WHEN DO STATES SAY UNCLE? NETWORK DEPENDENCE AND SANCTION COMPLIANCE

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Abstract. This article explores when and why states comply with sanctions. Previous literature has suggested a duration modeling approach is needed to adequately capture the time it takes for a sanction to "work." This approach, however, has failed to carefully account for important dynamics relevant to the modeling of sanction outcomes. Namely, present duration approaches fail to incorporate the network effects intrinsic to international sanction processes. At any given time, target states typically face both a set of sanctioners within an individual sanction case, as well as a general network of sanctioners including senders from multiple cases within any given year. We argue that a key network measure, reciprocity, influences the behavior of states and their willingness to comply to sanctions. We present a model that incorporates this interdependent nature of the international system by including measures of reciprocity within the duration model. In addition, we are able to test whether traditional conditions that the literature claims as critical for predicting sanction compliance, such as domestic institutions, are still influential once network dynamics are adequately modeled. In doing so, we test key hypotheses from the literature regarding the role of domestic conditions, instra-state relationships, and our own new hypotheses on the effect of reciprocity on sanction compliance.

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Introduction

Economic sanctions are a frequently used foreign policy tool in the realm of international relations. Typically, one or more states initiate sanctions against another when they perceive the target state as non-cooperative. The trigger 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.

Policymakers continually engage in heated debates over the efficacy of sanctions. The motivations for sanction initiation are cross-cutting, spanning a diverse and interdependent mix of policy issues and political actors. While the concept of sanctions–the idea that countries can put pressure via economic ties to other countries in order to influence policy–is relatively straightforward, the study of when and why sanctions work is complex.

Earlier research on sanctions argued that sanctions have little influence on targets (Lam 1990; Dashti-Gibson, Davis and Radcliff 1997; Morgan and Schwebach 1997; Drezner 1998). More recent research suggests that the effectiveness of sanctions is dependent on an interaction of several factors, namely: the number of senders acting as a part of the sanctioner group and the type of issue in dispute (Miers and Morgan 2002; Morgan, Bapat and Krustev 2009); the strength of domestic institutions within the target state; and the type of regime governing the target state (McGillivray and Stam 2004).

The theoretical and empirical literatures on economic sanctions demonstrate that several different, interacting conditions underline sanction outcomes. We argue, however, that scholars have thus far failed to incorporate a key factor into their analysis: reciprocity within the sanction network.[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 must be modeled as such. Reciprocity is a not a new concept to the

[1]With the one major exception being Cranmer, Heinrich and Desmarais (2014), which we discuss furher below.

field of international studies, but has its roots in previous theories of cooperation and the evolution of norms between states (Richardson 1960; Choucri and North 1972; Goldstein 1991; Rajmaira and Ward 1990; Ward and Rajmaira 1992). Yet the study of sanctions has not yet addressed how the reciprocity's effect on state behavior might condition the effects of other variables on sanction compliance.

We analyze this key endogenous structure inherent to network dynamics, reciprocity, and argue that the structure created by reciprocial interactions over time must be accounted for in studies of sanction outcomes. Further, we extend on previous work suggesting duration models as the most appropriate approach for modeling sanctions outcomes by incorporating network measures into the duration framework. In doing so we are able to return to key hypotheses from the literature and assess whether factors such as domestic political institutions and internal stability influence sanction outcome once network dynamics are adequately incorporated into the model.

We leverage the network modeling approach to produce an accurate test of when and why sanctions end. In the following section, we review previous work on compliance and introduce the network concept. We then present our central argument and hypotheses; in doing so we articulate the various ways that networks can be conceptualized in this context. Last, we present our findings and review the results.

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 the role of domestic factors. Marinov (2005) argues that sanctions "work" by destabilizing the leaders of the governments that sanctions punish. This focus on internal state conditions echoes other work which suggests that sanction outcomes are dependent on domestic stability and domestic institutions. For example, 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, Davis and Radcliff 1997).

Similarly, Dorussen and Mo (2001) suggest that domestic support determines the duration (or "ending") of sanctions whereby when the target state's domestic constituency supports resistance against the sanction, the leader has greater incentive 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 and Souva (2007) argues that because of differing institutional incentives, economic sanctions are more likely to succeed against nondemocratic regimes than democratic ones. While all of these studies present empirical evidence for the general claim that domestic factors condition sanction outcome, none of them account for network level dependencies that influence behavior between states over time.

Clearly, domestic conditions seem to matter for predicting sanction compliance. Yet, another realm of conditions also matters. Research has shown that it is important to consider whether the group of sanctioners for each sanction case have specific types of relationships with the target state, i.e. dependencies between countries manifested through trade relations, ally ties, or geographic proximity (McLean and Whang 2010). Each relationship between the sanctioner and the sanctioned takes on a slightly different influence dependent on these factors. If a neighboring state is greatly dissatisfied with the target's behavior, than a conflict of interest could have more serious repercussions than for a sanctioner who is geographically removed from the target. These types of external factors are housed within the groups of sanctioners for each and every sanction case. Importantly, Cranmer, Heinrich and Desmarais (2014) also argue that the sanction literature has not yet accounted for network dynamics. In their work they model the sanction network itself, and demonstrate that *onset* of sanction cases are best predicted by modeling the way in which the network complex interdependencies, such as reciprocity, evolve over time and influence the future decisions made by states. Critical concepts like these are currently ignored in the research on sanction compliance.

