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 for 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 over time, 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 are able to test two key hypothesis: key hypo here!

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 state 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. Take for example, in November of 2012 when the Obama administration imposed sanctions on the Iranian government for blocking Internet access, mobile-phone lines and satellite television channels from the public.

Policymakers continually engage in heated debates over the use of sanctions as a means to avoid war while still taking a stand. 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 on their economic ties to other countries in order to influence policy – is relatively straightforward, the study of when and why sanctions work is complex. While 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). Notably, the literature has not emphasized the role of past actions and the way in with these interactions influence future behavior.

We agree with the theoretical and empirical literatures that suggest several different, interacting conditions are at work when predicting the outcome of sanctions. We argue, however, that political scientists have thus far failed to incorporate a key factor into their analysis: reciprocity within the sanction network. 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 field of international studies, but has its roots in previous theories of cooperation (**?**). Yet the study of sanctions has not yet addressed how the intutition of reciprocity's effect on state behavior might condition the effects of other variables on sanction compliance.

We analyze this key endogenous structure inherit 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 third party effects, or network level dependencies.

Research on compliance has historically utilized a logit or probit-estimation approach. However, some have demonstrated that a duration modeling approach more accurately captures the important time-variant dynamics relevant to understanding the sanction process. 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 over time a specific factor, such as political instability or regime type, increases or decreases the probability that a target country will comply with a sanction.

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.

Clearly, domestic conditions seem to matter for predicting sanction compliance. While researchers have successfully applied duration approaches, the literature can be improved on in two main ways. First, it remains unclear whether external factors also influence the duration until compliance. It is important to consider whether network of sanctioners for each sanction case are critical trade partners, allies, or neighbors with the target state. Each relationship between the sanctioner and the sanctioned takes on a slightly different form dependent on these factors. If a neighboring state is greatly dissatisfied with the target's behavior, this conflict of interest could have more serious repercussions than a sanctioner who is geographically removed from the target. These types of external factors are housed within the network of sanctioners for each and every sanction case. Such factors have been incorporated into previous analysis as largely dyadic or monadic variables, but this approach fails to capture and account for the complex interdependence structure that international politics inherently exhibits. Take, again, for example international trade dynamics.

While it is intuitive to many researchers that trade dependence between target and sender states likely influences the duration of economic sanctions, in order to adequately measure trade interactions, one has to analyze the trade *network* relevant to each sanction case, which accounts for the fact that trade between dyads is not an independent process. 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) , conflict (Dorff and Ward 2013), alliances (Warren 2010) and intragovernmental organizations (Cao 2009; Greenhill 2010).

Second, 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.[1] 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. This paper aims to fill this gap.

Accounting for Network Effects

In this section, we present our argument for incorporating network features 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) characteristics of the entire sanction network in any given year; and (2) the types of influential relationships senders have to receiver states within particular sanction case, such as geographic proximity, cultural similarity, and previous compliance reciprocity.[2]

First, we visually present both the sanction-year and sanction-case network. Figure 1 depicts the network of sanction cases ongoing 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, demonstrating 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 such as we need an example from the agg network here, reciprocity here too?

[1] Results for this analysis are not included in the current draft.

[2] We call states that impose or threaten sanctions senders and those upon which they are imposed receivers.

