pertaining to pairs of countries) interactions that constitutes all the sanctions is a network. Using a temporal exponential random graph model, they found that existing sanctions significantly affect the likelihood of the development of other sanctions through several structural, endogenous processes such as reciprocity (Hanneke, Fu, Xing, et al., 2010). This means that the creation of sanctions by a sender state makes it more likely for target states to retaliate with sanctions of their own.

There are, however, some drawbacks to using dyadic relationships in analyzing economic sanction interactions among countries. Often, more than one country is involved in threatening or imposing a sanction. Consider the 1998 sanctions posed by the United States and Canada against India for nuclear proliferation (*United Nations Press Release DCF/332*, 1998). In a network that is composed of only dyadic relations, these events would be considered two different, independent interactions (one sanction issued by the United States and the other issued by Canada), but that independence assumption is incorrect since the sanction was issued by the United States and Canada together. A model based on such an independence assumption would incorrectly evaluate the development of these sanctions as separate events.

If we would, however, account for the nature of multilateral sanctions, we would model not only the development of the sanction events, but also the alliances that developed as a result of collaboration in sanction events. If these alliances then affect the development of sanctions, this could help to tell a network story about economic sanctioning behavior that goes well beyond that of the current empirical results.

Sanction threats, retaliations, and implementations are often not independent of each other over time. Multilateral sanctions do not occur independently of existing relations between states, whether positive or negative. As such, it is imperative to take the countries' collaboration and sanction history into account when studying sanction behavior. One important driving factor in the formation of many networks is the network actors' preference for balance. Balance theory provides a framework through which countries' relationships can be categorized as either balanced or unbalanced. In its original introduction, it refers to the stability of relations within a triad (Heider, 1946). Specifically, in the context of multilateral sanctions, if sanctions were considered a negative relationship and collaborations were considered positive, then some configurations of relations in this triad are considered balanced, while others are not. Moreover, such stability could have an effect on the further development of sanctions and collaborations in the international community. Balance theory has been a part of the theoretical foundation in various other disciplines, including in supply chain management and logistics (Choi & Wu, 2009).

In the following, we will focus on the role of balance theory in the creation of (collaborations in) multi-lateral sanctions. Specifically, we will use a temporal model to explore the development of ties between countries, the Dynamic Network Actor Model (DyNAM; Stadtfeld, Hollway, & Block, 2017). The basis for this model is that actors choose each other in order to form a tie. This process is known as choice coordination. In the context of multilateral sanctions, one would expect that countries typically mutually choose each other in order before issuing a sanction jointly. As such the setup for this model works well for the country collaboration aspect of multilateral sanctions.

To account for history in sanction development, the creation of new collaborations and sanctions is modeled as a function of preexisting sanctions in the network. We hypothesize that coordinated collaboration between states in the network relies heavily upon existing relations, and that in choosing who to collaborate with, countries will avoid unbalanced relationships as best as they can. To test this, we will integrate component from balance theory into a DyNAM.

We will study balance theory in the context of international sanctions based on the TIES data (Morgan et al., 2014). After providing some background on balance theory in Section 2, we will begin by describing and visualizing the network data. Visualizations of the network in two dimensions provide a more thorough descriptive analysis of the TIES data through existing network descriptive measures. In addition, we will operationalize balance theory in the context of sanction networks, and will measure the incidence of various balanced and unbalanced structures over time (Section 3).

In the second part of this thesis, we will model the evolution of multilateral sanction collaborations over time by applying the DyNAM to the TIES data. The main empirical points of consideration here are how countries partner for collaborations, important country attributes contributing to their attractiveness as partners, and how existing sanctions and elements of balance play a role in collaborations (Section 4). We will conclude with a discussion of our results and ideas for future work (Section 5).

2 Theoretical background

The majority of work related to statistical network analysis is in the realm of dyadic relationships, or, ties between two nodes in the network. Common ways to study networks of this format are through community detection, and node centrality and connectivity analyses (Carrington, Scott, and Wasserman, 2005; Newman, 2018). In social network science, these topics are typically analyzed classification into different categories, allowing scientists to evaluate how these different tie classes affect each other (Borgatti, Mehra, Brass, & Labianca, 2009). Modeling the development, creation, and dissolution of ties over time has created the basis for evaluating the TIES network. Explanatory variables for network models include structural and node covariates. As we intend to model ties with a focus on balance theory, we begin by discussing the definition and past applications of balance theory.

Heider (1946) first introduced balance theory as a framework to evaluate the state of combinations of positive and negative relations in a triad. If there is a positive relation between two nodes, they are said to be 'friends' for short, and if they have a negative relation, they are said to be 'enemies'. A balanced triad refers to an arrangement of ties over three nodes that do not violate the following set of rules (Cartwright & Harary, 1956):

A1: A friend of a friend is a friend.
A2: A friend of an enemy is an enemy.
A3: An enemy of a friend is an enemy.
A4: An enemy of an enemy is a friend.

For example, Choi and Wu (2009) discuss balance theory as triadic supply chain models in a "buyer-supplier-supplier" configuration. One balanced archetype in this context is when the buyer (equivalent in role to the country being sanctioned) harbors a negative relationship towards both suppliers (equivalent in role to the countries issuing sanctions). The suppliers in turn unite against their ill-willed buyer, forging a positive relationship with each other in the process. This "my enemy's enemy is my friend" setup tracks exactly with the conditions we may assume to take place in a sanction setting. According to Choi and Wu (2009), this archetype is stable, and the development of these archetypes can be measured.

Rawlings and Friedkin (2017) found that violations of the balance theory rules reduce over time, meaning a network tends towards a state of balance. They found this in the context of a network of interpersonal tensions in the Urban Communes dataset, a dataset of small, intentional communities in the United States (). International relations change frequently enough that observation in the interpersonal relations data's setting may break down in the context of sanctions, and is therefore worth exploring. Rawlings and Friedkin (2017) establishes that there are sixteen different tie configurations in a triad, the counts of which in a network form the so-called triad census. For networks with three-way relationship (e.g., two countries collaborate together to target a third one), the triad census is much larger. This is true for the sanction networks especially, considering the different types of relationships countries in this network may have (sanctions, collaborations, or no relationship).

In the context of sanction networks, two countries can simultaneously sanction each other and collaborate on a sanction. While we would consider this situation definitely unbalanced, it is not covered by the four rules posited by Cartwright and Harary (1956), because in their setting such an overlap was impossible. Therefore, we here add the assumption:

A5': A friend is not an enemy.

In the context of sanction networks, we can define an enemy as the actor at the other end of a sanction tie, and a friend as an actor at the other end of a collaboration tie. However, since two countries can also neither collaborate nor have a sanction tie between them, we add a sixth assumption:

A6': A null tie is a vacuously positive relationship.

The term "vacuously positive" here signifies that we simply do not have enough information to conclude a negative relationship between countries. Note that the definition of vacuous used

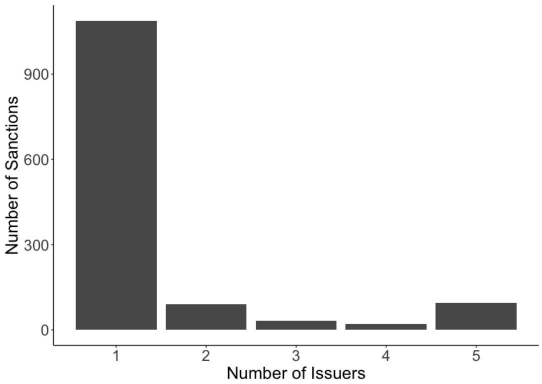


Figure 1: Distribution of the number of issuers for a given sanction, 1945-2005.

here is not quite the same as was used by Holland and Leinhardt (1977). In their paper, Holland and Leinhardt (1977) classified triads in the directed triad census as transitive and intransitive. In the cases where they did not have enough information from the structure to judge transitivity, they classified the structure as vacuously transitive. As such, we have that a triad is transitive until proven intransitive. Similarly, we have classified a relationship between two countries as positive until classified as negative (such as through a sanction).

