When Do States Say Uncle? Network Dependence and Sanction Compliance

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In this article we address the long-debated question of when and why states comply with sanctions. While the literature remains indeterminate as to whether the key mechanisms driving sanction compliance are tied to interstate relations, intrastate constraints, or a dynamic combination of the two, our theoretical framework and methodological approach provide a novel perspective that incorporates insights drawn from network theory to explain the time until countries comply. Specifically, we argue that reciprocity, a concept with deep roots in both network theory and international relations, has largely been overlooked in the study of sanction compliance. Though often ignored, this concept captures an essential aspect of how cooperation is fostered in the international system, and allows us to better analyze the strategic environment underlying sanctioning behavior. Given the theoretical importance of reciprocity in understanding interstate relations, we provide an approach that integrates estimations of this type of network interdependency into extant frameworks for modeling the time until countries comply with sanctions. Our results highlight that reciprocity not only has a substantive effect in explaining the duration of sanctions, but that models excluding this concept from their specifications do notably worse in terms of their predictive performance.

keywords: sanctions, network analysis, reciprocity, international cooperation.

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Economic sanctions are a frequently used foreign policy tool in the realm of international relations. Typically, one or more states initiate sanctions against another to force the target state to change policy. Policy change is expected to occur by depriving the sanction target of trade or other forms of economic exchange with the sanction initiator(s). Triggers for economic sanctions can occur in many contexts: the target state breaks a previous agreement, the target state openly disobeys international law, or the target state engages in behavior that is simply unfavorable to the political preferences of another state. The consequences of sanctions for the populations in target countries can be severe, including increased unemployment, foreign investment loss, and reduced trade flows (Hufbauer, Elliott, Cyrus & Winston 1997; Hufbauer & Oegg 2003).

Economic disruption is the general intent of economic sanctions, as Woodrow Wilson told the United States Senate sanctions are a "peaceful, silent deadly remedy" for coercing concessions from other states (Foley 1923). However, motivations for sanction initiation are cross-cutting, spanning a diverse and interdependent mix of policy issues and political actors. Though sanctions often succeed in disrupting economic activity in target states (Escribà-Folch & Wright 2010), their ability to force policy change is debated among both policymakers and scholars. While the concept of sanctions – the idea that countries can pressure each other via economic ties in order to influence policy – is relatively straightforward, the study of when and why sanctions work is complex. While early research argued that sanctions have little influence on targets (Dashti-Gibson, Davis & Radcliff 1997; Drezner 1998; Lam 1990; Morgan & Schwebach 1997), more recent work suggests that the effectiveness of sanctions is dependent on the interaction of several factors, namely: the number of senders sanctioning a target state and the type of issue in dispute (Miers & Morgan 2002; Morgan, Bapat & Krustev 2009); the strength of domestic institutions within the target state (Dashti-Gibson et al. 1997; Marinov 2005); and the type of regime governing the target state (Allen 2008; Lektzian & Souva 2007; McGillivray & Stam 2004).

We argue that scholars fall short in incorporating a key factor into their analysis of the time until sanctions end in compliance: reciprocity.[1] Drawing on the work in international relations on trade and conflict, we suggest that sanction cases are best conceptualized as a network phenomenon and should be addressed both theoretically and empirically in these terms. Reciprocity is not a new concept to the field of international studies, but has its roots in previous theories of cooperation and the evolution of norms between states.[2]

We posit that the structure created by reciprocal interactions over time should be accounted for in studies of sanction outcomes, and provide a framework through which to estimate these second order dependencies. Further, we incorporate our measures of reciprocal interactions into a duration modeling framework, thus enabling us to explicitly account for interdependencies in the time building up to the resolution of sanctions. In doing so we also test key hypotheses from the literature and assess the extent to which factors such as domestic political institutions and internal stability influence sanction duration once network dynamics are incorporated. Our results highlight that reciprocity not only has a substantive effect in explaining the duration of sanctions, but that models excluding this concept from their specifications do notably worse in terms of their predictive performance.

When do Sanctions End?

Previous work on the duration of sanctions, or when and why a target state will decide to comply with a particular sanction, has focused on both intrastate and interstate arguments, with an emphasis on the role that domestic factors play in preventing or promoting the efficacy of sanctions. Marinov (2005) argues that sanctions "work" by directly

[1] Previous work by Cranmer, Heinrich & Desmarais (2014) has highlighted the role that network effects such as reciprocity have in the creation of new sanctions, but they also did not address issues of compliance.

[2] See Choucri & North (1972); Goldstein (1991); Richardson (1960a); Ward & Rajmaira (1992)

destabilizing heads of states. Accordingly, destabilization of leaders is a necessary condition for successful coercion. This focus on internal state conditions echoes other work suggesting that sanction outcomes are dependent on domestic stability and institutions. For example, Dashti-Gibson et al. (1997) argue that if a regime is already experiencing a high level of internal conflict, such as protests or violent clashes, the onset of an economic sanction restricting trade would further weaken the regime. This heightens the cost of resistance against the sanction (Dashti-Gibson et al. 1997).

Similarly, Dorussen & Mo (2001) suggest that domestic support determines the duration (or "ending") of sanctions. They argue that when target states' domestic constituencies support resistance against sanctions, leaders have greater incentives to not comply with the sanction, which effectively increases the sanction's duration. Further supporting the idea that domestic institutions condition whether and when states comply with sanctions, Lektzian & Souva (2007) find that differing institutional incentives between nondemocratic and democratic regimes influence the success of economic sanctions. McGillivray & Stam (2004) employ a hazard model to analyze a data set of 47 sanctions cases. They find that leadership change does strongly influence the duration of sanctions, but only in the case of non-democratic states. Similarly, Bolks & Al-Sowayel (2000) consider the determinants of economic sanction duration, but these authors also restrict themselves to target state characteristics in determining time until compliance. These authors look inside the target state to define domestic conditions that influence sanction outcome. They suggest that the "decision-making" environment can either hinder or help the leader take countermeasures against the sanction. This "decision-making" environment is affected by factors such as a lack of coordination between government actors and local instability.

The literature has clearly argued that domestic conditions are an influential predictor of sanction compliance. Yet, interstate factors are also important to the decision-making environment: critical is the relationship between sanctioning and target states. Specifically, McLean & Whang (2010) argue that research must address how dependencies between countries, such as trade relations, affect sanction outcomes. They show, for example, that if an important trading partner is part of a sanctioning coalition, then the costs for the target state are raised, and the sanctioning state is more likely to succeed. These types of external factors characterize group level dynamics that exist within each sanction case. Whang, McLean & Kuberski (2013) argue that sanction success hinges on the existence and magnitude of a common interest between a sender and target state, as the sender state can exploit the common interest to coerce the target to change its behavior. To test this hypothesis they, like McLean & Whang (2010), define common interest through trading relationships, and find significant support for the argument that senders can exploit trading relationships to coerce targets to give into sanctions.

Recent work has also successfully paired modeling techniques with theoretical propositions by utilizing hazard-based duration models. The extant literature has demonstrated that this approach more accurately captures the important time-variant dynamics relevant to understanding the sanction process (Bolks & Al-Sowayel 2000). Clearly, if the goal of research is to both explain and predict when a target state is likely to comply with a sanction, then researchers have clear incentives to include time-variant data. Using a duration modeling approach allows for the assessment of whether a specific factor, such as political instability or regime type, increases or decreases the probability that a target country will comply with a sanction over time.