Research on compliance has historically included both these domestic state level and intrastate level variables within a logit or probit-estimation approach. However, research has recently demonstrated that a duration modeling approach more accurately captures the important time-variant dynamics relevant to understanding the sanction process and for testing those theories. Bolks and Al-Sowayel (2000) point out that a duration-modeling approach is able to include variables that fluctuate throughout the tenure of an individual sanction case. Clearly, if the goal of research is to understand and predict when a target state is likely to comply to 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.

McGillivray and 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 and Al-Sowayel (2000) consider the determinants of economic sanction duration using a duration model approach. These authors also 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.

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's behavior, these previous approaches fail to account for the evolution of interaction between states over time. Interactions between actors over time can be essentially captured by the network concept, allowing for a deeper understanding of how the history of sanctions and compliance between states influences future sanction cases. By avoiding these network attributes, researchers miss a wealth of structural information that is critical to understanding the ebb and flow of international cooperation and conflict. The insight that the international system is inherently a network and must be studied as such, is by no means original to this project, but has gained increasing support in the literature; most prominent is the work on trade networks (Hoff and Ward 2004; Ward, Ahlquist and Rozenas 2012), conflict (Dorff and Ward 2013), alliances (Warren 2010) and intragovernmental organizations (Cao 2009; Greenhill 2010).

Furthermore, current duration approaches are unable to account for the history of dependencies between countries over time, and thus ignore previous cases of compliance and sanction interdependence between target and sanctioning states. Over time, complex interdependencies likely emerge and drive behavior between states, where if country i complies often to country j, country j might also be more likely to comply to country i. This process is typically known as reciprocity, and is one of the network attributes we account for in our analysis below.

Accounting for Network Effects

In this section, we present our argument for incorporating reciprocity measures into models for predicting the time until sanction compliance, and describe our approach for capturing these features. In focusing primarily on domestic factors, as much of the extant literature has done, alternative explanations that incorporate external conditions relating to the sanctioning network have been ignored. The two explanations that we focus on are (1) reciprocity in the sanctioning network over time; (2) previous compliance reciprocity.[2]

[2] "Sender" states are those that impose or threaten sanctions, while "reciever" states are those that states in which sanctions are imposed.

