WHEN DO STATES SAY UNCLE? NETWORK DEPENDENCE AND SANCTION COMPLIANCE

Abstract. This article explores when and why states comply with sanctions. Previous literature suggests 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 theoretical and empirical investigation of sanction outcomes. Namely, present sanction studies do not incorporate the network effects intrinsic to international sanction processes. We argue that a key network measure, reciprocity, is a previously overlooked component of the strategic environment between states and influences 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 a duration modeling framework. In addition, we are able to test whether conditions the literature claims as critical for predicting sanction compliance, such as domestic institutions, remain influential once network dynamics are adequately modeled. In doing so, we test key hypotheses from the literature regarding the role of domestic conditions, intrastate relationships, and our own new hypotheses on the effect of reciprocity on sanction compliance.

Word Count: 8,668

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 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 and Oegg 2003; Hufbauer, Elliott, Cyrus and Winston 1997).

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). But 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 and 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 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,[1] but 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

[1]Lam (1990); Dashti-Gibson, Davis and Radcliff (1997); Morgan and Schwebach (1997); Drezner (1998)

of issue in dispute;[2] the strength of domestic institutions within the target state; and the type of regime governing the target state.[3]

We argue that scholars have thus far failed to incorporate a key factor into their analysis of sanction outcomes: reciprocity.[4] 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 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.[5] Yet the study of sanctions has not addressed how reciprocity drives states' strategic calculation of sanction compliance.

We analyze this key endogenous structure inherent to network dynamics and argue that the structure created by reciprocal interactions over time must be accounted for in studies of sanction outcomes. Further, we incorporate our measures of reciprocal interactions into a duration modeling framework, thus enabling us to explicitly account for interdependencies in the resolution of sanction cases. In doing so we are able to then return to test key hypotheses from the literature and assess whether factors such as domestic political institutions and internal stability influence sanction outcomes once network dynamics are adequately incorporated.

We leverage our 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 hypothesis; 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.

[2]Miers and Morgan (2002); Morgan, Bapat and Krustev (2009)

[3]McGillivray and Stam (2004)

[4]Previous work by Cranmer, Heinrich and 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.

[5]Richardson (1960); Choucri and North (1972); Goldstein (1991); **?**); Ward and Rajmaira (1992)

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 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, Davis and Radcliff (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, Davis and Radcliff 1997).

Similarly, Dorussen and 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 and Souva (2007) finds that differing institutional incentives between nondemocratic regimes than democratic ones influence the success of economic sanctions. 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, but these authors also restrict themselves to target state characteristics in determining time until compliance. 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.

The literature has clearly argued that domestic conditions are an influential predictor of sanction compliance. Yet, other factors are also important to the decision-making environment: critical is the relationship between sanctioning states and target states. Specifically, research must address how key dependencies between countries inform the strategic environment of states through an evolution of behavior in trade relations, ally ties, or geographic proximity over time; and how this complex, evolving strategic environment affects sanction outcomes (McLean and Whang 2010). Each relationship between the sanctioner and the sanctioned takes on a slightly different influence dependent on these factors. For example, 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 characterize group level dynamics that exist within each sanction case.

Recent work has also successfully paired modeling techniques with theoretical prepositions 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 and Al-Sowayel 2000). Clearly, if the goal of research is to both explain 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.

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 studies do not fully incorporate the evolution of interaction between states over time. Interactions between actors over time can be captured by a network approach, which can provide a deeper understanding of how the history of sanctions and compliance between states influences future behavior vis-à-vis compliance. Further not accounting for possible interdependencies can cause inappropriate empirical inferences (Erikson, Pinto and Rader 2014). Cranmer, Heinrich and Desmarais (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. Hafner-Burton and Montgomery (2008) also study sanction onset via a networked approach and show that increases in bilateral trade decrease sanctioning behavior between states.

Critical concepts like these are currently ignored in the research on sanction compliance. By avoiding network attributes, researchers miss a wealth of structural information that is critical to understanding the ebb and flow of international cooperation and conflict.[6] We provide a way to account for these network interdependencies within the context of a simple duration model.