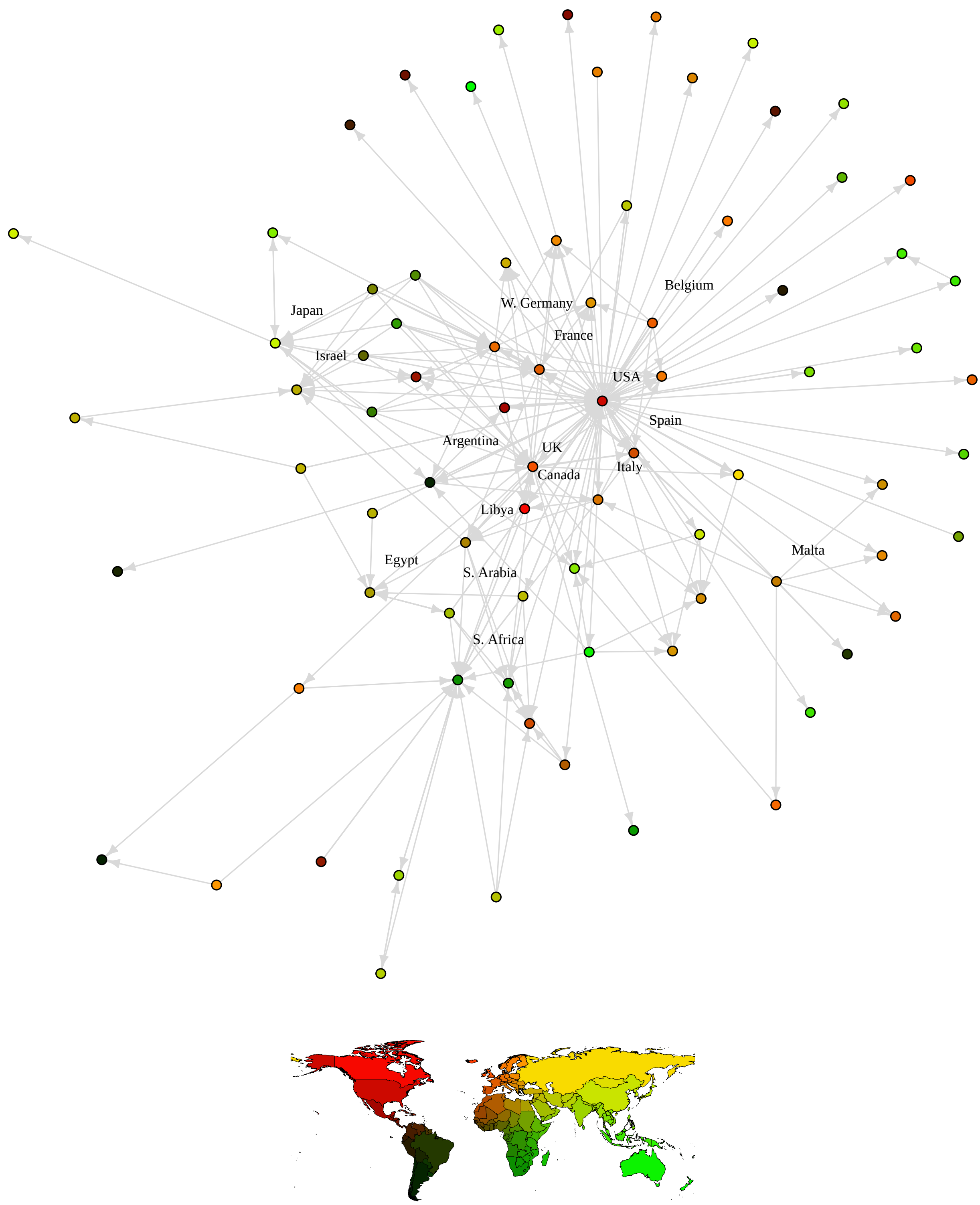


Figure 1: Here we show the sanction network in 1984, nodes are colored by geographic coordinates of countries. Data for sanction cases comes from Morgan, Bapat and Krustev (2009).

Next, we deconstruct this network 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 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 treating the sanctions facing South Africa as one wholistic network of interactions, we more accurately capture the complex reality of the sanction process. 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 **?** 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 (**??**). Critical mass is thus acheived through a network of state relationships and not through a dyadic, one-on-on framework. Our sanction-case network allows us to capture these dynamics 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. this last sentence needs work, what would expect to be different, we must get more specific in order to help support our theory. We need to talk about how these two networks would score differently.