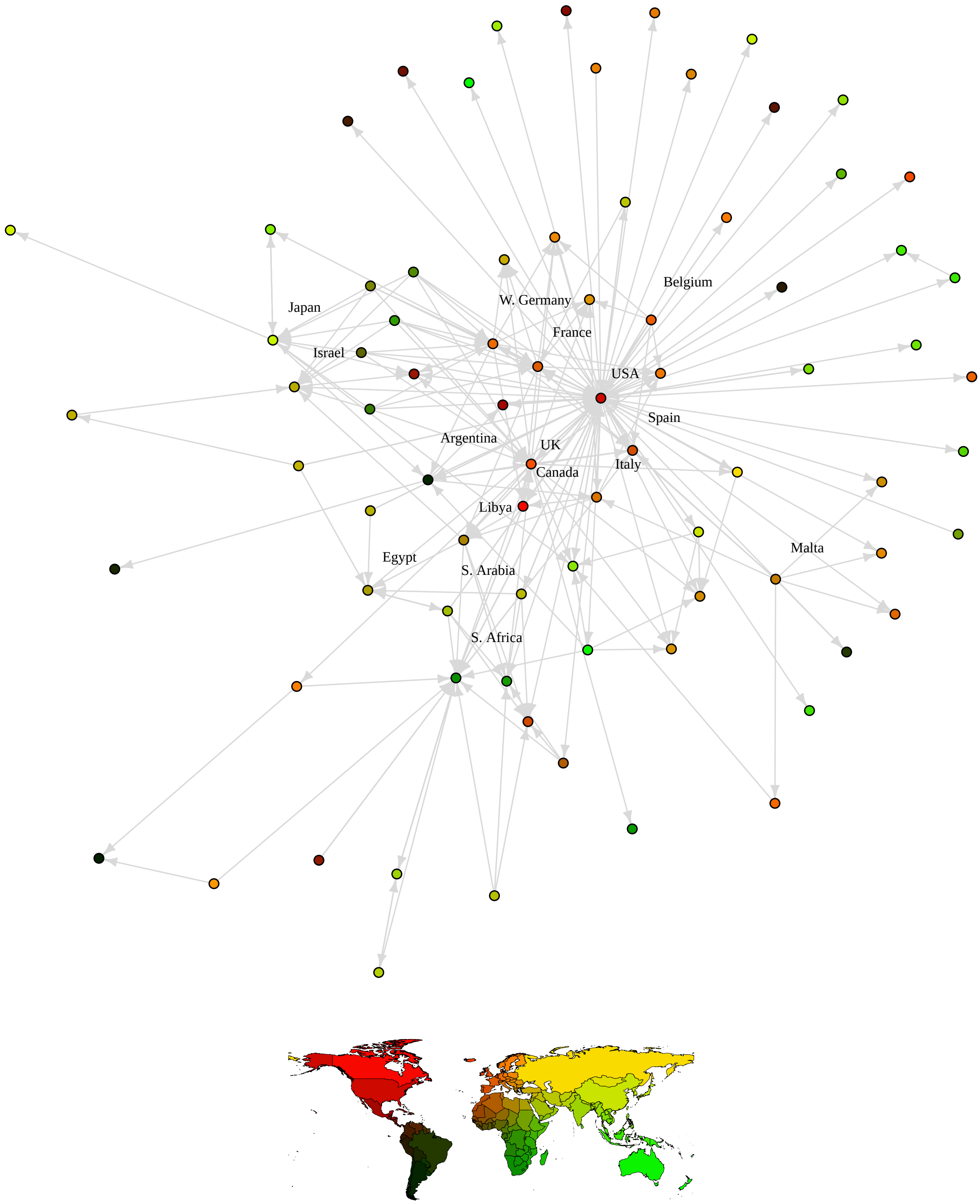


Figure 1. Here we show the sanction network in 1984, nodes are colored by geographic coordinates of countries. Data for sanction cases comes from Morgan, Bapat and Krustev (2009).

To demonstrate, we visually present the sanction-year network. Figure 1 depicts the network of sanction cases on-going and initiated by 1984. This network graph presents the entire sanction-year network. Nodes represent states and the directed edges denote the sender and receiver of sanctions. This figure is complex, showing that each yearly network contains important information about state behavior, whereby numerous states are involved in mulitple sanction cases during this individual year. Typical analysis on sanction duration does not capture sanction-year attributes and ignores how these network characteristics evolve over-time, and inform future sanction networks. In this sense, the concept of reciprocity has more than just methodological relevance, it has theoretical import as well. 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 (Keohane 1989; Goldstein 1991) and more recent work has continued to address this concern (Mitchell and Keilbach 2001; Cranmer, Heinrich and Desmarais 2014), yet studies on sanction compliance have not yet incorporated these insights.

We develop two reciprocity concepts that allow us to analyze the interdependencies inherent to the evolution of sanction dynamics. First, we outline a *compliance reciprocity* measure. By creating a yearly network, for each year available in our data, we are able to calculate compliance reciprocity over time. Essentially, this represents a target states' cumulative history of compliance with a particular sender relative to others in the network. This can be thought of as a record of compliance between an individual dyad pair, relative to all other dyads within the network.

Our measure of reciprocity allows us to capture whether those who have a history of cooperative behavior with each other also tend to have more cooperative behavior in the future with their partner states. Or, in a duration context, states who recieve sanctions from those with whom they have a history of reciprocal compliance are likely to comply sooner to those states than they would with lower compliance reciprocity.

Notably, this measure is different from a simple conceptualization of past interactions which might simply control for the number of times a state has complied. Such a simple measure completely ignores the fact that each state's actions are conditional on 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 interactions between country i and j over time, relative to how country i interacts with all other partners over time.

The majority of studies on sanctions treat all sanctions cases, as well as sanction actors, as independent from other another. Because multiple actors appear within multiple sanction cases in any given year, (i.e. the USA might act as a sender state against South Africa in several different economic sanction cases within one year), our approach allows for us to directly address the interdependencies both between sanction cases as between sanction senders.

We draw our measure of reciprocity from the Social Relations Model developed by Kenny (1994) and presented as a tool for political scientists by Dorff and 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 which has the value of each of the thirty interactions in each entry, with the main diagonal remaining empty:

$$\begin{bmatrix} & X_{12} & X_{13} & X_{14} & X_{15} & X_{16} \\ X_{21} & & X_{23} & X_{24} & X_{25} & X_{26} \\ X_{31} & X_{32} & & X_{34} & X_{35} & X_{36} \\ X_{41} & X_{42} & X_{43} & & X_{45} & X_{46} \\ X_{51} & X_{52} & X_{53} & X_{54} & & X_{56} \\ X_{61} & X_{62} & X_{63} & X_{64} & X_{65} & \end{bmatrix}$$

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, 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, how likely country i is to comply with country j, and country j is to comply with country i is calculated relative to how often country i tends to comply with all of the other countries, as well as how likely country j is to comply to all others.

- 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:
  $\hat{a}_i = \frac{(n-1)^2}{n(n-2)} X_{i\cdot} + \frac{(n-1)}{n(n-2)} X_{\cdot i} - \frac{n-1}{n-2} X_{\cdot\cdot}$
- Similarly the column mean for actor i is
  $\hat{b}_i = \frac{(n-1)^2}{n(n-2)} X_{\cdot i} + \frac{(n-1)}{n(n-2)} X_{i\cdot} - \frac{n-1}{n-2} X_{\cdot\cdot\cdot}$.
  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.
  $\hat{g}_{ij} = X_{ij} - \hat{a}_i - \hat{b}_j - X_{\cdot\cdot}$

The first two equation are to 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.[3]

We extend this intuition to our second key measure, *sanction reciprocity*. Following the same idea as compliance reciprocity, this is a measure of how often a target state has received sanctions from the senders of any given sanction case–relative to all other sanction interactions of states. The intuition behind this measures is to capture the concept of resolve: states who have been sanctioned against multiple times by a sender state are likely to build up a willingness of resistance and not cooperation. This suggests that states receiving sanctions from those with whom they have been sanctioned before are likely to more slowly comply to those states. The basic insight here is that those states which continually reciprocate sanctioning behavior are signaling more conflictual interactions rather than cooperative ones.