3 Methods

The TIES dataset Morgan et al. (2014) covers 1412 sanction events which occurred between 1945 and 2005. Each event is either a sanction threat (845 events, 40%) or an imposed sanction (60%). Sanctions and sanction threat can be either unilateral or multilateral, as they involve up to five sender states and a target state. Figure 1 displays the distribution of the number of senders in a sanction. 18% of the sanctions issued in this data were multilateral (at least two senders). The data also contain information on the start date and end date of the sanctions.

In this thesis, only imposed sanctions are analyzed. Within this subset, 371 events (43%) have no end date, and 61 events (7%) have no start date. There are 33 events (4%) for which neither the start date nor end date is known. The latter sanctions have been removed from calculations. Many sanction cases contain a date for which the sanction was last known to be in effect. When this information is available, sanctions with no end date are said to have ended on the date they were last known to be active. This covered 113 events (about a third of the missing data). For cases where this information is unavailable (the remaining 258 cases), the end of a sanction is estimated to be about 1510 days after the sanction is issued, since the average length of a sanction is about 1510 days (around 4 years and two months). This estimate is only used in calculations of the number of sanctions active in a given time frame in the exploratory data analysis, and for calculations of various balance configurations over the network's triad census.

A multilateral sanction in this network consists of up to five sender states and a single target state. For computational purposes, we have encoded the network information as a three-dimensional array $Y = (y_{ijk})$, where $y_{ijk} = 1$ if countries i and j jointly issued a sanction against j. This means that if countries i, j, and h are all collaborators on a sanction, this is encoded in three separate entries in Y – one with i and j collaborating, one with i and k collaborating, and one with j and k collaborating. Note that the value of array Y can change over time. Both the DyNAM collaborations and the triad census for balance theory are set up to be calculated with this format. Though this setup is still not perfect for modeling multilateral sanctions with more than two sender states, it allows us to capture some of the interaction that countries have when issuing sanctions together.

An important covariate for modeling sanction collaborations is the country regime. Feenstra, Inklaar, and Timmer (2015) published a dataset of the Polity IV scores for country regimes over the years, which are used here as the statistic function for each country's regime (Marshall, Gurr, Davenport, & Jaggers, 2002). The range of scores goes from -10 to 10, where a higher Polity IV score indicates that a country is more democratic. Over the whole dataset, the standard deviation in Polity IV score is 9.79. Due to data unavailability on some countries' regimes, specifically, Yugoslavia, West Germany, East Germany, and the European Union, we omit all collaborations involving these countries from the data. Note that all these countries are either countries that did not exist for the entire period of analysis or that are, in fact, a union of countries. If any of these countries were involved in a multilateral sanction, the whole sanction was removed. Due to this, 59 sanctions were removed from the data.

The remainder of this section outlines the approaches taken to operationalize balance theory in the context of sanctions, specifically in producing the triad census for this purpose and in classifying the triads. Finally, we discuss the DyNAM (Stadtfeld et al., 2017) and its use in the context of modeling collaboration in issuing sanctions.

3.1 Triad census for multi-way relations

The triad census for a (traditional) two-way network is given by the counts of all possible network configurations among three nodes (a triad; Carrington et al., 2005). This would yield $2^3 = 8$ configurations of all possible combinations ties in an undirected network. If we consider a tie between nodes to indicate a positive relationship and the absence of a tie to be a negative relationship, then each of these configurations can then be classified as balanced or unbalanced, using the rules proposed by Heider (1946). This setup is not directly transferable to the context of sanctions because our context maintains two separate kinds of ties (sanction and collaboration), and while we can classify ties as positive or negative, the absence of a tie is not exactly the same as a sanction or a collaboration. As such, we distinguish the case that there is a sanctions and/or collaboration between two countries from the case that there is no relationship. To clarify, this does not mean that ties cannot exist jointly. Namely, countries i and j can collaborate on a multilateral sanction while i sanctions j.

To create a complete triad census over the different combinations of collaborations and sanctions in a triad, we must enumerate what these are. This is done by crossing all the combinations of collaborations and sanctions in a given triad. The ten main collaboration structures are enumerated in Figure 2. In this diagram, a green edge represents a (positive) collaboration relationship, while the red edge attached to that tie is the (negative) sanction resulting from that collaboration. For example, case two shows a collaboration between two countries (let's call them i and j), while case three shows i and j collaborating to issue a sanction to the third node, k, in the triad.

These are different because in case two, the collaborators are issuing a sanction to a country that is not in the triad, but in case three, that country is in the triad. Note this illustrates that multilateral sanctions are inherently triadic or higher-order phenomena. In Figure 2, we can differentiate between configurations two and three, but in a network with just positive and negative ties, this would not have been possible. For example, if nodes i, j, and k followed configuration three such that i and j were in collaboration, assuming the joint sanction from i and j to k is the same as individual sanctions from i and j to k, respectively, would have made it impossible to tell is the sanctions are multilateral or individually issued.

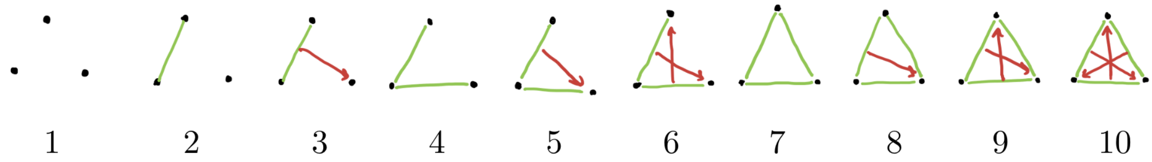


Figure 2: The ten basic collaboration configurations in a triad. A green edge represents a collaboration, and a red edge the sanction resulting from that collaboration.

If we enumerate collaborations only in the way we have outlined in Figure 2, we miss cases where an existing sanction between two nodes has nothing to do with the other node in the triad. For example, consider countries i, j, and k in a triad. If there exists a unilateral sanction from i to j, or if i collaborates with another node l to sanction j in the same time frame, neither of these would be considered by the collaboration-based triad census. These cases would, however, contribute to the balance in the triad. As such, to include these structures, we introduce another, sanction-based triad census in Figure 3. In this enumeration, we ignore the direction of the sanction because we assume the negative relationship persists no matter the direction of the sanction. More specifically, if a sanction exists from country i to j, i issues the sanction because it is offended by some behavior of j, and j in turn feels wronged by the imposition of the sanction, indicating negative sentiment from both actors. We also make the undirected sanction assumption to dramatically reduce the size of the triad census, making it much easier to enumerate. It is important to note that in Figure 3, structures two, three, and four are exactly the same. We keep them here because when we cross them with the structures in Figure 2, we will see that they yield unique structures. Note that we will also use the undirected sanction setup for the DyNAM.