While it is intuitive to many researchers that trade dependence between target and sender states likely influences the duration of economic sanctions, and that domestic conditions influence the target state's cost-benefit analysis, these previous studies do not fully incorporate the evolution of interactions between states over time. Interactions capture the behavior of states iteratively, and move research forward from a more static focus testing mechanisms based singularly on unidimensional ties such as trade or conflict. Such interactions between actors over time can be captured by a network approach, which provides a deeper understanding of how the comprehensive history of sanctions and compliance between states influences future behavior vis-à-vis compliance. Furthermore, overlooking possible interdependencies can cause inappropriate empirical inferences (Erikson, Pinto & Rader 2014). Cranmer et al. (2014) also argue that the sanction literature has not yet accounted for network dynamics, and provide a network based model to explore sanction initiation. They demonstrate that the *onset* of sanctions are best predicted by modeling the way in which interdependencies evolve over time and influence the future decisions made by states. Relatedly, Hafner-Burton & Montgomery (2008) also study sanction onset via a network approach and show that increases in bilateral trade decrease sanctioning behavior between states.

Critical concepts like these are currently given little attention in the research on sanction compliance. By avoiding network attributes, researchers miss a wealth of structural information that is key to understanding the ebb and flow of international cooperation and conflict.[3] We provide a way to account for these network interdependencies within the context of a simple duration model.

Sanctions as a Network Process and the Importance of Reciprocity

A contribution of our study is to demonstrate why sanctions processes should be considered in a network context. To do so, we provide an example. Figure 1 presents the entire sanction-year network for the year 1984. Nodes represent states and the directed edges denote senders and receivers of sanctions. The nodes are colored by the geographic position of a country, for example, countries in North America are colored in shades of red, and Asia in shades of yellow to green. This figure is complex, showing that each yearly network contains important information about state behavior, whereby numerous states are involved in multiple sanction cases during this individual year. IR scholars typically

[3] The insight that the international system is inherently a network and must be studied as such has gained increasing theoretical and empirical support in the broader international relations literature; most prominent is the work on trade networks,Hoff & Ward (2004); Ward, Ahlquist & Rozenas (2012) conflict,Ward, Siverson & Cao (2007) alliances, Warren (2010) and intragovernmental organizations.Cao (2009); Greenhill (2010)

treat each dyad as independent, despite that a singular actor, such as the USA, likely exist within multiple dyads. The appearance of multiple actors in multiple rows of the data violates assumptions of independence. Theoretically, however, this also means that scholars are unable to include second-order dependencies such as reciprocity into their analyses. While studies of international relations tend to recognize the interdependent nature of state behavior in the theoretical sense, they often fail to uphold this theoretical intuition in empirical analysis. Early attempts are noteworthy (Goldstein 1991; Keohane 1989) and more recent work has continued to address this concern (Cranmer et al. 2014; Mitchell & Keilbach 2001) yet studies on sanction compliance have not incorporated these insights.

[Figure 1 about here.]

Theoretical Expectations of Reciprocity and State Behavior

Assuming that sanctions processes are best considered through a network lens, we can then move forward to better incorporate the concept of reciprocity into our analysis. Given the wide range of literature on reciprocity in the study of international relations and foreign policy, we argue that it is necessary to consider how reciprocity plays a role in determining why, and when, sanctions end.

In studies of social and economic behavior, direct reciprocity–the notion that actors learn to "respond in kind" to one another–is argued to be an essential component of behavior.[4] The idea that individuals, or collectives, observe previously cooperative (or conflictual) behavior from others, and include this information into their own decision-making process, is a concept given great value for determining strategic outcomes. For example, reciprocity is shown to influence interactions across diverse settings including tax compliance (Smith 1990), wage selection (Campbell III & Kamlani 1997), and strike breaking (Brett, Shapiro & Lytle 1998). Reciprocity is also shown to play a critical role

[4]For example, see Bolton, Brandts & Ockenfels (1998); Charness & Haruvy (2002); Charness (2004); Cox, Friedman & Gjerstad (2007); Cox (2004).

in the development of interethnic attitudes whereby groups tend to reflect the attitudes that other groups hold toward them (Berry & Kalin 1979).

Intuition about reciprocity's effect on the behavior of individuals also extends to aggregate analysis. International relations and foreign policy scholars have expressed a long standing interest in how reciprocity influences the evolution of cooperative and conflictual interactions among states (Keohane 1989; Richardson 1960b). Rajmaira & Ward (1990) argue that reciprocity determines long-term foreign policy behavior among superpowers via norms creation. The authors importantly point out that reciprocity is a dynamic mechanism that changes over time. They show that while mutual reactivity between superpowers is often weak, high peaks in reciprocity create long-lasting and influential norms of behavior between countries. In other realms of international politics, reciprocity plays a key role in formulating expectations of state behavior. Ward (1981) even argued that reciprocity is a "golden rule" of politics between nations. Osiel similarly notes, "It is an empirical datum that people tend to respond to others with an implicit policy of like for like and that this facilitates cooperation between them. This elementary fact has profound implications for the effective design of law and institutions." (Osiel 2009, p. 19). Reciprocity has long been recognized by IR scholars as an important mechanism for the enforcement of agreements and instantiation of cooperation.

While reciprocity receives little attention in sanctions research, the literature instead focuses on how specific types of relationships between senders and targets–such as alliances and trade ties–expedite sanction resolution. The core mechanisms driving sanction outcomes are thus characterized in terms of a cost-benefit analysis, ignoring the plausible role that reciprocity plays in driving state behavior. Underlying the relational dimensions noted in the literature is the implicit argument that there are some set of countries from whom the sending of sanctions are more consequential, and will thus be complied to more quickly, than others. Much of this logic can be captured by the concept of reciprocity, yet by failing to directly consider reciprocity extant analyses ignores the rich history of interactions between countries.

To establish the existence of reciprocity we assume that (1) reciprocity is best conceptualized as a long-term mechanism that develops a common expectation of behavior between states; (2) departures from established expectations of behavior are possible (Moore 1995); and (3) reciprocity is a necessary but not sufficient condition for influencing strategic behavior between states (Goldstein, Pevehouse, Gerner & Telhami 2001). To the first point, early considerations of reciprocity characterized it as a reactive, short-term process (for example, tit for tat "reactionary" responses). Based on the evidence from Rajmaira & Ward (1990) and others, we assume that reciprocity is a long-term process, born out by multiple interactions between actors over time. In this way, reciprocity becomes a norm of behavior, or a set of expectations about how actors engage with one another, over time.[5] Our second and third assumptions relate to one another in that we acknowledge other influences might effect state behavior and that at different periods states could have incentives to break away from established norms of behavior; this is important because it suggests that state behavior is not easily locked into unidirectional spirals (Moore 1995).