> **H1**: states who recieve sanctions from senders they have a history of reciprocal compliance are likely to comply quickly.
>
> **H2**: states receiving sanctions from those with whom they have a history of higher sanction reciprocity will be slower to comply.

We also account for key conditions at the sanction-case level. To demonstrate, we deconstruct the broader yearly network example of 1984, to zoom in and narrow our focus to observe the individual sanction case of South Africa in 1984. In this case, South Africa is the target of multiple sanctions, as shown in Figure 2. Because of this, we construct a sanction network that represents each sanction South Africa faces during this year. As one can easily see, in most cases during 1984, South Africa faces more than one sanctioner, and these sanctioners vary across each sanction case. For example in the first

[3]Kenny (1994) woudl 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.

network graph, in the top left of Figure 2, we see that South Africa faces a sanction from India, Pakistan, and Jamaica. Yet in the top right network graph, we see that South Africa also faces a sanction from Canada, Sweden, the USA, Finland, and Austrialia.

By the 1980s, the South African apartheid regime had been in power since 1948. The international community moved to sanction the apartheid regime in hopes to end the violence and delegitimize the regime. As unrest intensified international action became inevitable and multilateral economic sanctions were initiated. As Kinne (2013) points out, the aim of delegitimizing a regime is a cooperative act between multiple actors, whereby its effectiveness is dependent on coordinated consent and action. To diplomatically exclude South Africa, successful coordination and cooperation amongst sanctioner states was key (Kinne 2013; Christopher 1994). Critical coordination was acheived through this group of state sanctioners. By also looking at the sanction-case network, we are able to-capture these state-level to test whether characteristics among sanctioners effect sanction compliance. For example, we might expect that a sanction from Pakistan, India, and Jamaica has substantially different implications than one from largerly "western" sanctioners such as Sweden, Canada, USA, Finland and Australia. We conceptualize these relationships as composed of "pressures" which likely influences the behavior of the target state. We present two hypotheses which focus on the sanction case network. First, it is intutitive that the number of senders should influence the willingness of the target state to comply because as the number of senders increases, the more constraints through multple relationships the target faces. The essential idea is that handling the demands of ten relationships is more influential than one.

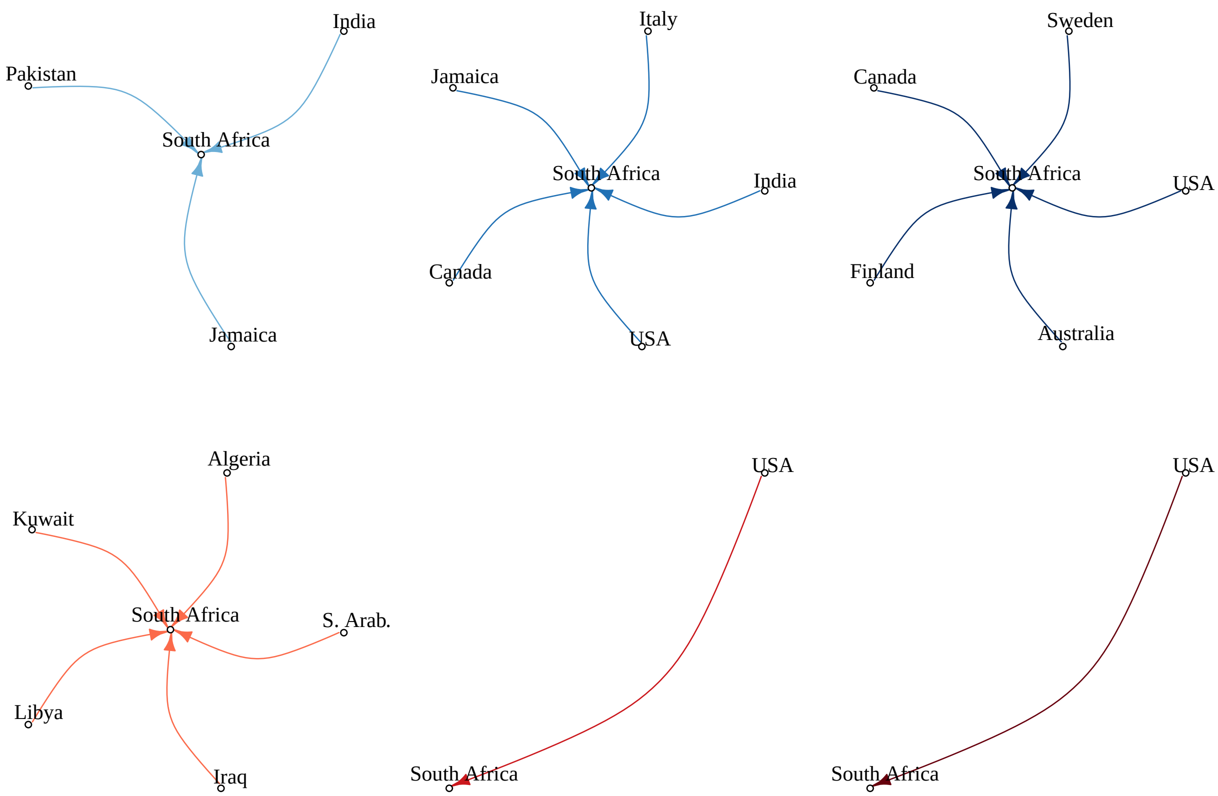


Figure 2. Network for each sanction case that South Africa faced in 1984.