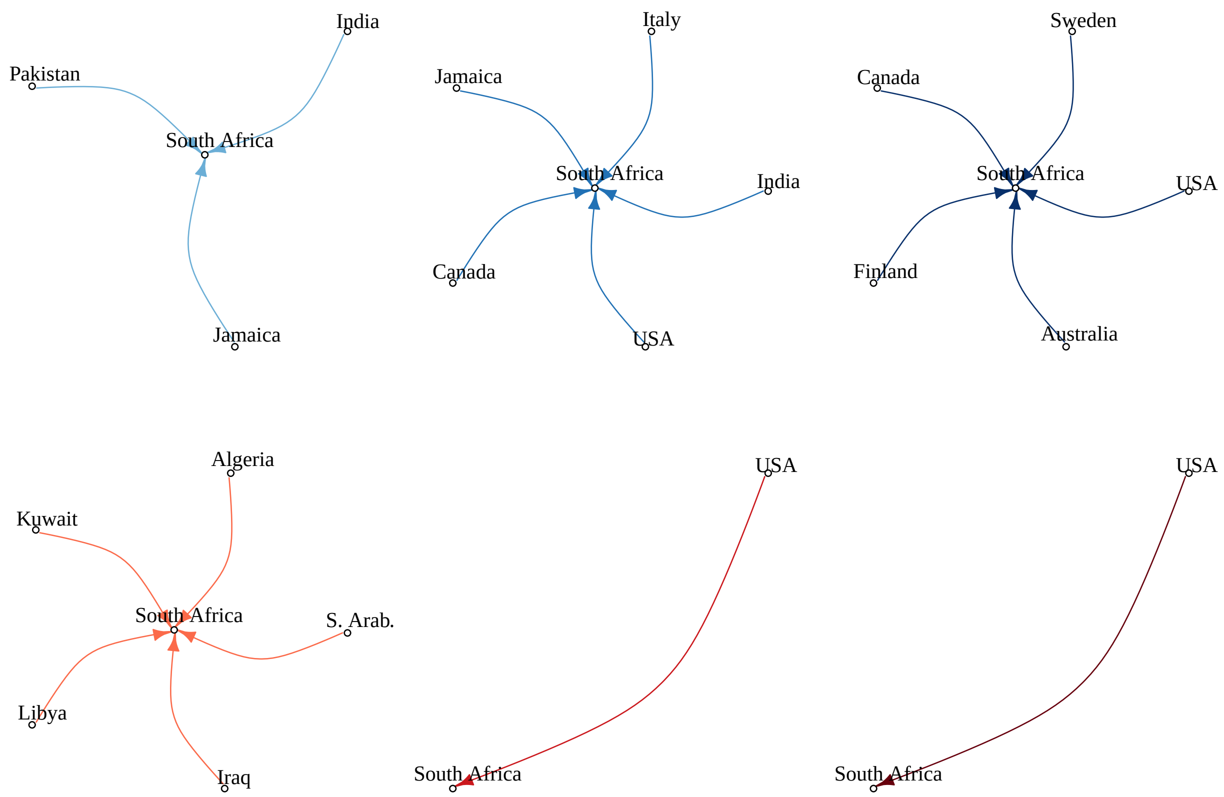


Figure 2: Here we show a network for each sanction case that South Africa faced in 1984.

Clearly these two networks, the sanction-year and sanction-case network, are composed of a diverse set of unique actors, all of which have a specific relationship with the target state. 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.

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.

H1: As the number of sender states increases for any given sanction case, the time to compliance will decrease.

H2: Sanction cases where relationships between sender(s) and receiver(s) are more proximate will be more quickly resolved.

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.[3] For the most part, each 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.[4] 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. Third, we measure alliances as the proportion of sender(s) that are allied with the receiver. Forth, we measure the average number of common IGOs that the sender(s) and target state belong to. Last, we create a measure capturing similarity in the religous/cultural makeups across receiver and senders.[5]

Thus far we have explained how the relationships between sanctioners and target states matter for predicting compliance. This view has focused on the individual sanction case.

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

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

[5]To determine religous/cultural similarity, we first calculate the correlation in religious makeups between countries for each year, data on religious makeups is taken from the COW World Religion dataset. For a single year this provides us with an $N \times N$ matrix where each $i-j$ cross-section represents how similar the populations of i and j are in terms of their religious denominations. We then add 1 to each of these scores so that the minimum value within a cross-section is 0 and the maximum is 2. We do this for every year providing us with $N \times N \times T$ matrices.

However, the six separate sanctions that South Africa faced in 1984 can also be thought of within the context of a yearly sanction network. In figure 3, we aggregate the six sanction networks into one where each separate sanction is denoted by a differing color. Here we hypothesize that states under the pressure of a multitude of sanctions will more quickly resolve sanction cases than those facing only a few.[6]

H3: States facing the pressure of a multitude of sanctions will more quickly resolve any one of those sanction cases.