Reciprocity captures the development of strategic expectations that shape state's compliance behavior during sanctions. Overtime, previous reciprocal interactions inform a target state's decision to comply. Our basic intuition is that when a target state has a richer history of reciprocal compliance with sender states, they will more swiftly comply with the senders' demands. This intuition generates the primary hypothesis of this study, that *reciprocity creates an underlying level of expected behavior which influences patterns of compliance among target states.* Importantly, our claim does not demand that reciprocity always work in some inherently "good" or "bad" way, but instead can prolong or shorten sanctions depending on which kind of past reciprocal behavior has occurred. This

[5]The temporal effects of reciprocity are empirically demonstrated in literature focused both on super power behavior (Rajmaira & Ward 1990) and behavior in regional conflicts (Goldstein & Pevehouse 1997).

concept thus requires that we specify which forms of reciprocity should matter in the case of sanctions. We argue that reciprocity influences sanction outcomes through two forms: *compliance reciprocity* and *sanction reciprocity.*

Compliance reciprocity represents a target states' cumulative history of compliance with a particular sender relative to all others in the network. We consider this relative history of compliance to indicate an established norm of cooperation between states. Thus, compliance reciprocity allows us to account for whether those who have a history of cooperative behavior with each other also tend to have more cooperative behavior in the future. In the sanction-duration context, states who receive sanctions from those with whom they have a history of reciprocal compliance are likely to comply sooner than they would with states to whom they have not had positive reciprocal interactions. Notably, this concept is distinct from a simple consideration of past instances of compliance with another state. Such a measure would completely ignore the fact that each state's actions are related to all other interactions between states. For example, if state i complies often to state j, is state i also more likely to comply with all other partner states? Or, relative to all other interactions, does state i comply more frequently and uniquely with state j? The latter idea is the one explicated within our concept of compliance reciprocity. Thus, reciprocity tells us information about the behavior between country i and j over time, relative to how country i interacts with all other partners over time.

We extend this intuition to our second key concept, *sanction reciprocity.* Following the same idea as compliance reciprocity, sanction reciprocity considers how often a target state has received sanctions from the senders of any given sanction case relative to all other sanction interactions. The intuition behind this concept is that sanction reciprocity indicates a deepening resolve between states. The basic insight is that states whom continually respond to sanctions by sending sanctions of their own are signaling more conflictual rather than cooperative behavior over time. These strategic expectations are a dominating factor for the initiation of sanction compliance.

Measuring Reciprocity

To operationalize our measure of reciprocity, we turn to the Social Relations Model developed by Kenny (1994) and Dorff & Ward (2013). To illustrate, consider the matrix X_{ij} below, in which we have six actors in a round robin (dyadic) format. These data are represented by the matrix below, which has a value for each of the thirty interactions, with the main diagonal remaining empty:

$$\begin{bmatrix} & X_1 & X_2 & X_3 & X_4 & X_5 \\ X_6 & & X_7 & X_8 & X_9 & X_{10} \\ X_{11} & X_{12} & & X_{13} & X_{14} & X_{15} \\ X_{16} & X_{17} & X_{18} & & X_{19} & X_{20} \\ X_{21} & X_{22} & X_{23} & X_{24} & & X_{25} \\ X_{26} & X_{27} & X_{28} & X_{29} & X_{30} & \end{bmatrix}$$

First, we begin with calculating the row column and total sums:

- The totals for each *row* are denoted $X_{i\cdot}$ where i is the row number, i.e., $X_{i\cdot} = \sum_{j=1}^{J} X_{ij}$;
- For each column the totals are denoted $X_{\cdot i}$ where i is the *column* number; and
- The total over all rows and columns is given by $X_{\cdot\cdot} = \sum_i \sum_j X_{i,j}$.

Given these quantities, one can calculate individual effects for a variety of concepts, such as the actor, partner, and unique dyadic effects, (as well as the variances attributed to each of these effects). The unique dyadic effects, or the reciprocal interactions between two countries within one pair, are calculated accounting for the general behavior of each country within the pair. Or, in other words, this measure captures the likelihood of i complying to j while controlling for the tendency of i to comply to others and for j to have had its sanctions complied to from other countries. By calculating the likelihood of a pair of countries complying to each other relative to how likely they are to comply to any other country we are able to control for nodal specific effects that often arise in networks. Specifically, we are able to account for the fact that some countries might simply be more likely to comply or refuse to comply to a sanction than others. Accounting for reciprocity in this way enables us to better measure the concept of reciprocity.

> The actor effect for observation i is the total of i's row mean and column mean, minus the overall mean. The means are just the sums, corrected for degrees of freedom, yielding an average row effect:
>
> $$\hat{a}_i = \frac{(n-1)^2}{n(n-2)} X_{i\cdot} + \frac{(n-1)}{n(n-2)} X_{\cdot i} - \frac{n-1}{n-2} X_{\cdot\cdot} \tag{1}$$
>
> Similarly the column mean for actor i is
>
> $$\hat{b}_i = \frac{(n-1)^2}{n(n-2)} X_{\cdot i} + \frac{(n-1)}{n(n-2)} X_{i\cdot} - \frac{n-1}{n-2} X_{\cdot\cdot\cdot} \tag{2}$$
>
> For a symmetric matrix, the row effect and the column effect will be identical. The unique dyadic effect, or reciprocity for specific dyad ij, simply subtracts the row and column effects along with the overall mean out of the value for dyad ij.
>
> $$\hat{g}_{ij} = X_{ij} - \hat{a}_i - \hat{b}_j - X_{\cdot\cdot} \tag{3}$$

The first two equations show how the final equation for reciprocity is calculated relative to the general actor and partner effects (or actor and partner average behavior) for each country.[6] In figure 2, we provide a visualization of the *compliance reciprocity* measure generated using the approach laid out above for 1972, 1992, and 2012. In each panel, we include the reciprocity scores for the ten countries that were most active in the sanctioning network at that year. Each of the edges are directional and indicate how likely a country is to reciprocate compliance from another; reciprocity scores that are negative are designated in red and positive are in blue. For example, in every panel shown here, Israel exclusively has negative incoming edges, indicating that the countries shown in these panels are all

[6]Kenny (1994) would suggest including the full compliment of the SRM into our model. We originally explored this approach, but gained little empirical leverage from it, and thus focus instead on the concept of reciprocity.

unlikely to reciprocate a compliant action from Israel. The implication of this is that even when Israel complies to an economic sanction from another state, that other state is relatively unlikely to comply to any sanctions sent by Israel. On the other hand, across all panels the United States almost exclusively has positive incoming edges, indicating that countries are very likely to reciprocate compliance behavior from the United States. More interesting, however, is the fact that there exists significant variation in whether countries reciprocate behavior. Canada is likely to reciprocate the actions of the United Kingdom but not Russia or Japan, while others countries like France are likely to reciprocate the behavior of Japan but not others like Germany.

[Figure 2 about here.]

Data and Analysis

To test the effects of network pressures on sanction compliance we use the Threat and Imposition of Sanctions (TIES) Database developed by Morgan et al. (2009). This database includes over 1,400 sanction case threats and initiations from 1945 to 2013. Only sanction cases initiated by 2005 are included but outcomes for cases are recorded until 2013. Our focus here is restricted to sanctions that have actually been imposed rather than simply threatened. Restricting our analysis to sanctions that have been imposed during the period of 1960 to 2005 still leaves us with over 800 unique cases. Our unit of analysis is the case-year, providing us with over 7,500 observations. For each case in the TIES database a final outcome is recorded to describe how and if the case has been resolved. We consider the target of a sanction to have complied, if the target state completely or partially acquiesces to the demands of the sanction senders or negotiates a settlement. This is the same definition of sanction success, which we refer to as compliance, that is employed by Bapat & Clifton (2009) and Bapat, Heinrich, Kobayashi & Morgan (2013). In using this definition of compliance, approximately 36% of cases in our dataset end with a state complying by 2013 while another 36% remain ongoing. The remaining 27%

of cases were terminated for other reasons show below in Table 1. Our focus here is on modeling the time until a target country complies to a sanction using the definition described above.

[Table 1 about here.]