We also expect that these relationships must be meaningful not just plentiful. 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. Thus, for each sanction case we determine the number of senders but we also measure other dimensions of each sender's relationship to the target. In addition, we calculate and control for the average number of other sanctions being sent by the senders of each particular sanction case.

> **H3**: As the number of sender states increases for any given sanction case, the time to compliance will decrease.

We now describe exactly what is meant behind our concept of "proximity." In figure 2, we show the six sanction cases faced by South Africa in 1984.[4] For the most part, each

[4]Data for sanction cases are from Morgan, Bapat and Krustev (2009) and is explained further in the following section.

sanction case involves a variety of actors with whom South Africa has differing cultural, geographic, diplomatic, and economic relationships. Within any individual sanction case we hypothesize (**H2**) that the proximity, (i.e. the ways in which the sender and target interact on a number of dimensions) of relationships between sender(s) of a sanction and a receiver influence whether a target state complies. We construct a number of covariates to test this idea that the normative closeness, or general "proximity" between sender(s) and receiver(s) increases sanction compliance.

We focus on five key measures of the "proximate" nature of relationships First, we measure the average distance between sender(s) and reciever.[5] We utilize the Correlates of War (COW) data to construct the remaining four variables. 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. Last, we measure alliances as the proportion of sender(s) that are allied with the receiver.

> **H4**: Sanction cases where relationships between sender(s) and receiver(s) are more proximate will be more quickly resolved.

Last, we include a number of covariates to account for domestic explanations of sanction compliance in the extant literature. First is a measure of the target states' domestic institutions from the Polity IV data (Marshall and Jaggers 2002).[6] This measure is computed by substracting 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

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

[6]Specifically, we use the "polity2" variable from the Polity IV data.

to 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.

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, Bapat and Krustev (2009). This database includes over 1,400 sanction case threats and initiations from 1945 to 2013.[7] Our focus here is restricted to threats and sanctions that are prompted as the result of economic issues such as expropriation, trade practices, and implementation of economic reforms.

Restricting our analysis to threats or sanctions stemming from these issues during the period of 1960 to 2005 leaves us with over 800 cases. Our unit of analysis is the case-year, providing us with a total of 5,303 observations. For each case in the TIES database a final outcome is recorded to describe how and if the case has been resolved. The purpose of our analysis is to assess the time until a state complies to a threat or sanction. We consider a case to have been resolved by compliance if the target state completely or partially acquiesces to the demands of the sanction senders or negotiates a settlement.

In using this definition of compliance, approximately 37% of cases in our dataset end with a state complying by 2013 while 40% remain ongoing. The remaining 23% of cases were terminated for other reasons show below in table 1.

[7]Only sanction cases threatened and initiated up until 2005 are included but outcomes for cases are recorded up until 2013.

Outcome	Frequency
Capitulation by Sender in Threat Stage	77
Stalemate in the Threat Stage	11
Capitulation by Sender After Imposition	58
Stalemate after Sanctions Imposition	38

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

Modeling Approach. Next we discuss our modeling approach. To estimate the effect of network pressures on the ability of a 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:

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

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. The covariates $\boldsymbol{X}$ operate multiplicatevely on the hazard rate, shifting the expected risk of compliance up or down depending on the value of β (Crespo-Tenorio, Jensen and Rosas 2013).[8]

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 of the continuous covariates in our model required modeling with splines, we carried out tests of

[8]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 frailities, so we report results without the inclusion of this additional term.

non-proportionality. For those covariates where the non-proportional effects assumption does not hold, we include interactions between the covariate and spell duration (log scale). The only covariate showing evidence of non-proportionality is the average similarity of religious profiles.

We also imputed missing values to avoid excluding instances of compliance. If we employed list-wise deletion, we would lose over 438 country-year observations, 32 of which contained instances in which a state complied to a sanction. Previous research (e.g., see Rubin 1976; Honaker and King 2010) has already highlighted how simply deleting missing observations can lead to biased results. 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 unimputed dataset, which are nearly identical, can be found in the Appendix.

Below we show our full model specification:

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

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.

Results

Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t-1}$			0.212^{**}
			(0.063)
Sanction Reciprocity$_{j,t-1}$			-0.103^{**}
			(0.033)
Number of Senders$_{j,t}$		0.255^{**}	0.234^{**}
		(0.062)	(0.062)
Distance$_{j,t}$		0.531^{**}	0.497^{**}
		(0.183)	(0.187)
Trade$_{j,t}$		16.795^{*}	16.106^{*}
		(9.393)	(9.398)
Ally$_{j,t}$		0.029	0.096
		(0.159)	(0.164)
Polity$_{i,t-1}$	-0.029^{*}	-0.015	-0.022
	(0.016)	(0.017)	(0.017)
Ln(GDP per capita)$_{i,t-1}$	-0.088	-0.08	-0.03
	(0.065)	(0.07)	(0.073)
GDP Growth$_{i,t-1}$	0.011	0.02	0.015
	(0.018)	(0.019)	(0.019)
Population$_{i,t-1}$	-0.172^{**}	-0.16^{**}	-0.102^{**}
	(0.039)	(0.043)	(0.05)
Internal Conflict$_{i,t-1}$	0.001	0.004	-0.001
	(0.017)	(0.017)	(0.017)
n	6517	6483	6483
Events	191	190	190
Likelihood ratio test	36.91 (0)	59.55 (0)	70.76 (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.