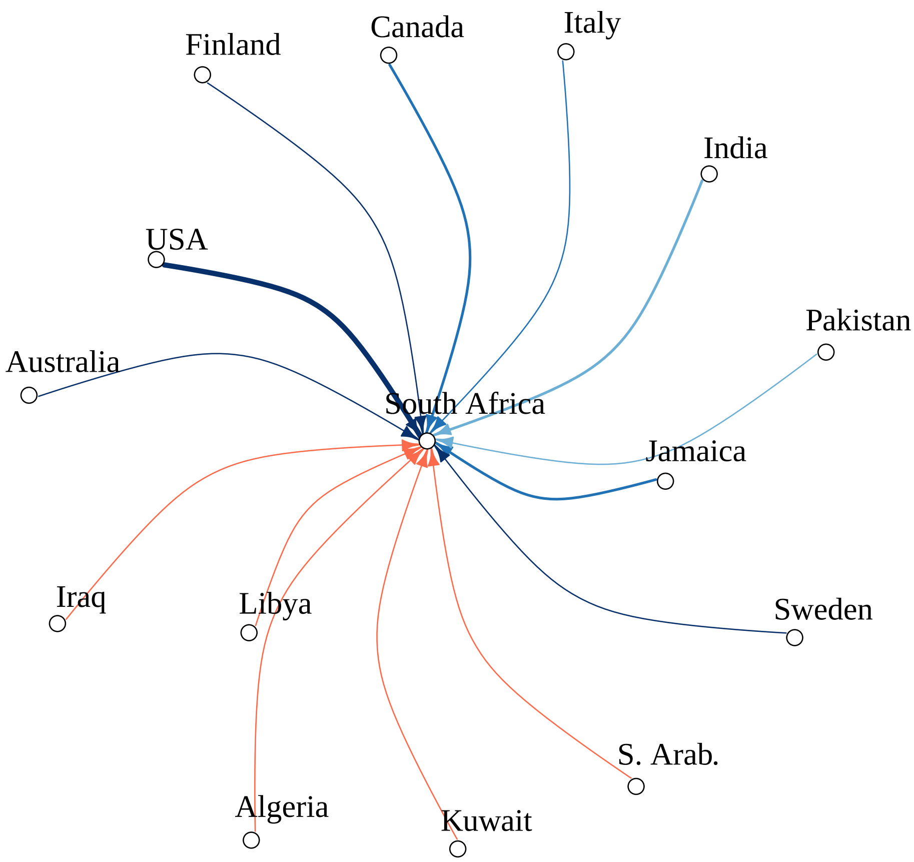


Figure 3: All sanctions faced by South Africa in 1984 collapsed to one network

Last, we include a number of covariates to account for domestic explanations of sanction compliance in the extant literature. First is a measure of domestic institutions from Henisz (2000). This measure provides an estimate of the degree of constraints underlying the political institutions of a country. Second, we include a measure of a country's internal stability from the International Country Risk Guide Dataset (ICRG). The measure

[6]Our next step in this project is to include measures of reciprocity over time. This will allow us to test the argument presented in the earlier half of the paper where we suggest accumulated dependencies over time will influence the likelihood of compliance (e.g. reciprocity: if country i often complies with country j, will country j be more likely to comply with country i?).

ranges from 0 to 12, where lower scores corresponds to greater internal instability. The expectation in the extant literature would be that countries with higher levels of internal instability would be more likely to comply 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 succesful 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 an economic issue. The TIES database categorizes the issue(s) involved in the threat or impositions of sanctions, we focus on three:

- Expropriation/seizure of citizens, property, or material
- Trade practices
- Implement economic reform

Restricting our analysis to threats or sanctions stemming from these issues during the period of 1984 to 2005 leaves us with 272 cases. Our unit of analysis is the case-year, providing us with a total of 1,920 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 and we consider a case to have been resolved in compliance if any of the follwing conditions are met:

- Complete/Partial Acquiescence by Target to threat
- Negotiated Settlement

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

- Total/Partial Acquiescence by the Target State following sanctions imposition
- Negotiated Settlement following sanctions imposition

In using this definition of compliance, approximately 37% of cases in our dataset end with a state complying by 2013 while 42% remain ongoing. The remaining 21% of cases were terminated for other reasons show below in table 1.

Outcome	Frequency
Capitulation by Sender in Threat Stage	29
Capitulation by Sender After Imposition	19
Stalemate after Sanctions Imposition	2
Stalemate in the Threat Stage	1

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 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.