Modeling Approach

Next we discuss our modeling approach. To estimate the effect of network pressures on the ability of threatened or sanctioned states to resist compliance, we use Cox proportional hazard (PH) models of the length of threat or sanction periods. Specifically, the dependent variable, sanction spell, is the number of years that a state has not complied to a threat or sanction at time t. We model the expected length of sanction spells as a function of a baseline hazard rate and a set of covariates that shift the baseline hazard. The Cox PH specification that we employ is:

$$\log h_i(t|\boldsymbol{X}_i) \;=\; h_0(t) \times \exp(\boldsymbol{X}_i\beta), \tag{4}$$

where the log-hazard rate of compliance in a sanction case, i, conditional on having not complied for t years is a function of a common baseline hazard $h_0(t)$ and covariates $\boldsymbol{X}$. In employing this approach, we assume no specific functional form for the baseline hazard and instead estimate it non-parametrically from the data.[7] The covariates $\boldsymbol{X}$ operate multiplicatively on the hazard rate, shifting the expected risk of compliance up or down depending on the value of β (Crespo-Tenorio, Jensen & Rosas 2013).

Providing no specific functional form for the baseline hazard necessitates testing the proportional hazard assumption. Keele (2010) notes that not inspecting this assumption in the covariates can lead to severely biased parameter estimates. To address this issue, we first fit smoothing splines for all continuous covariates. After ascertaining that none

[7] To ensure against bias in our parameter estimates we included a vector of case-level shared frailties to account for variations in unit-specific factors. We found similar results with and without the shared frailties, so we report results without the inclusion of this additional term.

of the continuous covariates in our model required modeling with splines, we carried out tests of non-proportionality.[8]

We also impute missing values to avoid excluding instances of compliance. If we employed list-wise deletion, we would lose almost 1,000 country-year observations and 100 unique sanction cases. Previous research has already highlighted how simply deleting missing observations can lead to biased results.[9] To impute missing values, we use a copula based approach developed by Hoff (2007). Details on our imputation process and results based on the original dataset, which are nearly identical, can be found in the Appendix.[10]

In addition to including our two key measures of reciprocity, discussed in the previous section, we control for a variety of other components identified as being important in determining whether a target states complies to a sanction. First, is a simple counter of the number of sender states involved in a sanction to account for the evidence that multilateral sanctions appear to lead to compliance more frequently than unilateral sanctions (Bapat & Clifton 2009). However, along with many others in the literature, we expect that what determines compliance it is not simply the number of senders involved but also the relationships that a sanctioned state has with senders.

Some of the recent literature on sanction compliance has turned to examining the relationships between the senders and receiver of a sanction. Just as one would imagine that a person is less swayed by the demands of 10 strangers than the demands of a few close friends, we conceptualize senders as most influential when they interact with the target state on a number of dimensions. For example, McLean & Whang (2010) argue that countries are more likely to comply if they are sanctioned by their major trading partners. To account for these types of explanations, we incorporate a number of variables

[8]For those covariates where the non-proportional effects assumption does not hold, we include interactions between the covariate and spell duration (log scale).

[9]For example, see Rubin 1976; Honaker & King 2010.

[10]We include summary statistics of the original and imputed datasets used for analysis in the Appendix as well.

that describe the relationship a sanctioned state has with its senders. First, we measure the average distance between sender(s) and receiver.[11] Our second covariate relating to proximity is trade, which we measure as the total share of the receiver's trade in that year accounted for by sender states.[12] Last, we measure alliances as the proportion of sender(s) that are allied with the receiver.[13]

Finally, we include a number of covariates to account for domestic explanations of sanction compliance in the extant literature. First, previous work has examined the relationship between sanctions and regime type (Allen 2005); to control for this we include a measure of the target states' domestic institutions from the Polity IV data.[14] This measure is computed by subtracting a country's autocracy score from its democracy score, and is scaled from 0 to 20. Previous research has shown that sanctions will be more effective when the target states' domestic institutions are more democratic. Second, we control for the level of internal conflict within a country using the weighted conflict index from the Cross National Time-series Data Archive (Banks 2011). The expectation in the extant literature is that countries with higher levels of internal instability would be more likely to comply with sanctions. Finally, we use a logged measure of GDP per capita and the percent change in annual GDP, from the World Bank, to account for the argument that economically successful states are better able to weather the pressures of these agreements.

Below we show our full model specification:

[11] To construct this measure we use the minimum distance between countries from the Cshapes Dataset (Weidmann, Kuse & Gleditsch 2010).

[12] Data for this measure is taken from the Correlates of War (CoW) Trade dataset (Barbieri, Keshk & Pollins 2009).

[13] Data for this measure is obtained from the CoW Formal Alliances dataset (Gibler & Sarkees 2004).

[14] See Marshall & Jaggers (2002). Specifically, we use the "polity2" variable from the Polity IV data.

$$
\begin{aligned}
&Compliance_{i,t} = && (5)\\
&\quad Sanction\ Reciprocity_{j,t-1} + Compliance\ Reciprocity_{j,t-1} + \\
&\quad No.\ Senders_j + Distance_j + Trade_{j,t-1} + Ally_{j,t-1} + \\
&\quad Polity_{i,t-1} + Ln(GDP\ Capita)_{i,t-1} + \\
&\quad GDP\ Growth_{i,t-1} + Internal\ Conflict_{i,t-1} + \epsilon_{i,t}
\end{aligned}
$$

where i represents the target of the sanction, j represents the relationship between the set of sender(s) for a particular sanction case and i, and t the time period – variables without a t subscript are time-invariant.

Results

Table 2 displays the results from our model. To contrast with findings from the extant literature, we run the model in three ways. The first column tests the explanations of sanction compliance centered on target state characteristics. In the second column, we add covariates to account for a target's relationships with sender states. The final model incorporates our reciprocity measures.[15]

[Table 2 about here.]

We find no support for the argument that high levels of internal stability may prompt a country to comply. Across each specification, we do find that countries with higher levels of GDP per capita take longer to comply with a sanction case, indicating that wealthier countries are able to resist complying to sanctions for lengthier durations. Additionally, like previous work in the literature, when we control for the relationships that a sanctioned state has with its senders, we find that more democratic countries are likely to take a

[15] In the appendix, we run a similar analysis using a set of sanctions that are imposed for security related reasons such as pursuing weapons of mass destruction. Our results for this smaller set of sanctions are consistent with what we present in Table 2.

shorter time to comply with sanctions. However, this effect becomes insignificant once we incorporate our network-related covariates.

Since it is difficult to interpret the substantive meaning of point estimates from the hazard function in Table 2, we depict Kaplan-Meier estimates of survival probabilities. The y-axis in these charts represents the probability of survival, or in this case the probability that a country will not comply with a sanction, and the x-axis represents time since sanction initiation (measured in years). To depict the substantive effect of our covariates, we set up two scenarios, one in which the value for the covariate of interest is set to its minimum value, depicted in red, and another where it is set to its maximum, depicted in blue. All the other covariates are set to their median. The darker shaded area around the line represents the 90% confidence interval and the lighter shaded area the 95% confidence interval. Using these plots, we trace the effect of GDP per capita, in Model 3, on the probability of sanction compliance as a function of time; the results are shown in Figure 3. The predicted difference in compliance probabilities between regimes with varying levels of GDP per capita, on the other hand, is quite stark. Just five years after sanction initiation, extremely poor regimes are 15% more likely to comply than wealthier regimes.

[Figure 3 about here.]