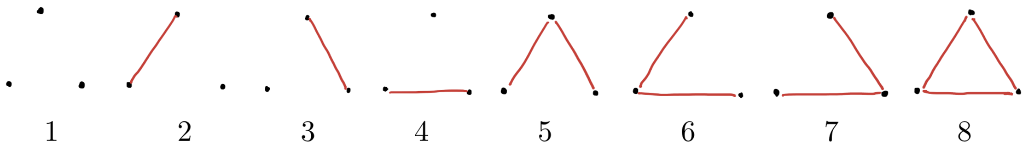


Figure 3: The eight basic sanction configurations for a given triad. A red edge refers to a sanction in either direction between two countries. Isomorphic cases are not removed here, as this census will be crossed with the collaboration census.

To enumerate all combinations of edge states in a triad, we combine the ten base configurations from Figure 2 with the eight cases in Figure 3. From this we obtain a set of 80 possible configurations over three nodes, as in Figure 4. Some of these configurations are isomorphic and as such are not shown in Figure 4.

3.2 Balance theoretical classification of triads

After obtaining the matrix of 56 configurations as in Figure 4, classification of each of these figures is carried out based on the rules of balance defined by Cartwright and Harary (1956), augmented with the two additional rules given in Section 2. We classify them into the following seven categories: unbalanced, balanced, vacuously balanced, empty, one positive tie, one negative tie, and vacuously unbalanced. We use the term "vacuous" in "vacuously balanced" to indicate that the configuration is considered balanced assuming the missing tie is a positive

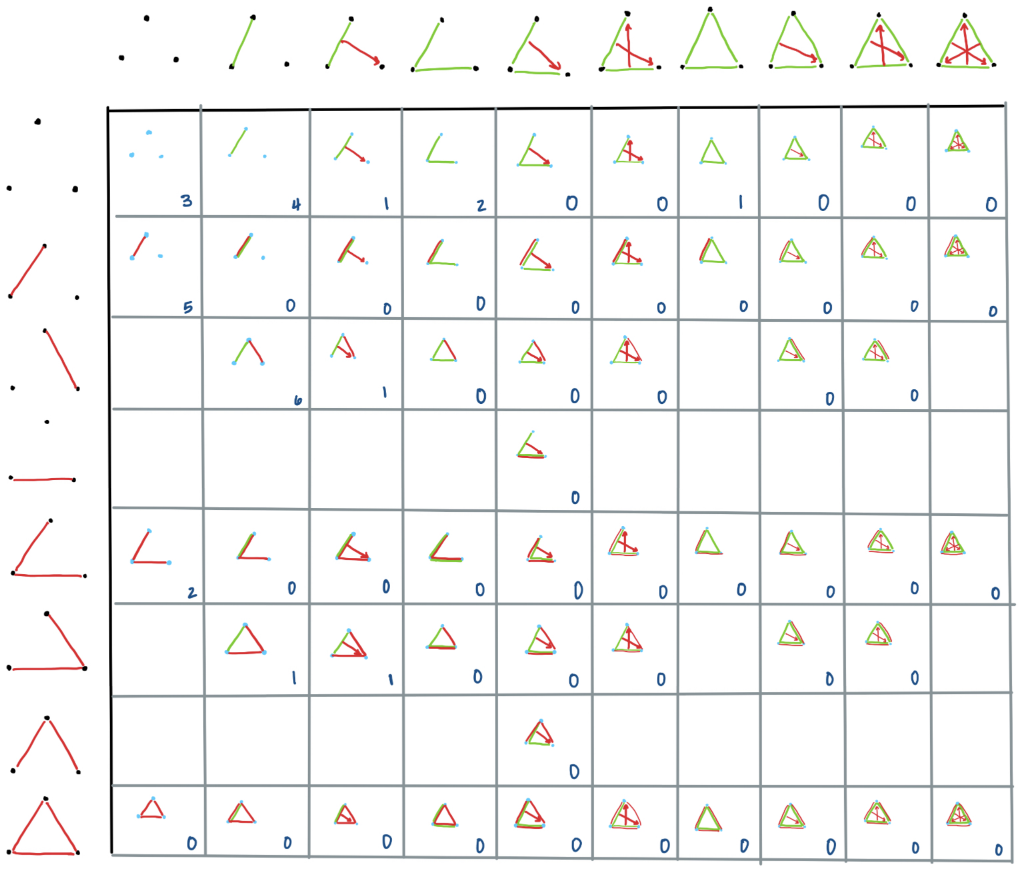


Figure 4: All possible triad configurations. Blank squares correspond to configurations that are isomorphic to one of the other enumerated configurations. Legend: 0. Unbalanced, 1. Balanced, 2. Vacuously balanced, 3. Empty, 4. One positive tie, 5. One negative tie, 6. Vacuously unbalanced.

one. The same goes for a vacuously unbalanced configuration.

Note that some configurations in this setup are inherently more likely than others to the point where they disproportionately outnumber the other configurations. Since the network is generally sparse, these are the configurations with no ties, one positive tie, and one negative tie. Since these cases are also more trivial than the more complicated structures in this census, we give each their own category. This allows us to better evaluate the role of more complex structures in the model.

3.3 Modeling sanction collaboration

To model collaborations for multilateral sanctions, we use the Dynamic Network Actor Model (DyNAM; Stadtfeld et al., 2017). The DyNAM was proposed for the analysis of relational event data, and Stadtfeld et al. (2017) in particular model coordination in network choices, corresponding to undirected relational events. For our purposes, this means agreement to collaborate on a sanction, and a new collaboration tie between two nodes signifies such an event. Relational event data are set up as in Table 1.

The basic premise of this model is that as countries in the set of all countries N forge collaborations, they evaluate all their options, propose a collaboration to their most favorable partner, and wait for their chosen partner to respond. In turn, the country receiving the collaboration request evaluates all of its options, then responds either positively or negatively. The only data that are actually recorded, however, are the cases where the recipient responded positively. In this context, the recorded datum would be the multilateral sanction that resulted from the collaboration.

Collaborator 1	**Collaborator 2**	**Time**
India	Pakistan	1946-03-11
United States	United Kingdom	1947-12-05
United States	France	1947-12-05

Table 1: Example of relational event data.

We begin by introducing some notation. The full network at the current time is denoted x. This network with an additional collaboration between countries i and j is denoted by $x^{i \leftrightarrow j}$. Though multilateral sanctions tend to dissolve after a certain period of time in the real world, we do not model sanction (and therefore collaboration) dissolution here. Instead, we use the network built from the relational event data to track only the number of collaborations countries share historically. It is important to note self-loops are not possible in the choice coordination setting, that is,

$$x^{i \leftrightarrow i} = x. \tag{1}$$

To model collaboration over time, we want to measure the role of attributes of both the countries and the network structure itself. Suppose there are M covariates. We denote the value for the m-th covariate for node i conditioned on the network x by

$$s_m(i, x). \tag{2}$$

We refer to this as a statistic function. For each covariate, we estimate a weight or parameter that corresponds to how important it is to tie formation. The vector of parameters is given by

$$\beta = (\beta_1, \dots, \beta_M), \tag{3}$$

where β_m corresponds to the parameter for the m-th covariate. Additional effects include node activity rate effects $s^\tau(i, x)$, which are attributes of the node which affect the speed or rate of tie formation. The parameters corresponding to these effects are denoted by θ. As we will describe in the next section, in this study, we assume that the rates of tie formation are equal across countries and we thus do not include effects $s^\tau(i, x)$ in the final model.