Below we show our full model specification:

$$\begin{aligned}
Compliance_{i,t} = {} & No.\ Senders_{j,t} + Distance_{j,t} + Trade_{j,t} + \\
& Ally_{j,t} + IGOs_{j,t} + Religion_{j,t} + \\
& Sanc.\ Sent_{j,t-1} Sanc.\ Rec'd_{i,t} + \\
& Constraints_{i,t} + Ln(GDP\ Capita)_{i,t-1} + \\
& GDP\ Growth_{i,t-1} + Internal\ Stability_{i,t} + \\
& \epsilon_{i,t}
\end{aligned}$$

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

Table **??** displays the results from our model. As expected, we find support for hypothesis one, which states that as the number of sender states increases for any given sanction

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

case, the time to compliance will decrease. Generally, we also find support for our second hypothesis, that more proximate relationships between sender and recievers result in quicker compliance by the target state. However, support for this hypothesis is limited to the type of relationship or proximity that is measured. Our findings reveal that distance, alliance, and religion are influential for predicting compliance – though the latter measure has an effect opposite to what we expected. This suggests that target states are most sensitive to sanctions by those states who are both neighbors and allies. We also find support for hypothesis three, that states are more likely to comply to one sanction when they are simultaneously facing a number of others.

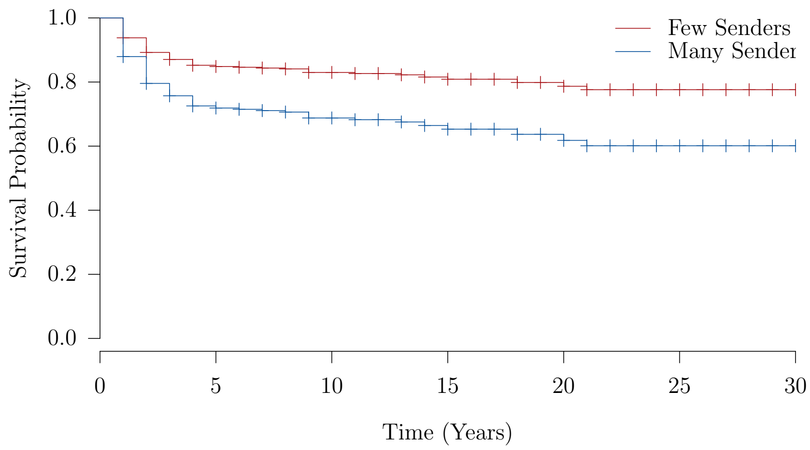
Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t}$			0.967**
			(0.086)
Sanction Reciprocity$_{j,t}$			-0.395^{**}
			(0.04)
Number of Senders$_{j,t}$		0.216**	0.174**
		(0.069)	(0.08)
Distance$_{j,t}$		0.45**	0.599**
		(0.202)	(0.242)
Trade$_{j,t}$		31.135**	20.261**
		(7.431)	(8.323)
Ally$_{j,t}$		0.017	0.263
		(0.178)	(0.201)
Constraints$_{i,t-1}$	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)
Ln(GDP per capita)$_{i,t-1}$	0*	0	0
	(0)	(0)	(0)
GDP Growth$_{i,t-1}$	0	0	0
	(0)	(0)	(0)
Internal Stability$_{i,t-1}$	-0.002	-0.002	-0.001
	(0.002)	(0.003)	(0.003)
n	6273	5419	4023
Events	158	157	120
Likelihood ratio test	11.25 (0.02)	35.96 (0)	156.78 (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.

We control for the prominent idea from the literature that domestic factors influence sanction compliance. We find that while our measure of internal stability does not play a role, domestic institutions do matter. Interestingly, we find little support for trade and similar IGO memberships having an influence on compliance. Because it is difficult to interpret the effect of point estimates on the hazard function in tabular form, we present graphical interpretations figures 4, 5, and 6.