We also find strong support for the argument that states are more likely to comply with sanctions involving multiple actors, and the effect of this variable remains consistent even after controlling for our network level covariates in Model 3. Using Figure 4 we can quickly see that there is a stark difference in the likelihood of non-compliance between a sanction case involving single and multiple senders. After just five years the probability of non-compliance drops to approximately 60%, whereas a sanction from a single sender by that time still has an 85% chance of non-compliance. Unlike the extant literature, we do not find strong evidence for the ability of trading partners to obtain quick and successful resolutions to sanction cases. States are also not likely to comply more quickly to sanctions sent by allies, and are actually less likely to comply with sanctions sent from neighbors.

[Figure 4 about here.]

Our key hypothesis relates to the effect of compliance and sanction reciprocity. We incorporate these variables in the last column of Table 2 and here we find that target states comply much more quickly to sanctions sent from countries with whom they have a strong history of reciprocal compliance relative to others in the network. On the left side of Figure 5, we can see that after just five years, the probability of non-compliance in sanction cases where target and sender states have a history of reciprocal compliance is approximately 60%, compared to about 90% when this history does not exist between senders and receivers.

[Figure 5 about here.]

Our sanction reciprocity measure tells a similar story, but focuses on the consequences of past reciprocal adverse relations. Here we can see that countries whom have sanctioned each other in the past without complying to one another are not likely to comply with one another in the present. On the right side of Figure 5, we can again demonstrate that within just five years the probability of non-compliance in a case where target and sender states have not had adverse past relations is half compared to a case where past adverse relations are present. This points to important consequences for sender states, namely that the continuous sanctioning of a particular state without previous compliance from the target state may build up the target's resistance to comply with future sanctions.

Performance. To assess the accuracy and performance of these estimates we employ a six-fold cross validation procedure.[16] We use this procedure both to determine the

[16] Results of analysis were similar when employing a 10-fold cross validation as well, however, we limit to showing six here due to space limitations.

robustness of our coefficient estimates when estimated on different subsamples of our dataset, and to assess how well the results of our model would generalize to an independent dataset. To begin the cross-validation, we split the sanction cases in our dataset into six approximately equal subsets. We then run each model shown in Table 2 six times, where in each iteration we left out one subsample to use as a test set. This allows us to compare the prediction accuracy of each model, thereby helping us to determine the gains from incorporating the reciprocity covariates that are key to our argument.

First, however, we show the results for our reciprocity covariates when we rerun our survival analysis on each of the six folds from the cross-validation. This analysis helps us to understand whether some of the subsets in our dataset follow a different pattern than what is in the broader set.[17] Figure 6 shows that this is not the case for the analysis we present here, the coefficient estimates for compliance and sanction reciprocity remain consistent across each of these subsamples.[18]

[Figure 6 about here.]

A key question that remains, however, is whether we are able to better explain sanction compliance through the incorporation of these network level covariates. Figure 7 shows out-of-sample time-dependent AUC (Area Under the Curve) results from the six-fold cross validation procedure. When calculating the time-dependent AUC we vary the time parameter to range from 0 to 15 years.[19] We set the max for 15 years because only 4% of sanction cases in our dataset that extend past 15 years end with compliance by a target state. This leads to the AUC statistics for each model. After that time point, the accuracy of any of the models begin to coalesce. Before the 15 year mark, however, we see considerable variation in the time-dependent AUC statistics for each model. Most importantly, we can see that Model 3, where we incorporate our network level covariates,

[17]See Beck (2008) for more on this approach.

[18]The parameter estimates for the other covariates also remain consistent across each of the six folds but we leave them out here due to space constraints.

[19]Time-dependent AUCs were computed using the formula provided by Chambless & Diao (2006).

provides a noticeably higher AUC than the alternatives that we examined. Even simply accounting for proximate relationships, as we did in Model 2, does not provide a noticeably higher level of performance than target-state focused explanations.

[Figure 7 about here.]

Conclusion

We have outlined both theoretical and empirical reasons for how the initiation and duration of sanctions between states is dependent upon network attributes and shown that integrating these network attributes into the study of sanction compliance is essential for robust inferences. Our empirical analyses clearly demonstrate the key role of reciprocity in determining the duration of economic sanctions. We find strong support for the influence of reciprocal compliance, suggesting that the most effective sanctions are likely to be those initiated by a higher number of senders with a history of positive reciprocal interactions. Similarly, we highlight a previously little examined aspect of sanction behavior and show that countries whom have sanctioned each other in the past without complying to one another are unlikely to comply with another in the present.

Incorporating these network attributes into our models of sanction compliance, clearly enables us to arrive at more precise models of when the targets of sanctions comply. Further, our findings strongly complement the existing literature. We continue to find that wealthier countries are less likely to comply quickly, and we find that multilateral sanctions are more effective. Unlike the extant literature, however, we find little support for other prominent hypotheses such as the argument that more democratic institutions comply sooner and that countries are more likely to comply when faced with sanctions by trading partners.

More importantly, while much of the research on international sanctions has focused on explaining how monadic characteristics of target states or formalized linkages between states drive sanction outcomes, our study provides a theoretical framework of interstate politics as a nuanced networked phenomenon wherein relations between states develop overtime as a function of continued informational and behavioral exchange. Ignoring network attributes in our study of sanction compliance forces us to assume that the likelihood of any sanction case being resolved is independent of any other. This is an untenable assumption; international politics, more broadly, is a system in which actors are interacting with one another simultaneously across a host of issues, and these interactions provide us with a great deal of information on how we can expect them to behave in the future. Utilizing network theory allows us to incorporate these interactions in a principled way, as we have demonstrated here in our study of sanction compliance.

Appendix

Imputation Procedure. The copula based approach developed by Hoff (2007) is estimated through a Markov chain Monte Carlo (MCMC) algorithm. We run the MCMC for 6,000 imputations, saving every sixth imputation, using the `sbgcop.mcmc` function in the `sbgcop` package in $\mathcal{R}$. To account for time trends and obtain better performance from this imputation procedure, we create five lags of each variable, except for polity, prior to imputation. Every imputation of the MCMC leads to the creation of one dataset with all missing values imputed. Running this algorithm on our dataset then produces a total of 1,000 imputed datasets. Results across these 1,000 imputed datasets are then averaged, thereby accounting for a portion of the uncertainty in the imputed values. We then used the average of the results from these 1,000 imputed datasets to generate the regression estimates in table 2.

[Table 3 about here.]

Regression results on the original dataset are shown in table 3. The results, particularly for our reciprocity variables, are nearly identical.

Summary Statistics. Below we show summary statistics for the imputed, table 5, and original, table 4, datasets.

[Table 4 about here.]

[Table 5 about here.]

Security Sanctions. Below we show the results for model 3 from Table 2 when limiting our analysis to sanctions that were imposed for security related reasons.

[Table 6 about here.]

Acknowledgements

This was prepared for 72^{nd} annual Midwest Political Science Association Conference in Chicago, April 2-6 2014. We are grateful for comments on earlier versions of this paper received at the ISSS-ISAC Conference in Washington, D.C., October 4-6 2013. This publication was made possible (in part) by a grant from the Carnegie Corporation of New York. The statements made and views expressed are solely the responsibility of the author. Alphabetical order implies equal authorship, all mistakes are our own.
Replication material and instructions are available at https://github.com/s7minhas/magnesium.