3.3.1 The model

We assume a Poisson process governs the wait times between subsequent collaboration requests between countries. The rate parameter for this Poisson process is given

$$\tau_i(x, \theta) = \exp(\theta_0 + \sum_{r=1}^{R} \theta_r s_r^\tau(i, x)), \tag{4}$$

where there are R node activity rate covariates and θ_0 corresponds to the general rate parameter (analogous to an intercept) for this formulation. Country i's probability of proposing a collaboration with country j is assumed to follow a multinomial choice model. This is built on a linear objective function composed of the tie effects,

$$f_i(x^{i\leftrightarrow j}, \beta) = \sum_{m=1}^{M} \beta_m s_m(i, x^{i\leftrightarrow j}). \tag{5}$$

From this, we define the probability of country i to choose country j as collaborator by

$$p_{i\to j}(x, \beta) = \frac{\exp(f_i(x^{i\leftrightarrow j}, \beta))}{\sum_{k\in N} \exp(f_i(x^{i\leftrightarrow k}, \beta))}. \tag{6}$$

We use only a single-directional arrow ($i \to j$) in the above equation to denote that the probability relates to country i's tendency to propose or accept a coordination tie $x^{i\leftrightarrow j}$ (Stadtfeld et al., 2017).

We assume that the rate parameter is conditionally independent of the tie probability given the network x. As a consequence, the combination of individual Poisson rates and choice probabilities constitutes a Poisson process (Waldmann & Stocker, 2012). The probability that a tie change between countries i and j is the next to be observed is

$$p_{i\leftrightarrow j}(x, \beta) = \frac{(\tau_i(x, \theta) + \tau_j(x, \theta))p_{i\to j}(x, \beta)p_{j\to i}(x, \beta)}{\sum_{k,l\in N,k\leq l}(\tau_k(x, \theta) + \tau_l(x, \theta))p_{k\to l}(x, \beta)p_{l\to k}(x, \beta)}, \tag{7}$$

where the numerator expresses the propensity of dyads i and j to be updated in the network, and the denominator expresses the same summed over all dyads in the network. Note that the two summands in the numerator are there since an undirected tie $i \leftrightarrow j$ can come about by i proposing its formation and j accepting it – this occurs at Poisson rate $\tau_i(x, \theta)p_{i\to j}(x, \beta)p_{j\to i}(x, \beta)$ – or vice versa. If we assume that the rate parameters are the same for all the countries in the network, the terms $\tau_i(x, \theta)$ cancel each other out in (7). In this case, we obtain

$$p_{i\leftrightarrow j}(x, \beta) = \frac{p_{i\to j}(x, \beta)p_{j\to i}(x, \beta)}{\sum_{k,l\in N,k\leq l} p_{k\to l}(x, \beta)p_{l\to k}(x, \beta)}. \tag{8}$$

This is the model we will focus on in the remainder of the thesis.

3.3.2 Statistic functions

In general, statistic functions can be at the level of the individual, the dyad, the triad, or of higher order. They can also come from weighted effects or from other networks. In this paper, we denote the collaboration network as $x^{(1)}$, and the (undirected) sanction network as $x^{(2)}$. In this thesis, we use all of the above, except for higher-order effects. These effects are unweighted degree alter (individual), weighted degree alter (individual), country regime alter (individual), similarity of regime (dyad), simultaneous sanction tie (dyad), transitivity (triad), and mixed transitivity (triad).

Individual-level effects refer to attributes of potential partners that affect their attractiveness for collaboration. One such effect is the degree effect. We calculate the degree effects as a weighted measure and as an unweighted measure, as well as in the ego setting and the alter setting. In the unweighted setting, the degree simply signifies the process of adding an additional collaborator, whereas in the weighted setting it signifies adding an additional collaboration. In the unweighted setting we denote the binarized collaborations for country i in the collaboration

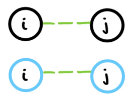
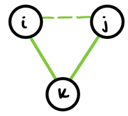
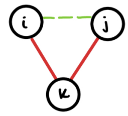
	Effect name	Effect $s_i(x,z)$	Network representation
1	Degree ego	$\dot{x}_{i+}^{(1)}$	
2	Degree alter	$\sum_j x_{ij}^{(1)} \dot{x}_{j+}^{(1)}$	
3	Covariate alter	$\sum_j x_{ij}^{(1)} v_j$	
4	Covariate similarity	$\sum_j x_{ij}^{(1)} \mathrm{sim}(v_i, v_j)$	
5	Transitivity	$\sum_{j,k} x_{ij}^{(1)} \dot{x}_{ik}^{(1)} \dot{x}_{jk}^{(1)}$	
6	Mixed transitivity	$\sum_{j,k} x_{ij}^{(1)} \dot{x}_{ik}^{(2)} \dot{x}_{jk}^{(2)}$	
7	Simultaneous tie	$\sum_j x_{ij}^{(1)} \dot{x}_{ij}^{(2)}$	

Table 2: Selection of effects for modeling network evolution as used in Models 1 and 2. Here, a red edge symbolizes at least one existing sanction, a green edge is at least one existing collaboration, a dotted green edge symbolizes a potential new ally ($\dot{x}_{ij}^{(1)}$ increases by 1), and a dashed green edge symbolizes a potential new collaboration ($x_{ij}^{(1)}$ increases by 1). An edge with a number over it is a weighted edge.

network as

$$\dot{x}_{i+}^{(1)} = \sum_k \dot{x}_{ik}^{(1)} \tag{9}$$

where we binarize the collaboration network, that is,

$$\dot{x}_{ik}^{(1)} = I(x_{ik}^{(1)} > 0), \tag{10}$$

where $I(\cdot)$ denotes the indicator function. In the weighted setting, we omit this binarization step to keep the original network. For the ego setting, we measure the covariate for a given node, but in the alter setting we measure the covariate value for a potential partner. In this paper, we will use the unweighted degree ego and weighted degree alter. These effects are calculated as in Table 2. When we estimate degree alter effects, we are measuring the attractiveness of a potential partner based on the number of connections that partner has. As such, we will call this effect the popularity effect, where the weighted degree alter is weighted popularity.

Dyad-level effects used in this model capture combinations of attributes of potential partners, as well as how past or existing interactions between potential partners both within and outside the current network contribute to the possibility of an additional collaboration. We include the existence of a tie between potential partners in the sanction network as a covariate. This means that the statistic function for existing ties in $\dot{x}^{(2)}$ is as line seven in Table 2. In this manner, we measure the role that the rule “A friend is not an enemy” has to play in how collaborations are formed in the network.

Triad level effects capture how triadic relations affect the propensity for two nodes to collaborate. The most notable example of this is the transitivity effect, where we measure how the existence of a mutual collaborator between two potential partners plays a role in the formation of their partnership. In the unweighted setting, this is measured as in line five of Table 2. In this effect, we measure the role that the rule "A friend of a friend is a friend" has to play in how collaborations are formed in the network.

A special case of this statistic function is when the two existing edges are part of another network. In our case, this is the sanction network. This means that we use the measure of mixed transitivity to denote the propensity of two countries to collaborate given both countries have an existing sanction in either direction with the mutually connected node. The statistic function for this effect is given in line six of Table 2, and operationalized another effect of the undirected, binarized sanction network $\dot{x}^{(2)}$ on collaboration formation. In this effect, we measure the role that the balance theory rule "An enemy's enemy is a friend" plays in how collaborations are formed.