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 explanations of sanction compliance centered on target state characteristics. In the second column, we add covariates to account for the relationship that a target state has with the senders of the sanction, and the last model incorporates our reciprocity measures.

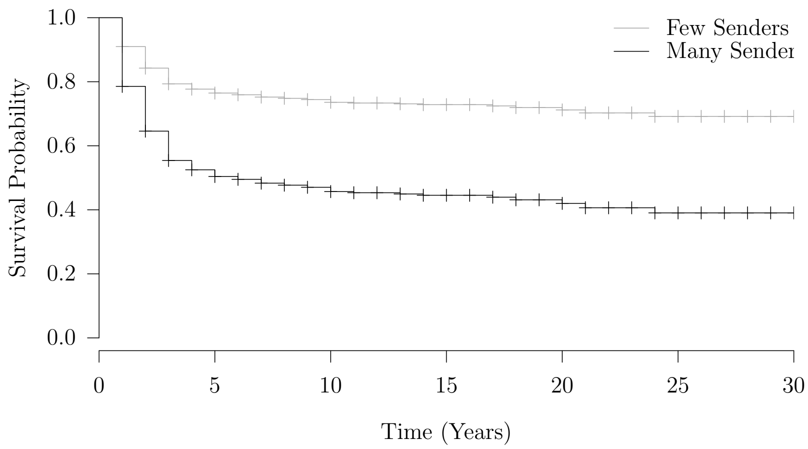
As we go from left to right across the table, we see that explanations of sanction compliance centered on the target state become less prominent. We find no support for the argument that high levels of internal stability may prompt a country to comply. In

Models 1 and 2, we find that countries with higher levels of GDP per capita take longer to comply to a sanction case, but after accounting for the network level characteristics the coefficient estimate for that variable more than halves. Our findings for the effect of a country's regime type on sanction compliance also diverge from what the extant literature would predict. Instead of finding that democracies are more likely to comply to a sanction case, we see that countries rated as more democratic take longer to comply than countries that are more autocratic. However, this effect is marginal at best, and once we control for the relationship between sender and target states this effect also becomes much weaker.

We find strong support for our third hypothesis which states that target states are more likely to comply to sanctions involving multiple actors, and the effect of this variable remains consistent even after controlling for our network level covariates in Model 3. Because it is difficult to interpret the substantive meaning of point estimates from the hazard function in table 2, we utilize Kaplan-Meier estimates of survival probabilities in figure 3. The y-axis represents the probability of survival, or in this case the probability that a country will not comply to a sanction, and the x-axis represents time since sanction initiation (measured in years). The grey line represents the scenario where the number of senders variable is set to a low value, in this case one, and the black line represents the scenario where this variable is set to its high value, in this case five. All the other covariates were set to their median.

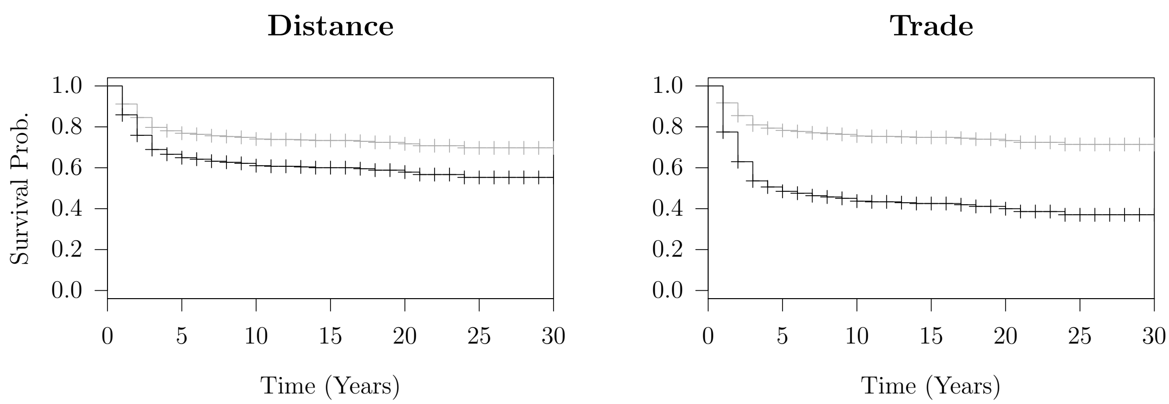
Using figure 3 we can quickly see that there is a stark difference in the likelihood of non-compliance between a sanction case involving single and multiple senders. After just five years the probability of non-compliance drops to approximately 50%, whereas a sanction from a single sender by that time still has almost an 80% chance of non-compliance. This finding is in sharp contrast to previous research arguing that multilateral sanctions can actually be counterproductive (e.g., see Drezner 2000).