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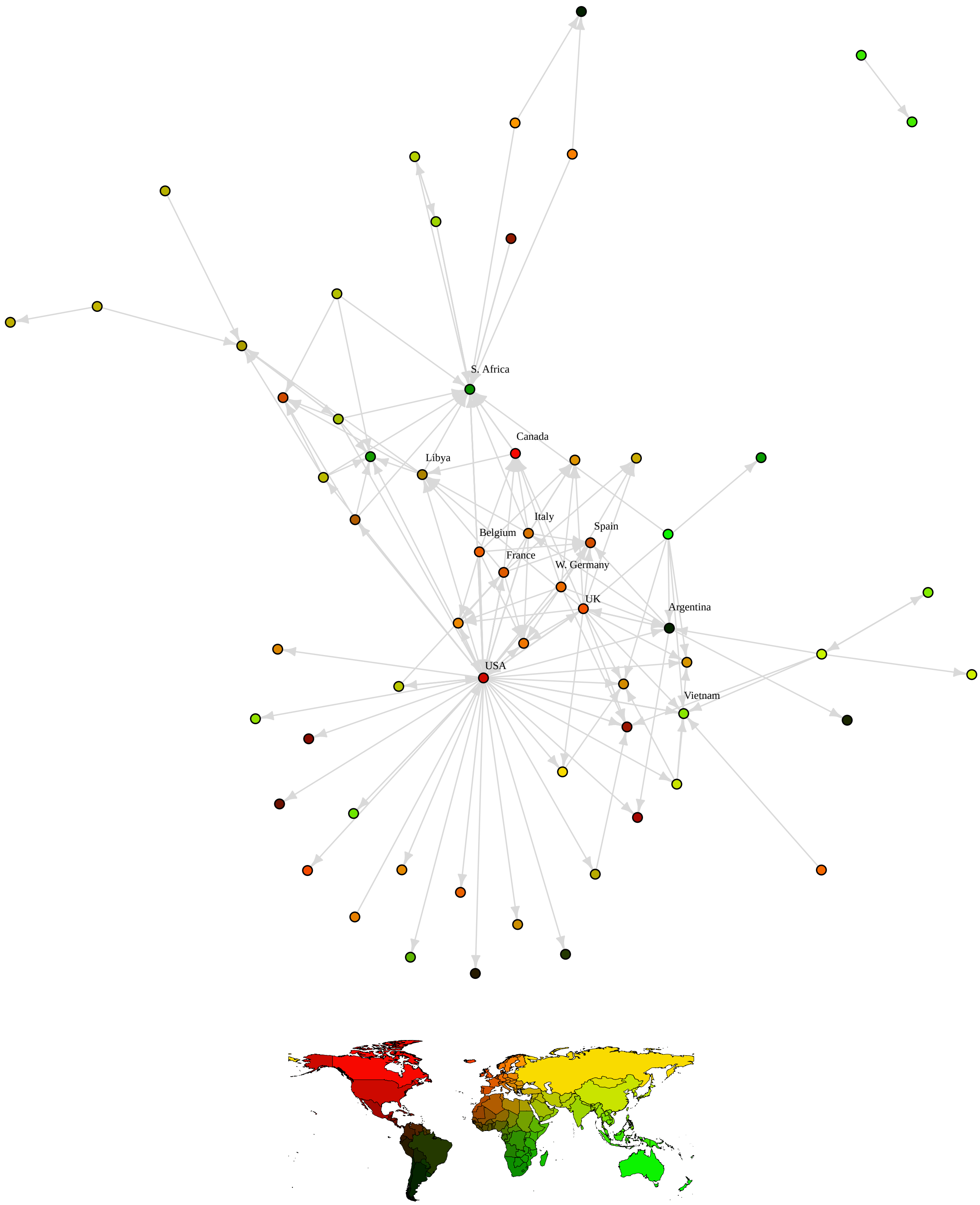
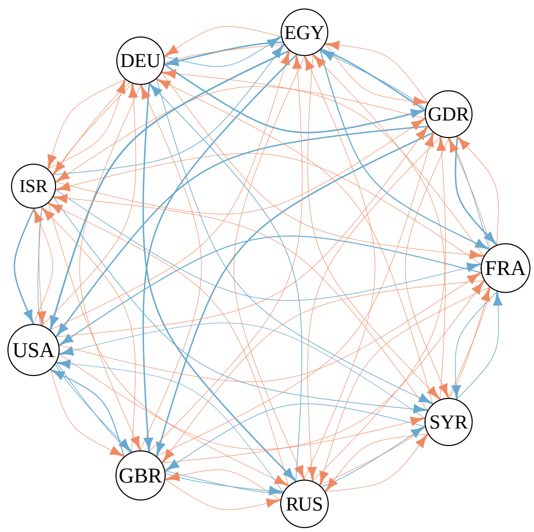
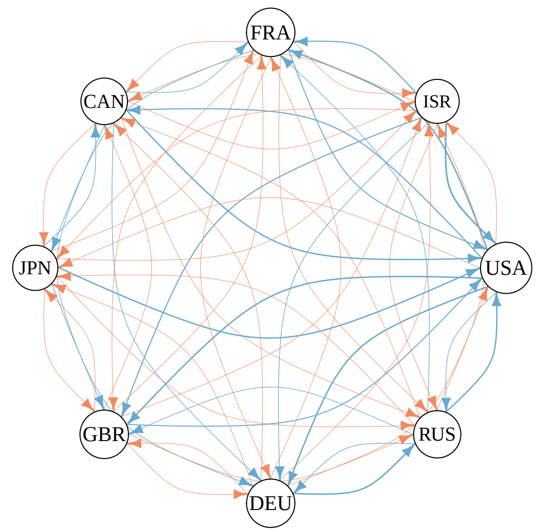


Figure 1 Here we show the sanction network in 1984, nodes are colored by geographic coordinates of countries. Data for sanction cases comes from Morgan et al. (2009).

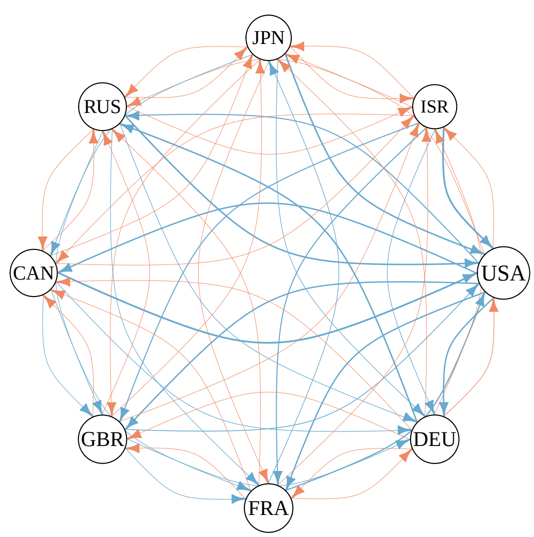
Figure 2 Reciprocity plots



(a) Compliance: 1972



(b) Compliance: 1992



(c) Compliance: 2012

Figure 3 Survival probabilities over time by $Ln(GDP\ Capita)_{i,t-1}$. Red designates scenarios in which the covariate is set to its minimum value and blue where it is set to its maximum value. Darker shaded around each line represents the 90% confidence interval and the lighter shaded area the 95% confidence interval.