Reciprocity & Network Effects

In studies of social and economic behavior, direct reciprocity–the notion that actors tend to "respond in kind" to one another–is argued as an essential component of human behavior (for example, see Bolton, Brandts and Ockenfels (1998); Charness and Haruvy (2002); Charness (2004); Cox, Friedman and Gjerstad (2007); Cox (2004)). The idea that individuals, or collectives, observe previously cooperative (or conflictual) behavior

[6]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 and Ward (2004); Ward, Ahlquist and Rozenas (2012) conflict,Author (2013) alliances,Warren (2010) and intragovernmental organizations.Cao (2009); Greenhill (2010)

from others, and include this information into their own decision-making is a concept given great value to determine strategic outcomes. For example, reciprocity is shown to influence interactions across diverse settings including tax compliance (Smith 1990), wage selection (Campbell III and Kamlani 1997), and strike breaking (Brett, Shapiro and Lytle 1998). Reciprocity is also shown to play a critical role in the development of interethnic attitudes whereby groups tend to reflect the attitudes that other groups hold toward them (Berry and Kalin 1979).

International relations scholars have long argued that reciprocity is critical to the evolution of cooperative and conflictual interactions among states. This assertion dates back to early research on foreign policy. Scholars concerned with understanding the onset of World War I acknowledged the importance of tit-for-tat interactions (Holsti 1972). This same logic is rooted in research investigating the prisoner's dilemma. Axelrod and Keohane (1985) outlines the basic logic of reactive response in repeated interactions and highlights how reciprocal interactions over time foster cooperation. Rajmaira and Ward (1990) find that reciprocity determines long-term foreign policy behavior among superpowers. In other realms of international politics, reciprocity plays a key role in formulating expectations of state behavior. Take, for example, the theoretical weight of reciprocity in the literature on international laws of war; a literature which has been traditionally assessed whether one state will "respond in kind" to another state's treatment of prisoners, soldiers, and civilians during wartime. As one scholar 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 itself has long been recognized by IR scholars as an important mechanism for the enforcement of agreements and instantiation of cooperation, so why do current theoretical accounts of international sanctions ignored the role of reciprocity?

A common analogy in the coercive diplomacy literature centers on the contrast between "sticks" and "carrots". When applied to the economic sanctions literature, this analogy frames economic sanctions as sticks, and economic incentives as carrots. Countries can use sanctions as sticks with those to whom they share strong strategic ties to resolve trade related disputes. Compliance in sanction cases involving actors with strong strategic ties to one another are often assumed to be more assured because it is unlikely that the involved countries would risk jeopardizing their positive relations with one another. However, this comes with an important caveat: compliance in these cases is only more likely if the involved actors have previously reciprocated compliance to one another. The process of sanction compliance is thus driven by this endogenous evolution between states' shared strategic environment and past reciprocal behavior.

Much of the literature focusing on external conditions–such as ally relations and trade between states–aims to capture these types of strategic linkages. However, previous analysis of these strategic linkages have left out an important endogenous process whereby previous interactions between two countries (relative to all other countries) influence the importance of such linkages between states. Namely, we posit that reciprocity influences sanction outcomes by engaging with the broader strategic environment through two key processes: behavioral expectations and information sharing. The first process is that which is promoted by existing work on reciprocity and cooperation: one actor has incentive to "respond in kind" to the previous behavior of their partner. In international relations, states that are perceived as cooperative will be more likely to have future partners cooperate with them. The second process echoes the broader literature on international bargaining and information sharing.

The sanctioning process has been conceptualized as form of international bargaining (Morgan and Miers 1999, Marinov 2002, Lacy and Niou 2004). In any sanction case, there is uncertainty about the target state's willingness and capacity to endure the sanction. Any time a sanction is endured information is shared between states as both the sender and target state decide how to respond to one another's behavior. During this time, each state reveals more information about their preferences and resolve. We argue that the evolution of ties between sender and target states influences the calculation states make over time through revealing previously unknown preferences for cooperation. The two explanations that we focus on are (1) reciprocity in the sanctioning network over time; (2) previous compliance reciprocity.[7]

To demonstrate these two forms of reciprocity, 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 multiple 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 to inform future behavior within sanction networks. 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,[8] and more recent work has continued to address this concern,[9] yet studies on sanction compliance have not yet incorporated these insights.