Figure 3. Survival probabilities reflecting variation in the number of senders in a sanction case. Grey designates the scenario where the number of senders is set to its minimum value and black the scenario where it is set to its high value (90th percentile).



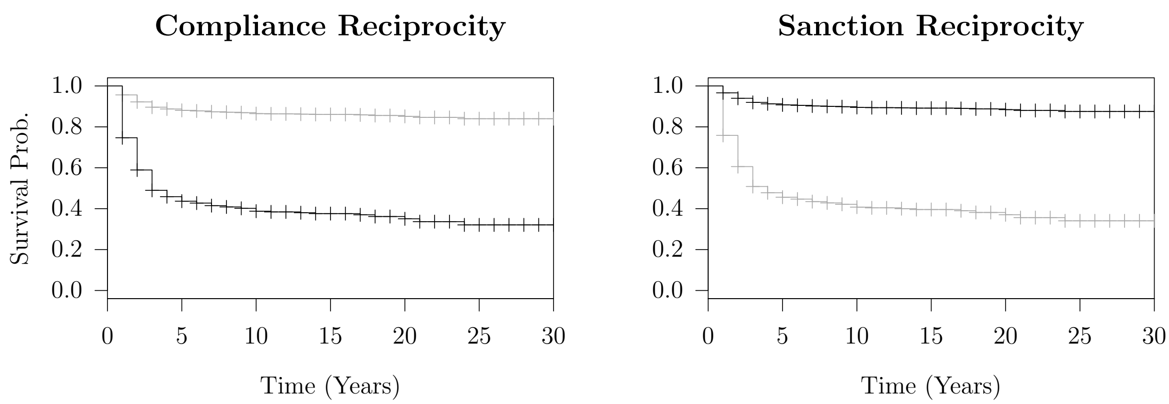
Like the extant literature (e.g., McLean and Whang 2010), we do find strong evidence for the ability of trading partners to obtain quick and successful resolutions to sanction cases. This is in line with our fourth hypothesis, that more proximate relationships between sender and recievers result in quicker compliance by the target state. But support for this general proximity hypothesis is limited to trade. States are not likely to comply more quickly to sanctions sent by allies, and are actually less likely to comply to neighbors. The graphs in figure 4 demonstrate the effects of the "proximate" relationships that were significant in table 2. The panel on the left shows the effect for distance. Here we can see that even though the coefficient estimate for this variable was significant, its substantive meaning is almost nil. For trade, on the other hand, there is a strong effect. We can clearly see that when a target state faces a sanction from countries with whom they frequently trade, they are likely to comply sooner.

Figure 4. Survival probabilities by "proximity" covariates. Grey designates scenarios in which the covariate is set to its minimum value and black where it is set to its high value (90th percentile).



Our key hypotheses relate 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 40%, compared to about 95% when this history does not exist between senders and receivers. Thus the compliance reciprocity variable tells a story of how friendly reciprocal relations in the past can explain future friendly interactions.

Figure 5. Survival probabilities predicted by network level covariates. Grey designates the scenario where the number of senders is set to its minimum value and black the scenario where it is set to its high value high value (90th percentile).



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 to one another in the present. On the right side of figure 5, we can again see 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 continuous sanctioning of a particular state without that target every compyling may build up a resistance to compliance to future sanctions.

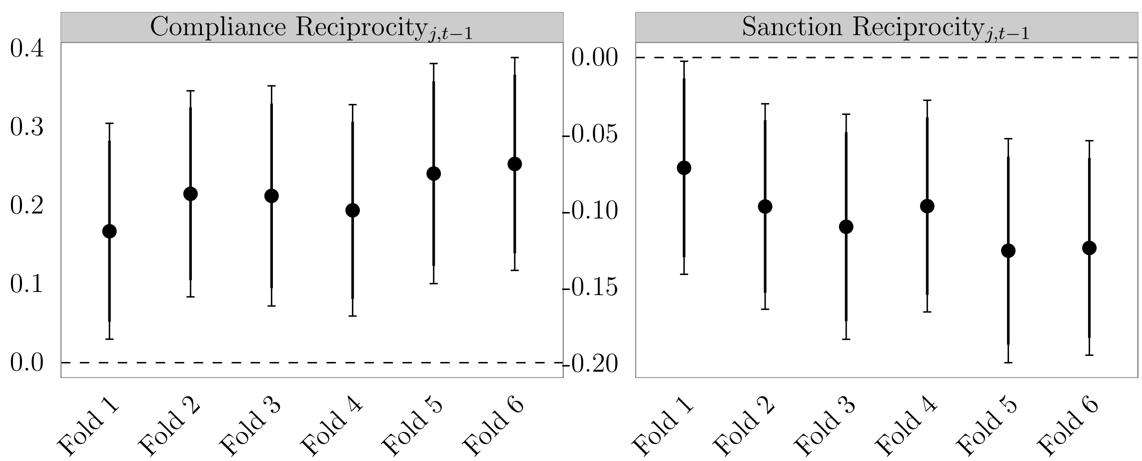
Performance. To assess the accuracy and performance of these estimates we employ a six-fold cross validation procedure.[9] We use this procedure both to determine the robustness of our coefficient estimates when estimated on different subsamples of our dataset, and to assess how well the results of our model would generalize to an independent dataset. To begin the cross-validation, we split the 653 sanction cases in our dataset into

[9]Results of analysis were similar when employing a 10-fold cross validation as well, however, we limit to showing six here for the sake of space.