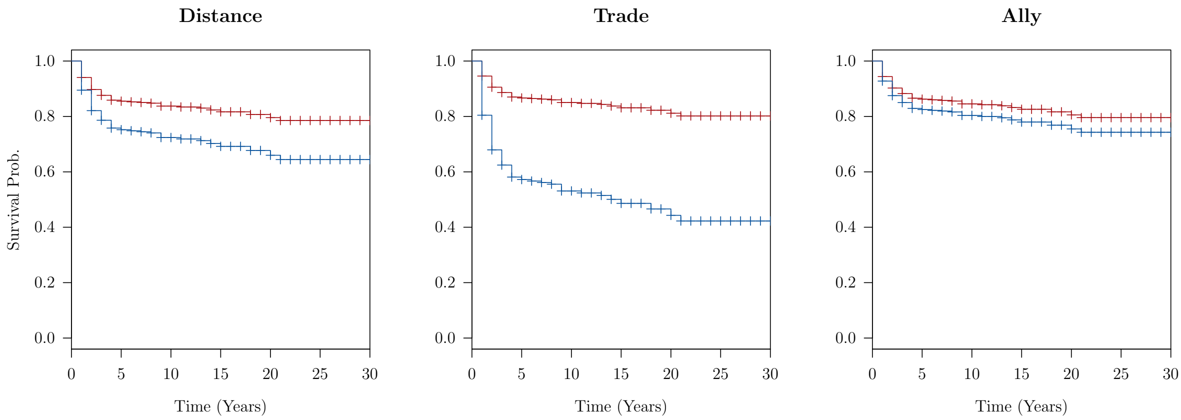
In each figure, the y-axis represents the probability of survival, or in this case the probability that a country will not comply and the x-axis represents time (measured in years). We use a red and a blue line to represent high and low values in our covariates of interest. In each graph, the red line represents the covariate of interest set to a low value (its lower quartile), and the blue line represents the covariate at a higher value (upper quartile). This allows us to more easily interpret the effects of each covariate. Figure 4 captures the "number of senders" covariate. In this case, the red line indicates a low number of senders and the blue line, a higher number. It is evident that as the number of senders increase, the liklihood of survival, or time to compliance, substantially decreases and almost halves in a few years. This supports our first hypothesis that for any given sanction episode, states faced with a large number of sanctioners are more likely to comply sooner than states facing a small number of sanctioners.

Figure 4: Survival probabilities by varying number of senders in a sanction case. Red designates scenario where the number of senders is set to its low value and blue the scenario where it is set to its high value.



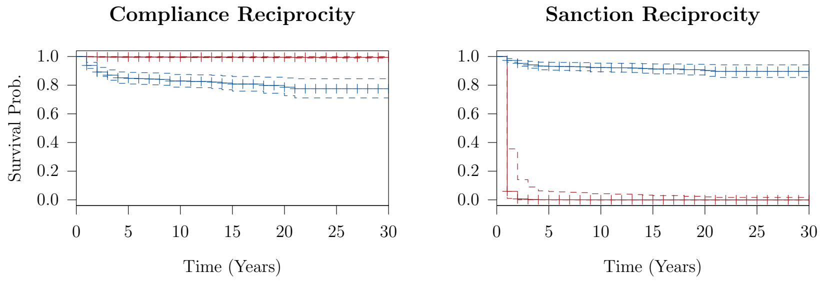
The graphs in figure 5 demonstrate the effects of "proximate" relationships. In the panel on the far left we show the effects for distance, and we can see that when the distance between states is large (the blue line) compliance is predicted to take longer than when states are geographically closer together (the red line). Not surprisingly, we also see that when target states are allies with sanction senders, (the blue line) they are more likely to comply – though the effect of this variable is much more marginal than the other covariates that we are highlighting. Interestingly, our argument that religious similarity should also pressure states into quicker compliance is not supported. We see in the graph for religion that as religious similarity increases (the blue line) the probability of survival, or denying compliance, also increases. This suggest that when target states share the same religious culture to sanctioning states, the target is less likely to comply to the sanction by a very large degree.

Figure 5: Survival probabilities by "proximity" covariates. Red designates scenarios in which covariate is set to its low value and blue where it is set to its high value.



In figure 6, we show the results for our covariate measured at the yearly sanction network. Specifically, we accounted for the total number of sanctions that a country faced in any given year, with the idea that states facing a multitude of sanctions in any given year will be more likely to resolve any one of those cases. Here we can see that this has a noticeable effect on the probability of compliance, indicating that countries facing multiple sanctions have a higher probability of complying to any one of them than others.

Figure 6: Survival probabilities by varying number of sanctions received by a country at a yearly level. Red designates scenario where the number of senders is set to its low value and blue the scenario where it is set to its high value.



Conclusion

In this paper we have shown that network variables do indeed play a substantive role in predicting sanction compliance. This indicates to us that the extant literature's focus on employing models that just capture the situation in the sanctioned country omits important information when it comes to understanding compliance. More work on our part, however, is necessary as well. A key next step is to determine the predictive accuracy of our models incorporating network characteristics, overall, and vis-a-vis models providing determinants at just the level of the sanctioned state. Additionally, we also hope to incorporate more substantive measures of the sanction network so that we can model the complex interdependencies that likely emerge and drive sanction and compliance behavior between states.

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