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

[8] Keohane (1989); Goldstein (1991)

[9] Mitchell and Keilbach (2001); Cranmer, Heinrich and Desmarais (2014)

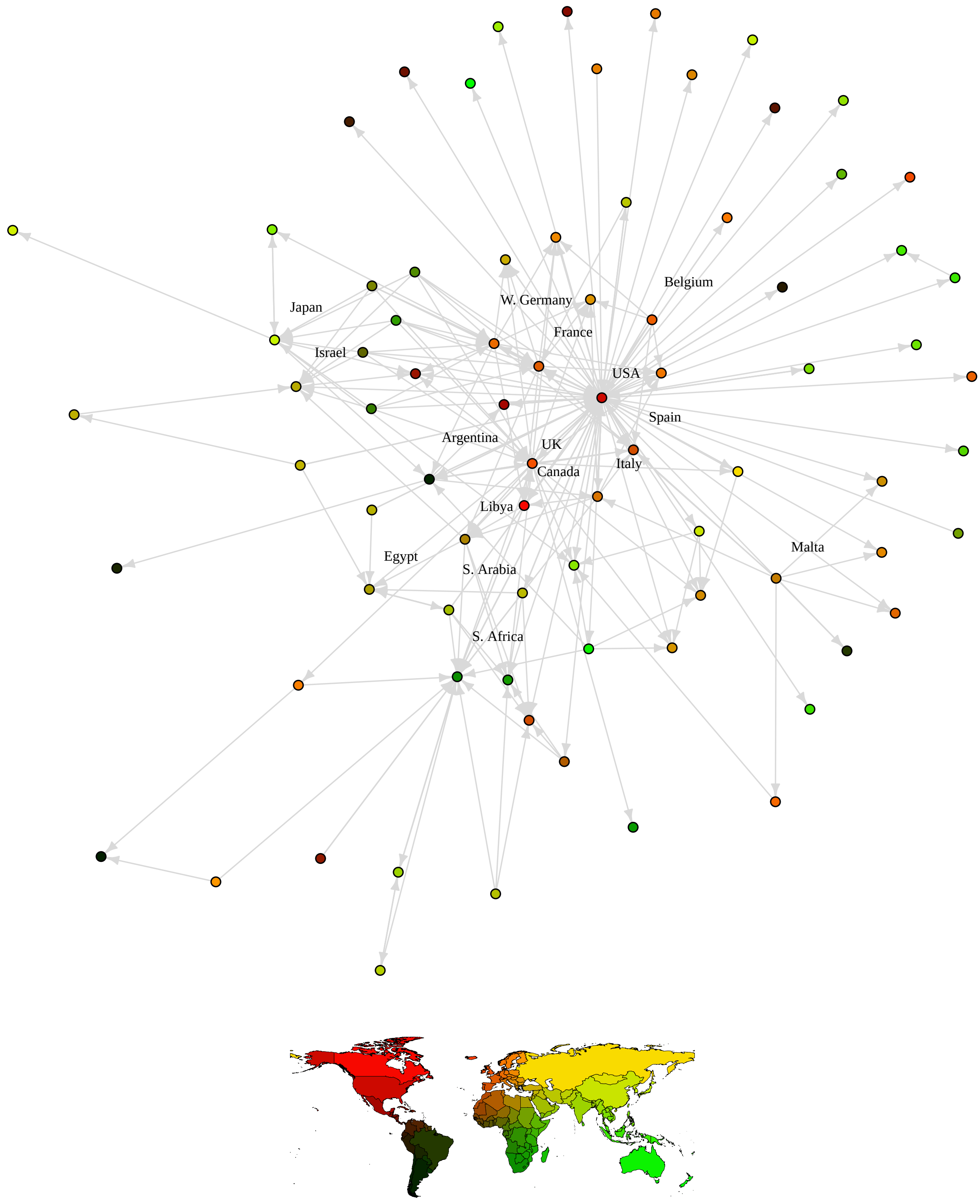


Figure 1. Here we show the sanction network in 1984, nodes are colored by geographic coordinates of countries. Data for sanction cases comes from Morgan, Bapat and Krustev (2009).