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 (Beck 2008). 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.[10]

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

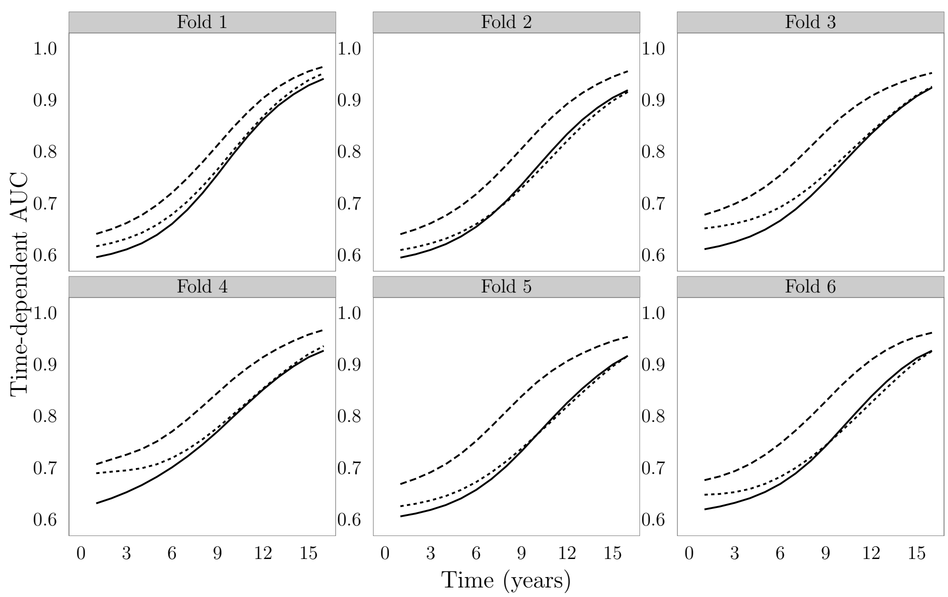


A key question that remains, however, is whether we are able to better explain sanction compliance through the incorporation of these network level covariates. Figure 7 shows out-of-sample time-dependent AUC results from the six-fold cross validation procedure. When calculating the time-dependent AUC we vary the time parameter to range from 0 to

[10]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.

15 years.[11] 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 noticeable 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, 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. 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 Model2, and the dashed line represents Model 3.



Conclusion

Interational economic sanctions are not disappearing from global politics anytime soon. Indeed, in response to the current crisis in the Ukraine, the European Union and the

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

United States are both launching sanction intiatives against Russia, and Russia is now poised to respond with retaliative sanctions. Such an exchange highlights one key theme of this paper: sanctions are driven by the interdependent nature of the international system.

We have outlined both theoretical and empirical reasons for why sanctioning behavior between states constitutes a network, and thus requires scholars to incorporate network attributes into the study of sanction compliance. We have then demonstrated the key role of reciprocity in determining the duration of economic sanctions in the international network, while also assessing longstanding hypothesis from the literature. In doing so, we are able to construct a more accurate representation of sanction dynamics than has yet been presented in the literature.

We find strong support for the influence of reciprocal compliance as well as the number of sender states within the sanction network, suggesting that the most effective sanctions are likely to be those composed of a higher number of senders with this shared compliance history. Similarly, we highlight a previously underexamined aspect of sanction behavior and show that countries whom have sanctioned each other in the past without complying to one another are not liekly to comply to another in the present. We also find support that bolsters previous claims from the literature: even when accounting for network effects, trade partners are more likely to successfully utilize sanctions against target states.

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 imputaiton 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.

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

Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t-1}$			0.293**
			(0.068)
Sanction Reciprocity$_{j,t-1}$			-0.13^{**}
			(0.033)
Number of Senders$_{j,t}$		0.358**	0.33**
		(0.065)	(0.067)
Distance$_{j,t}$		0.438**	0.408**
		(0.198)	(0.203)
Trade$_{j,t}$		97.145**	102.839**
		(24.315)	(24.462)
Ally$_{j,t}$		0.025	0.056
		(0.196)	(0.193)
Polity$_{i,t-1}$	-0.013^{*}	-0.007	-0.008
	(0.007)	(0.008)	(0.008)
Ln(GDP per capita)$_{i,t-1}$	-0.126^{**}	-0.019	-0.005
	(0.06)	(0.075)	(0.078)
GDP Growth$_{i,t-1}$	0.024	0.042**	0.032
	(0.02)	(0.021)	(0.021)
Population$_{i,t-1}$	-0.072	0.041	0.137*
	(0.054)	(0.064)	(0.07)
Internal Conflict$_{i,t-1}$	-0.004	0	-0.011
	(0.017)	(0.018)	(0.018)
n	6140	6106	6106
Events	160	159	159
Likelihood ratio test	17.31 (0)	59.16 (0)	77.77 (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.

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