3.3.3 Estimation

In order to estimate parameters β in model (8), we must optimize over the likelihood of all the events in the dataset. The likelihood of a single event ω is calculated as

$$L_\omega(x_\omega, \beta, i_\omega \leftrightarrow j_\omega) = \frac{p_{i_\omega \to j_\omega}(x_\omega, \beta) p_{j_\omega \to i_\omega}(x_\omega, \beta)}{\sum_{k,l \in N, k \leq l} p_{k \to l}(x_\omega, \beta) p_{l \to k}(x_\omega, \beta)}, \tag{11}$$

where i_ω and j_ω denote the two collaborators at time t_ω in event ω, and x_ω refers to the network before the collaboration $i_\omega \leftrightarrow j_\omega$ is created. Therefore, if we denote the log-likelihood for an additional tie between countries i_ω and j_ω to the existing network state by $\log(L_\omega(x_\omega, \beta, i_\omega \leftrightarrow j_\omega))$, the log-likelihood for all the data is given by

$$\begin{aligned} \sum_\omega \log(L_\omega(x_\omega, \beta, i_\omega \leftrightarrow j_\omega)) = \sum_\omega \Bigg[& \log(p_{i_\omega \to j_\omega}(x_\omega, \beta)) + \log(p_{j_\omega \to i_\omega}(x_\omega, \beta)) \\ & - \log\Big(\sum_{k,l \in N, k \leq l} p_{k \to l}(x_\omega, \beta) p_{l \to k}(x_\omega, \beta) \Big) \Bigg]. \end{aligned} \tag{12}$$

By maximizing this likelihood over the whole dataset, we obtain estimates for the parameter vector β.

4 Results

In the following, we discuss the results of our work. To begin, we provide insights from network exploratory data analysis, including basic metrics for both the sanction and collaboration network. We then move on to analysis from operationalizing balance theory in the context of this network, and finally end with two models. The first uses basic network metrics to evaluate collaboration tendencies for countries, and the second build on the first with added balance theory effects.

4.1 Exploratory data analysis

Figure 5 shows the number of new and total ongoing sanctions from 1945 to 2005. The data record 1412 sanctions and sanction threats over 176 countries in this period. The breakdown of sanctions versus threats follows almost an even split, with 845 (60%) of sanctions and 567 (40%) threats. Over time, the number of true sanctions initiated appeared to increase, though there is a clear general decline in the number of ongoing sanctions towards the end of the time period for this data. Despite this, there is a clear upward trend in total new sanctions over time.

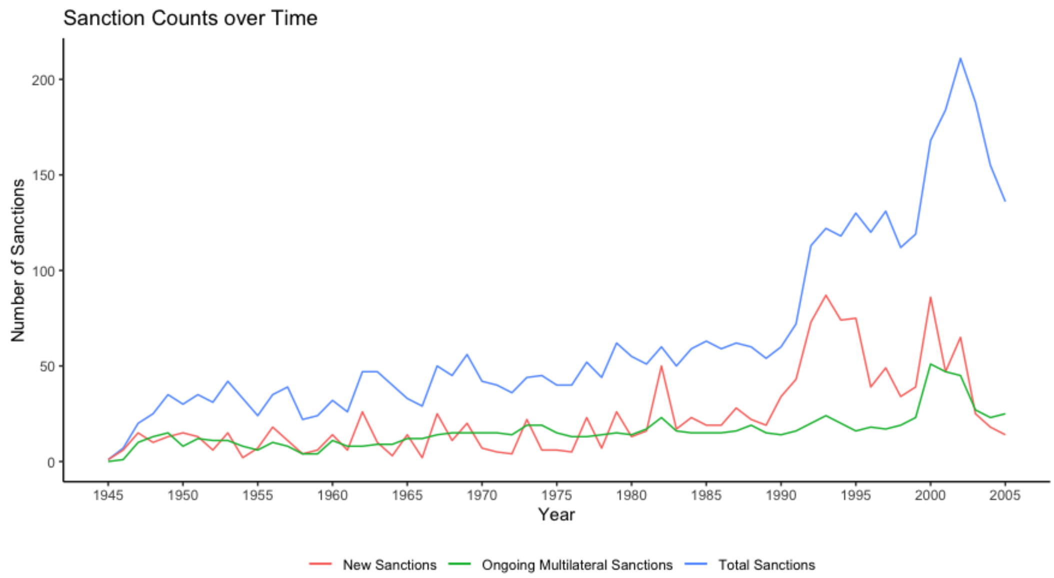


Figure 5: True sanction counts over time

The sharp uptick in sanctions around 1993 is associated with instability in Eastern Europe following the fall of the Soviet Union. A change in network structure follows the dramatic shift in international geopolitics from that time. In 1991, there appear to be multiple more central actors (including the United States) that execute multiple sanctions. However, with the fall of the Soviet Union in 1992, the United States took on the role as the main central actor in the network. The labeled actors in Figure 6 reflect the most popular sanction senders and receivers over time.

The visualization from 1991 to 1993 indeed shows an uptick in active sanction network participation after 1992, supporting the spike observed in active sanctions at that time. The next dramatic spike occurs from 1995 to 2000. Figure 6 also shows the existing sanctions in these networks to indeed observe a quite dramatic change in the sanction network.

There is an increase in the number of involved actors overall, as well as heavy centralization within certain key actors in the 2000 sanctions network, who were the senders of the majority of sanctions in this time. Specifically, the largest sender of sanctions since 1945, the United States, is responsible for 49% of the sanctions issued from 1945 to 2005. In 2000, the contribution of the United States in sanction issues jumps to 65%.

A majority of sanctions appear to take place among a subset of all the countries involved. As such, we consider the distribution of sanction senders and targets for each country. In the context of the overall network, this is represented by the countries' indegrees (number of countries that issued a sanction to a country) and their outdegrees (number of countries sanctioned by a