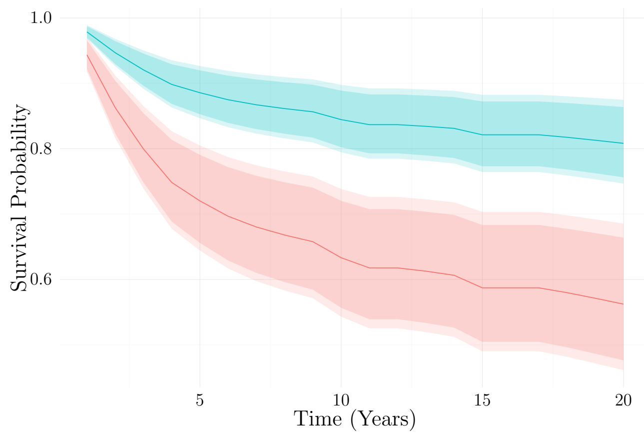


Figure 4 Survival probabilities over time by the number of senders in a sanction case.

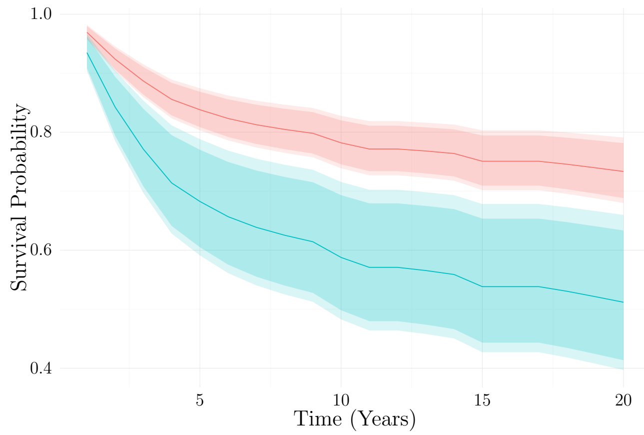
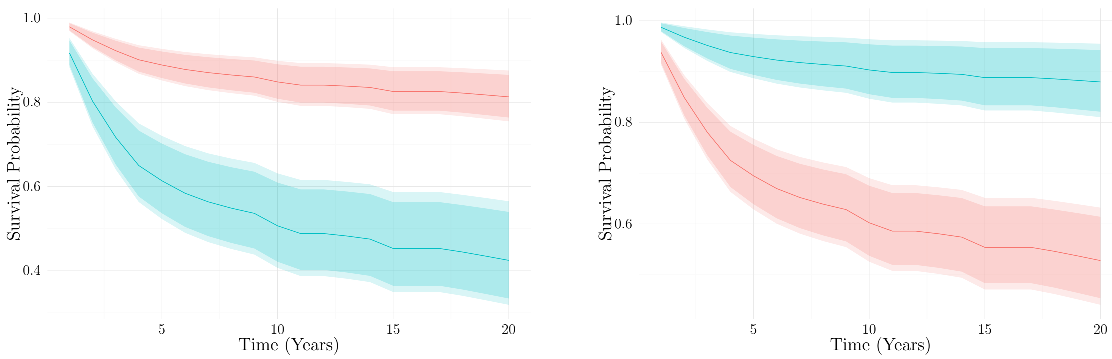


Figure 5 Survival probabilities reflecting over time by network level covariates.



(a) Compliance Reciprocity **(b)** Sanction Reciprocity

Figure 6 Reciprocity coefficient estimates from each of the six-folds of the cross validation procedure.

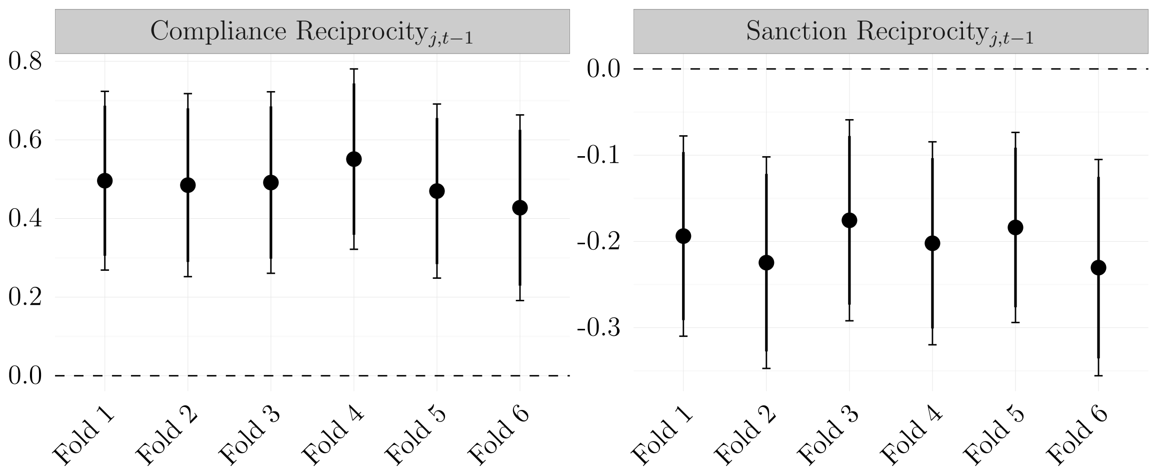
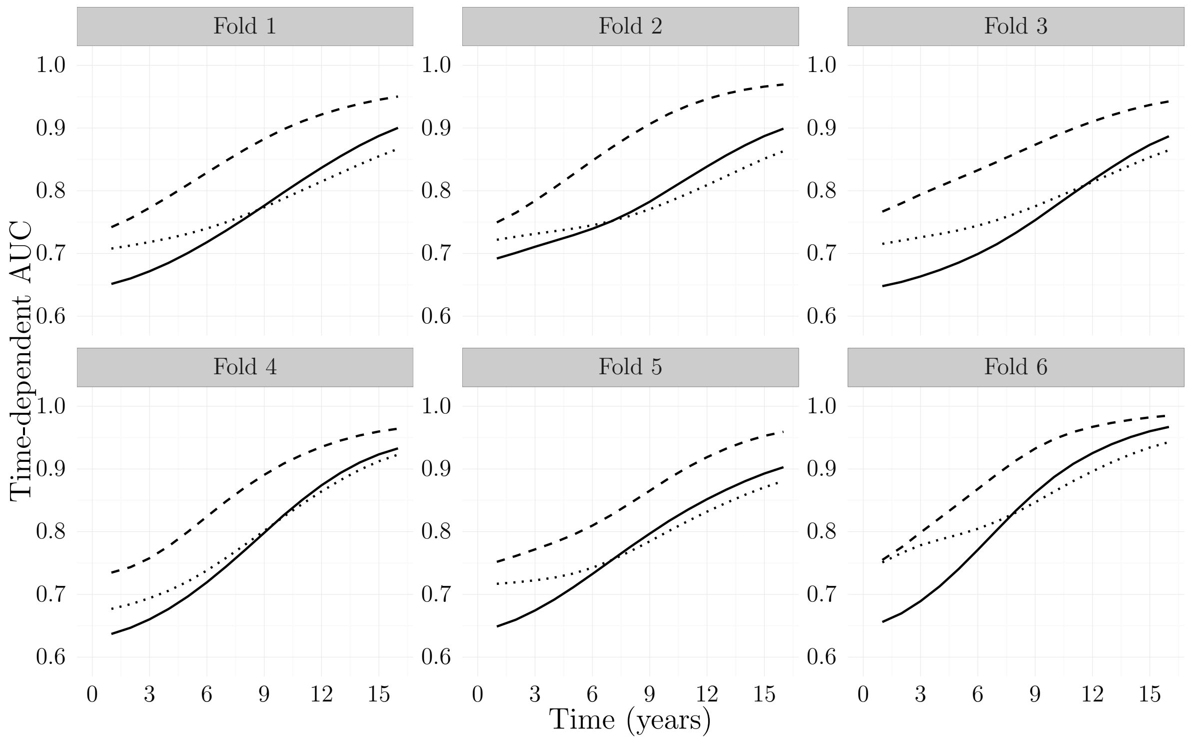


Figure 7 Out-of-sample time-dependent AUC statistics from six-fold cross validation procedure for each model shown in Table 2. The solid line represents Model 1, the dotted line represents Model 2, and the dashed line represents Model 3.