We develop two reciprocity concepts that allow us to analyze the interdependencies inherent to the evolution of sanction dynamics: compliance reciprocity and sanction reciprocity. We first outline the *compliance reciprocity* measure. By creating a yearly network, for each year available in our data, we are able to calculate compliance reciprocity over time. This represents a target states' cumulative history of compliance with a particular sender relative to all 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 compliance 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 partner states. In a duration context, states who receive 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 and thus does not capture these information flows in a meaningful way. 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 draw our measure of reciprocity from the Social Relations Model developed by Kenny (1994) and presented as a tool for political scientists by Author (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:

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

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 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 how likely country i is to comply with country j; and the likelihood that 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.

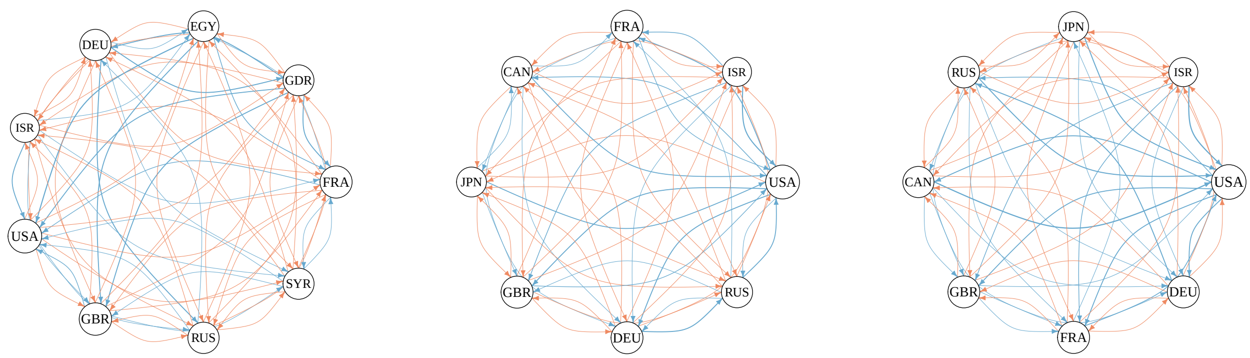
- The actor effect for observation i is the total of i's row mean and column mean, minus the overall mean. The means are just the sums, corrected for degrees of freedom, yielding an average row effect:
  $\hat{a}_i = \frac{(n-1)^2}{n(n-2)} X_{i\cdot} + \frac{(n-1)}{n(n-2)} X_{\cdot i} - \frac{n-1}{n-2} X_{\cdot\cdot}$
- 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. $\hat{g}_{ij} = X_{ij} - \hat{a}_i - \hat{b}_j - X_{..}$

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.[10] 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 unlikely to reciprocate a compliant action from 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.

[10]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.

Figure 2. Reciprocity plots



(a) Compliance: 1972 **(b)** Compliance: 1992 **(c)** Compliance: 2012

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 measure is to capture the concept of creating expectations of resolve: states who have been sanctioned 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 is that states whom continually reciprocate sanctioning behavior are signaling more conflictual behavior rather than cooperative behavior over time. This endogenously formed strategic environment is a dominating factor for the initiation of sanction compliance. Thus, in a world of changing information and strategic incentives, a country will not continue to repetitively comply to a partner state simply out of perceived strategic ties. Countries require continuous signals to build trust and cooperation over time and to maintain a shared understanding of strategic importance to one another. For this reason, we argue that reciprocity is an essential component endogenous to the strategic environment whereby an increase in reciprocity results in an increase in the likelihood of sanction compliance.

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.[11] 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.

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.

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.

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.

[11]Only sanction cases initiated by 2005 are included but outcomes for cases are recorded until 2013.

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.[12] 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.[13]

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.[14]

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.[15] To impute missing values, we use a copula based approach developed by Hoff (2007). Details on our imputation process and

[12] 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.