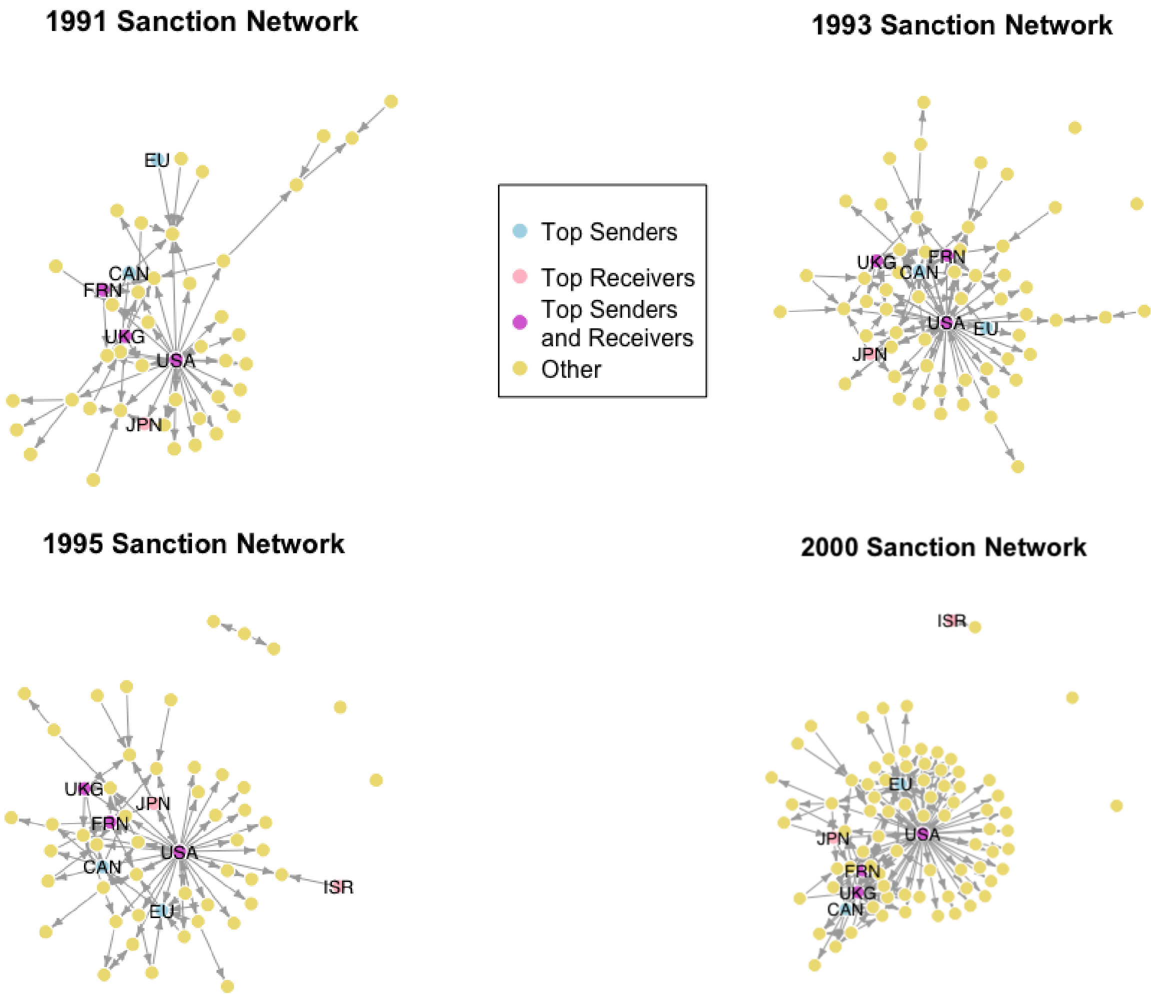


Figure 6: Visualization of the 1991, 1993, 1995 and 2000 sanction networks. An edge from country i to j indicates that country i sanctioned country j.

country). This is visualized in Figure 7. In this graph, the seventy countries with indegree zero (countries with no sanctions issued to them through the duration of this time period) have been removed. Of the remaining countries, the very vast majority have one or two sanctions, with a steep drop in sanctions from there. There is one outlier (the United States) which by far has the largest number of sanction senders in history, followed by Japan, South Korea, China and the European Union, which is considered a separate entity in these data.

The United States has issued the most sanctions to other countries from 1945 to 2005, followed by the United Kingdom, Canada, the European Union, and France (in order). The distribution of sanctions issued is slightly thicker in the tail than for sanctions received. Combining observations so far, it appears that more countries tend to issue sanctions than receive them, but for those that do receive heavy sanctions, they tend to be singularly targeted by the international community. This singular targeting is partly due to multilateral sanctions, where multiple countries will target a single country. Top receivers of sanctions (in order) are the United States, Japan, the United Kingdom, France, and Israel.

Since collaboration on sanctions is a mutual relation, we only measure the degree distribution of sanction collaboration. Here, we found a thicker tail in the distribution for collaborations, though there is still an extreme right skew (see Figure 8). Further, 105 countries with no

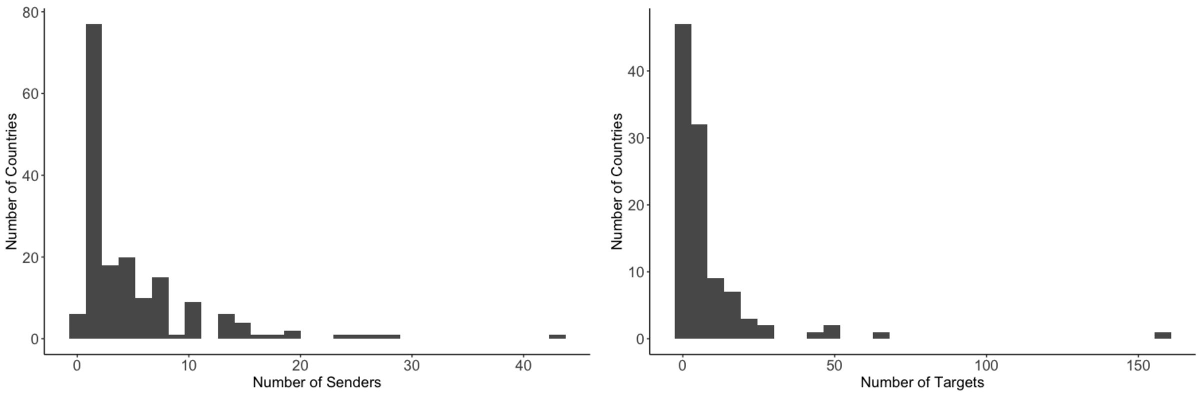


Figure 7: Distribution of the indegrees of the countries (number of countries who issued them a sanction) in the (cumulative) sanction network (left) and their outdegrees (number of countries they sanctioned; right).

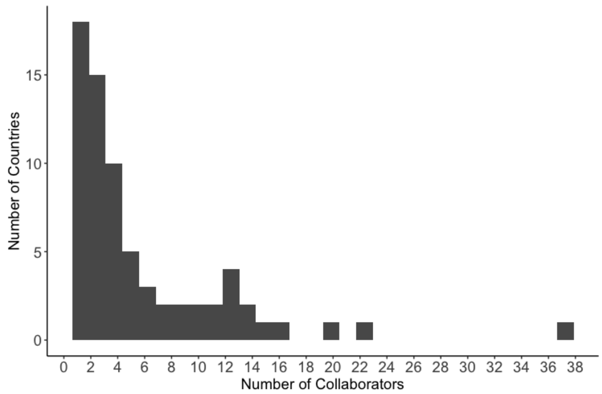


Figure 8: Degree distribution of country collaborations from 1945-2005.