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Outcome	Frequency
Capitulation by Sender After Imposition	160
Stalemate after Sanctions Imposition	71

Table 1 Outcomes of sanction cases no longer ongoing where compliance was not achieved.

Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t-1}$			0.51^{**}
			(0.1)
Sanction Reciprocity$_{j,t-1}$			-0.22^{**}
			(0.06)
Number of Senders$_j$		0.22^{**}	0.19^{**}
		(0.05)	(0.05)
Distance$_j$		0.85^{**}	0.82^{**}
		(0.19)	(0.19)
Trade$_{j,t-1}$		-3.68	-2.46
		(5.35)	(4.15)
Ally$_{j,t-1}$		-0.03	0.03
		(0.17)	(0.17)
Polity$_{i,t-1}$	0.02	0.03^{**}	0.02
	(0.01)	(0.01)	(0.01)
Ln(GDP per capita)$_{i,t-1}$	-0.27^{**}	-0.27^{**}	-0.22^{**}
	(0.06)	(0.06)	(0.06)
GDP Growth$_{i,t-1}$	0	0.01	0
	(0.01)	(0.01)	(0.01)
Population$_{i,t-1}$	-0.18^{**}	-0.19^{**}	-0.11^{**}
	(0.04)	(0.05)	(0.05)
Internal Conflict$_{i,t-1}$	0.02	0.02	0.01
	(0.01)	(0.01)	(0.01)
n	6206	6183	6183
Events	190	189	189
Likelihood ratio test	54.73 (0)	89.16 (0)	117.21 (0)

Table 2 Duration model with time varying covariates estimated using Cox Proportional Hazards. Standard errors in parentheses. ** and * indicate significance at $p < 0.05$ and $p < 0.10$, respectively.

Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t-1}$			0.53^{**}
			(0.11)
Sanction Reciprocity$_{j,t-1}$			-0.22^{**}
			(0.06)
Number of Senders$_j$		0.28^{**}	0.25^{**}
		(0.05)	(0.05)
Distance$_j$		0.85^{**}	0.81^{**}
		(0.21)	(0.21)
Trade$_{j,t-1}$		-2.95	-2.31
		(4.86)	(4.33)
Ally$_{j,t-1}$		-0.06	-0.01
		(0.18)	(0.18)
Polity$_{i,t-1}$	0.01	0.03^{*}	0.02
	(0.02)	(0.02)	(0.02)
Ln(GDP per capita)$_{i,t-1}$	-0.27^{**}	-0.27^{**}	-0.21^{**}
	(0.06)	(0.06)	(0.07)
GDP Growth$_{i,t-1}$	0	0	0
	(0.02)	(0.01)	(0.02)
Population$_{i,t-1}$	-0.21^{**}	-0.21^{**}	-0.12^{**}
	(0.05)	(0.06)	(0.06)
Internal Conflict$_{i,t-1}$	0.02^{*}	0.02	0.02
	(0.01)	(0.01)	(0.01)
n	5342	5324	5324
Events	150	149	149
Likelihood ratio test	46.93 (0)	83.49 (0)	108.17 (0)

Table 3 Duration model on unimputed data with time varying covariates estimated using Cox Proportional Hazards. Standard errors in parentheses. ** and * indicate significance at $p < 0.05$ and $p < 0.10$, respectively.

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
Compliance	6183	0.03	0	0.17	0	1
Compliance Reciprocity$_{j,t-1}$	6183	0.53	-0.01	1.05	-0.81	4.15
Sanction Reciprocity$_{j,t-1}$	6183	3.36	1.9	4.21	-1.1	21.19
Number of Senders$_j$	6183	1.51	1	1.24	1	5
Distance$_j$	6183	0.14	0	0.34	0	1
Trade$_{j,t-1}$	6183	0.01	0.01	0.02	0	1
Ally$_{j,t-1}$	6183	0.44	0	0.49	0	1
Polity$_{i,t-1}$	6183	14.45	18	6.96	0	20
Ln(GDP per capita)$_{i,t-1}$	6183	8.23	8.19	1.72	3.86	11.22
GDP Growth$_{i,t-1}$	6183	3.6	3.66	4.5	-42.45	46.5
Population$_{i,t-1}$	6183	17.42	17.63	1.64	11.14	20.99
Internal Conflict$_{i,t-1}$	6183	3.04	1	5.34	0	87

Table 4 Summary statistics of parameters included in duration model using imputed data.

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
Compliance	5324	0.03	0	0.16	0	1
Compliance Reciprocity$_{j,t-1}$	5324	0.56	0	1.08	-0.81	4.15
Sanction Reciprocity$_{j,t-1}$	5324	3.66	1.96	4.45	-1.1	21.19
Number of Senders$_j$	5324	1.45	1	1.17	1	5
Distance$_j$	5324	0.14	0	0.34	0	1
Trade$_{j,t-1}$	5324	0.01	0.01	0.02	0	1
Ally$_{j,t-1}$	5324	0.48	0	0.5	0	1
Polity$_{i,t-1}$	5324	15.56	19	6.3	0	20
Ln(GDP per capita)$_{i,t-1}$	5324	8.46	8.51	1.68	3.86	10.94
GDP Growth$_{i,t-1}$	5324	3.54	3.48	4.36	-42.45	34.8
Population$_{i,t-1}$	5324	17.68	17.79	1.49	13.49	20.99
Internal Conflict$_{i,t-1}$	5324	3.16	1	5.45	0	87

Table 5 Summary statistics of parameters included in duration model using original data.

Variable	Model 1	Model 2
Compliance Reciprocity$_{j,t-1}$	0.68**	0.75**
	(0.34)	(0.25)
Sanction Reciprocity$_{j,t-1}$	-0.52^{**}	-0.48^{**}
	(0.23)	(0.18)
Number of Senders$_j$	0.1	0.11*
	(0.07)	(0.06)
Distance$_j$	0.39	0.51*
	(0.34)	(0.28)
Trade$_{j,t-1}$	-2.99	-2.73
	(5.72)	(4.88)
Ally$_{j,t-1}$	-0.31	-0.18
	(0.29)	(0.25)
Polity$_{i,t-1}$	0.02	0.02
	(0.02)	(0.02)
Ln(GDP per capita)$_{i,t-1}$	-0.02	-0.03
	(0.1)	(0.09)
GDP Growth$_{i,t-1}$	0	0
	(0.02)	(0.02)
Population$_{i,t-1}$	-0.05	-0.02
	(0.09)	(0.07)
Internal Conflict$_{i,t-1}$	0.01	0
	(0.02)	(0.02)
n	1535	2245
Events	71	101
Likelihood ratio test	12.17 (0.35)	17.02 (0.11)

Table 6 Here we focus on predicting the time until compliance for sanctions not related to economic issues. The first column shows duration model results on unimputed data with time varying covariates estimated using Cox Proportional Hazards, and the second with using imputed data. Standard errors in parentheses. ** and * indicate significance at $p < 0.05$ and $p < 0.10$, respectively.