[13] Crespo-Tenorio, Jensen and Rosas (2013)

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

[15] For example, see Rubin 1976; Honaker and King 2010.

results based on the original dataset, which are nearly identical, can be found in the Appendix.[16]

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 and Clifton Morgan 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 and 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 that describe the relationship a sanctioned state has with its senders. First, we measure the average distance between sender(s) and receiver.[17] 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.[18] Last, we measure alliances as the proportion of sender(s) that are allied with the receiver.[19]

Finally, 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'

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

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

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

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

domestic institutions from the Polity IV data.[20] 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.[21] The expectation in the extant literature is 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 successful states are better able to weather the pressures of these agreements. Below we show our full model specification:

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

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

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

[20] See Marshall and Jaggers (2002). Specifically, we use the "polity2" variable from the Polity IV data.
[21] Banks (2011)

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.

Variable	Model 1	Model 2	Model 3
Compliance Reciprocity$_{j,t-1}$			0.508^{**}
			(0.1)
Sanction Reciprocity$_{j,t-1}$			-0.218^{**}
			(0.056)
Number of Senders$_{j,t}$		0.216^{**}	0.193^{**}
		(0.048)	(0.048)
Distance$_{j,t}$		0.85^{**}	0.825^{**}
		(0.186)	(0.188)
Trade$_{j,t}$		-3.677	-2.464
		(5.351)	(4.149)
Ally$_{j,t}$		-0.029	0.026
		(0.166)	(0.166)
Polity$_{i,t-1}$	0.016	0.028^{**}	0.022
	(0.014)	(0.014)	(0.014)
Ln(GDP per capita)$_{i,t-1}$	-0.269^{**}	-0.269^{**}	-0.22^{**}
	(0.057)	(0.059)	(0.062)
GDP Growth$_{i,t-1}$	0.003	0.007	0.003
	(0.014)	(0.014)	(0.014)
Population$_{i,t-1}$	-0.18^{**}	-0.189^{**}	-0.112^{**}
	(0.043)	(0.046)	(0.05)
Internal Conflict$_{i,t-1}$	0.017	0.018	0.013
	(0.012)	(0.012)	(0.013)
N	6206	6183	6183
Events	190	189	189
Likelihood ratio test	54.73 (0)	89.16 (0)	117.21 (0)

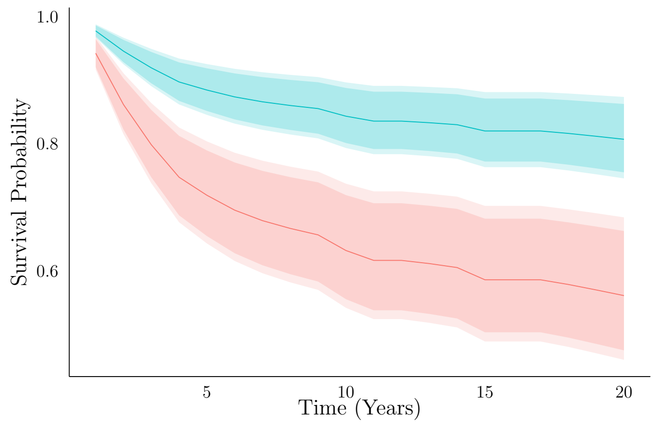
Table 2. Duration model with time varying covariates estimated using Cox Proportional Hazards. Standard errors in parentheses. ** and * indicate significance at $p < 0.05$ and $p < 0.10$, respectively.

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 to 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 shorter time to comply to 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 to 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.