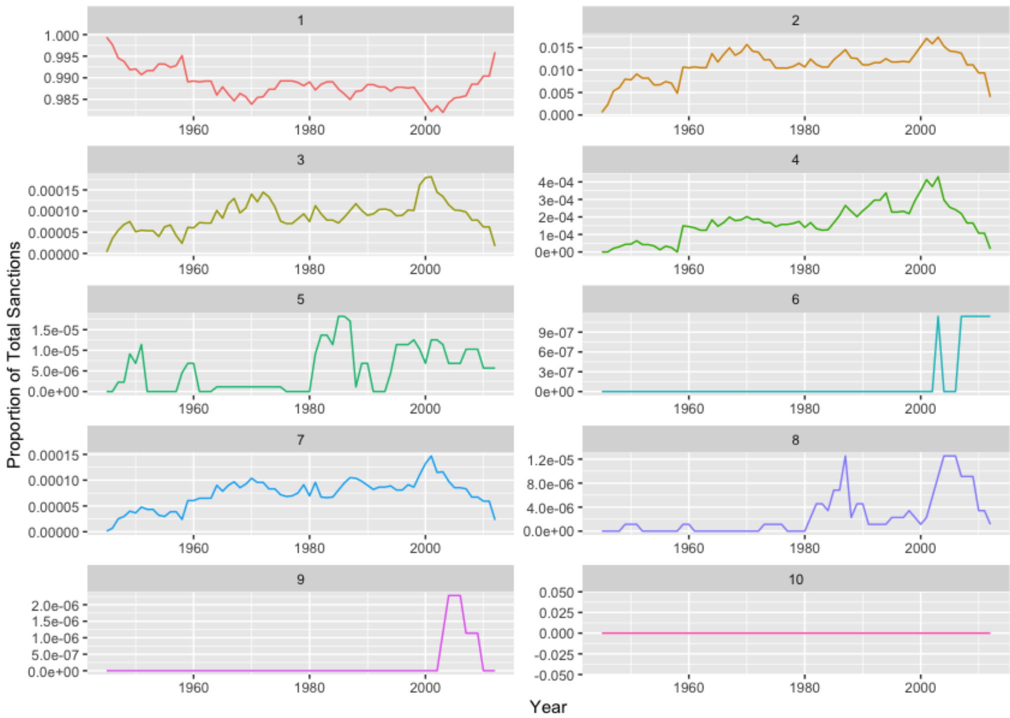


Figure 9: Proportion of triads that belong to each of the configurations in Figure 2.

collaborations have been dropped from the histogram. This implies that the very vast majority of sanctioning countries have never collaborated with anyone else. Barring the zero-mode, we observe that there is a second, smaller mode at 12-13 total collaborations. This implies that in the time period observed (1945–2005), there is still a large number of countries (about 70) that tend to collaborate at all, and that many of those (27 countries) have collaborated with at least 5 other countries historically. This growing mode is an indication, according to historians, of the increased effectiveness of multilateral sanctions (Morgan et al., 2014). In recent years, there has also been a greater tendency towards multilateral sanctions, even as the number of sanctions themselves has dropped sharply towards the end of the data series (Figure 5; Morgan et al., 2014).

4.2 Balance in the context of sanctions

The observation of a generally low level of collaboration is confirmed by the triad census. The proportion of total possible configurations for three actors over time as outlined in Figure 2 are given by Figure 9. We calculated the collaboration triad census of the $\binom{148}{3} = 529,396$ triads for every year to generate the latter figure.

In the triad census of basic collaborations (Figure 9), we observe the most common structure is the relationship with no ties. Following that in popularity are cases two and three in Figure 9. Following these is configuration seven, then four and five. Configuration seven is the case where all members of the triad collaborate with each other. Interestingly, we see this configuration peak in popularity in 2000 before dying down.

In Figure 10, corresponding to the triad census as depicted in Figure 4, the most common configuration for three nodes is that there is no relationship at all. Following that, we have the configurations where a sanction occurs between two actors (configuration two), and the setting where two actors are collaborating (configuration nine). As we had expected these configurations to dominate the triad census, each of these belong to their own category (no ties, single sanction tie, single collaboration tie). Following these in popularity is configuration ten, or the case where two nodes in the triad have a simultaneous collaboration and sanction. This is a classic unbalanced structure by the rule that an enemy cannot be a friend. Following this structure in popularity (by a heavy lag) is configuration 11. This is the vacuously balanced case where there is one sanction and one collaboration in the triad, but they do not overlap. Following this structure, the next most popular structures are configurations five and 25. These structures are extremely similar. Structure five is the case where two of three possible edges in the triad exist, and both are sanctions. Structure 25 is the same, but both are collaborations. Both of these structures are vacuously balanced. Following these two in popularity are the balanced structures 14 and 49. Structure 14 is the case where two edges are sanctions and the third is a collaboration, and structure 49 is the case where all three edges are collaborations.

Some of the configurations in Figure 4 do not occur at all. One of these is configuration 73, where all three members of the triad collaborate to sanction the other member of the triad (ie: i and j jointly sanction k, i and k jointly sanction j, and j and k jointly sanction i all at once). This is extremely unlikely to happen in real life. Another configuration we do not expect is configuration 80, which is the same as configuration 73 but with collaborators sanctioning each other as well (ie: i and j jointly sanction k while i sanctions j separately, i and k jointly sanction j while i sanctions k separately, and j and k jointly sanction i while j sanctions k separately, all at once). If all of these events occurred simultaneously in the same year, this would indicate a very unexpected setup for alliances and political censure.

Figure 10: Yearly proportion of all possible node configurations in sanction network triad census from 1945-2005. Some slots are blank as they are isomorphisms.

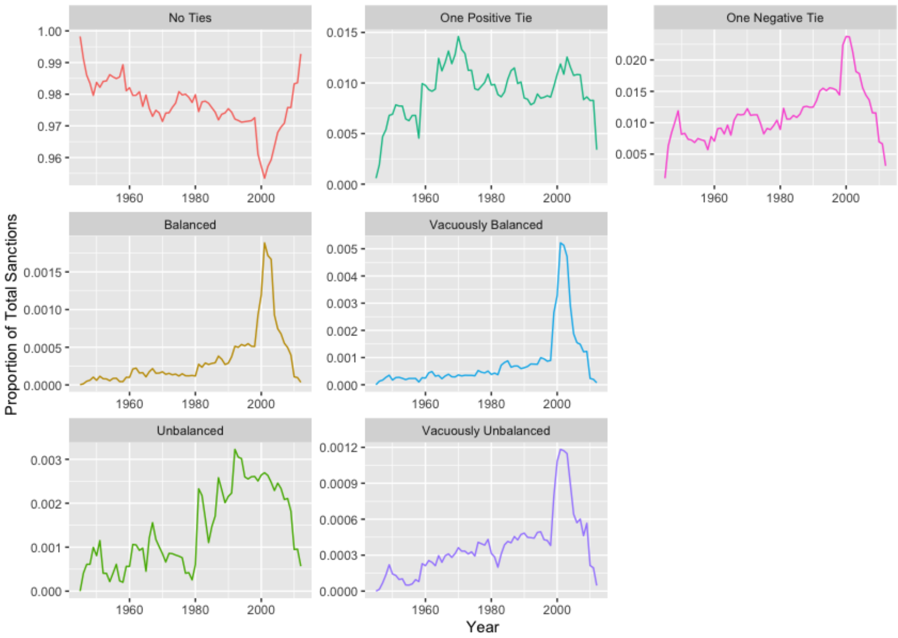


Figure 11: Summary of balance structure categorizations over time, as classified in Figure 4.

Overall, the majority of the popular structures are balanced. While we expected unbalanced structures to prevail in the network, it is interesting to note that the largest quantity of triads tend to be balanced. However, it is important to take note of the more popular unbalanced structures in the network, particularly configuration ten. This provides preliminary evidence that it may not matter if history indicates enmity between states as long as there is due cause for collaboration at the current time. This rule could also apply in the reverse direction, where past collaborations do not stop a country from issuing sanctions to a given target.

Figure 11 summarizes the yearly counts of each configuration as they are organized into the seven categories of balance, as described in Figure 4. Comparing only cases of balanced and unbalanced ties (including those that vacuously fall under each category), it is clear that unbalanced configurations are far more common in the sanction network. This follows, as under the current definition, a configuration is far more likely to be unbalanced than balanced. A notable observation is that balanced and unbalanced structures are not strictly inversely related. However, the behavior of unbalanced configurations does seem to follow the trend for balanced configurations after a slight lag. This would mean that as balanced structures that include sanctions rise, unbalanced structures do too, but after a small delay. One hypothesis for this trend is that in more complex geopolitical settings (especially times when countries may need to rely on their allies), countries will try to respect their alliances as well as they can, and, when they can no longer do so, engage in unbalanced relationships to achieve their political goals. Bearing this in mind, we test the effect of aspects of balance and other structural effects on sanction collaboration using a DyNAM.

4.3 Modeling collaborations

In this section, we will present the results of two models. In the first model, we model collaboration by a DyNAM with the effects of unweighted degree ego, unweighted popularity, transitivity, regime, and similarity in regime. In the second model, we added balance-related covariates to the first model. We test model parameters by two-sided tests at level $\alpha = 0.05$.

	Model 1		Model 2	
	par.	s.e.	par.	s.e.
Unweighted degree (ego)	-0.570^{***}	0.022	-0.568^{***}	0.022
Weighted popularity	0.081^{***}	0.004	0.085^{***}	0.004
Transitivity	0.139^{***}	0.008	0.134^{***}	0.010
Regime (alter)	0.013^{***}	0.004	0.014^{***}	0.004
Similar regime	0.001	0.004	0.001	0.004
Mixed transitivity			0.001	0.004
Tie in sanction network			-0.150^{*}	0.059
AIC	*14105*		*14101*	

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 3: DyNAM results for the two models of collaborations.

Model 1 in Table 3 shows the simplest version of structural effects for collaboration. Here we measure the effects of degree and transitivity with the node-level covariate of country regime and dyad-level covariate of similar regimes. All these effects, except for regime similarity, are found to be significant.

According to the results in Model 1, we observe a negative coefficient on the unweighted degree ego parameter. This indicates that a country with one additional collaborator has 43% lower odds of gaining another collaborator, meaning, in general, countries do not prefer to collaborate on sanctions. However, the weighted popularity effect shows that if a potential partner has one additional collaborator, the odds of forming a collaboration with that partner increase by 8%. Still, this does not mean that countries will tie with just any other country. The positive coefficient in transitivity indicates that countries prefer to collaborate with countries with which they have a mutual collaborator. The presence of a mutual collaborator improves the odds of a collaboration by almost 15%. This provides support for the balance axiom, "my friend's friend is my friend." Additionally, countries generally prefer partners that have a more democratic governmental structure. An increase in Polity IV score of one improves the odds of being chosen for collaboration by 1%. We find no evidence that similarity of regime between potential partners matters in the formation of collaborations.

In Model 2, we factor in historic sanctioning behavior. This provides an important explanation to the propensity for collaboration. In studying the balance dynamic of the network over time, we hypothesized that rules of balance would hold when countries evaluate possible collaborators. From this hypothesis it would follow that countries are more likely to work with those that sanction (or are sanctioned by) the same countries as them historically, but we see that in practice this is not necessarily true. We find no evidence that the presence of a past mutual enemy affects the odds of an additional collaboration (non-significant mixed transitivity effect). We still see, however, that countries have an aversion to collaborating with potential partners they have sanctioned or from whom they have received sanctions. The sign of the parameter indicates that enmity with a potential collaborator reduces the odds of collaboration by almost 14%. In the context of balance theory, this tracks well with the assumption that an enemy cannot be a friend.

5 Discussion

Our descriptive network analysis provided important initial insight into the high-level sanction and collaboration dynamics in this network. Most importantly, the analysis reveals the propensity for sanctions and collaborations to center over a small subset of all the countries, namely the United States, Canada, England, France, and the European Union. Measures of various balanced and unbalanced structures in the network indicates the propensity for stability in sanction relations, mainly through the sheer volume of balanced structures present, despite the many possible unbalanced structures. This leaves room to explore the role balance plays in the development of collaboration ties when examining both the structures of the collaboration network and within the context of the sanction network. Here, we found that countries prefer not to collaborate with new partners. In addition, countries generally prefer to work with more democratic countries, but similarity in governmental structure does not necessarily matter.

Regarding the balance-related effects, we found that past mutual collaborators heavily drive the creation of collaborations. This provides evidence for the balance axiom of "My friend's friend is my friend." In contrast, we found no evidence for mutual enmity as a driving force for collaboration. As such, it is not necessarily true that an enemy's enemy is a friend. This could be for a variety of reasons. First, if the enmity is far enough into the past, it may matter less than in one in the current time. Since all past enmity is treated the same, there is no way to tell if countries are collaborating if they share solidarity after being offended by the behavior of a mutual country, or if there is some other reason. Additionally, countries may simply have already dealt with their mutual enemy in other ways, and as such need a more compelling reason to work together.

While this thesis provides a new approach to study international collaboration on sanction, there are some limitations to the modeling approach used here. First, it is not completely suited to modeling multi-way network relations. Specifically, the model is unable to include the full set of collaborators as one new addition to the network, and, rather, breaks each set of collaborators in a multilateral sanction to groups of two. Likely, this has contributed to the positivity of the transitivity parameter in the model, and therefore the degree to which countries are willing to work together due to mutual collaborators is overestimated.

Additionally, the creation of an additional collaboration is based on all the events that came before it, rather than just a set few. For example, if country i sanctioned country j in 1945, this is probably not very relevant deterrent to their collaboration in 2000. To control for this, it would be wise to add windowed effects to the model, where we can, for example, check if country i sanctioned country j only in the last ten years rather than since 1945.

Moreover, the data imputation performed for sanction start and end dates leaves room for further improvement. Multiple imputation provides the potential for better estimation of start and end dates, and can ultimately provide more accurate insight into how multilateral sanctions develop over time (Rubin, 1987; Rubin, 1996).

Finally, the presented model does not model the development of the full multilateral sanction network, but rather only one aspect of it – the collaborations. In order to build a model that can account for the introduction of a full multilateral sanction at each timestep, both accounting for all collaborators and simultaneously the issued sanction relation, we require some changes to the existing framework for the DyNAM.

To further explore options for modeling the network in a multi-way format, we define a twofold task. Assuming the creation of collaboration ties is conditioned upon the creation of a sanction tie, the new proposed model should first capture the likelihood of the next most probable sanction tie, and second, the likelihood of a choice-coordinated collaboration of all dyads within a collaboration subnetwork rooted in that sanction. For example, given a sanction from i to j, and co-sanctioners k and l, the probability of that multilateral sanction would come from the probabilities that

1. i chooses to sanction j,
2. i chooses k and l as partners to jointly issue the sanction,
3. k and l choose i back, and
4. k and l choose each other.

This sanction-conditioned coordination assumption holds consistent with sanctions in real life since each sanction in the TIES data comes with a primary sender. This setup supports that the primary sender first chooses to issue the sanction, then, based on that choice, chooses partners who respond in kind.

The main benefit for using this format is that we can more accurately account for country collaboration in the creation of multilateral sanctions in the network. However, computing the denominator in the multi-way sanction edge probability in this case is extremely computationally expensive. Specifically, the model requires checking all possible collaborations between countries of all possible size of collaborators. This is an extremely computationally expensive calculation, and may require further assumptions to reduce the computational overhead of such a calculation.

Other ways to encode and evaluate multilateral sanctions include hypergraphs, i.e., graphs where an edge joins any number of vertices. This setup is particularly useful for modeling collaborations in our context. Additionally, hypergraphs have proven useful for some basic modeling and clustering techniques, while being much more efficient with calculation than a typical network (Wolf, Klinvex, & Dunlavy, 2016). Though there is plenty to explore with hypergraphs, they provide a promising avenue for future work with modeling collaboration in multilateral sanctions.

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