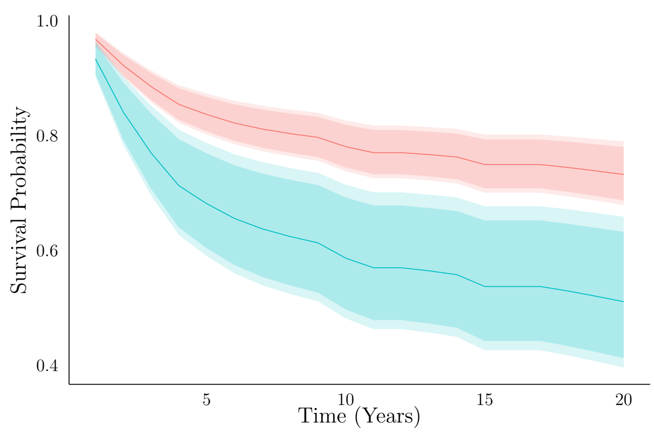
We also find strong support for the argument that states are more likely to comply to sanctions involving multiple actors, and the effect of this variable remains consistent even after controlling for our network level covariates in Model 3. Using Figure 4 we can quickly see that there is a stark difference 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

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.



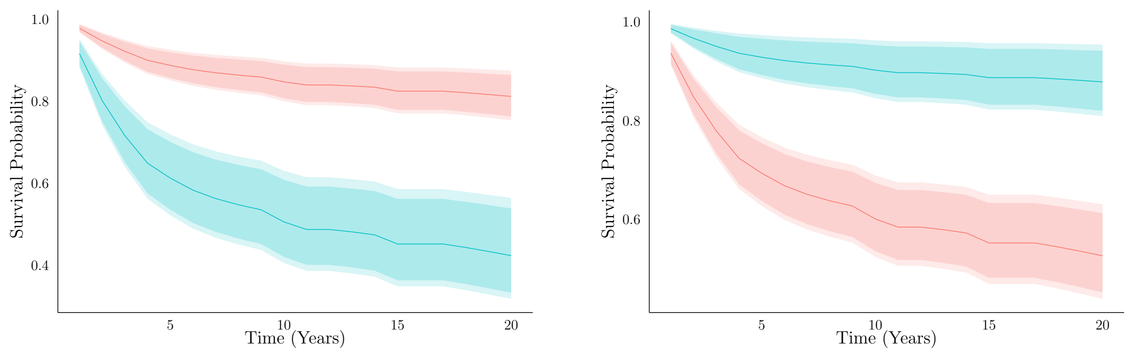
to sanctions sent by allies, and are actually less likely to comply to sanctions sent from neighbors.

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



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. Survival probabilities reflecting over time by network level covariates.



(a) Compliance Reciprocity

(b) Sanction Reciprocity

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 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 to future sanctions.

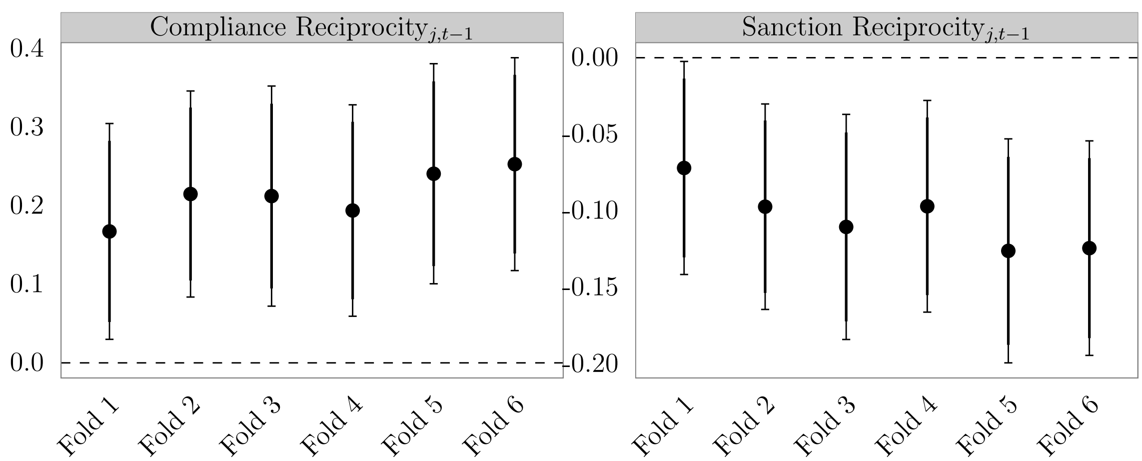
Performance. To assess the accuracy and performance of these estimates we employ a six-fold cross validation procedure.[22] We use this procedure both to determine the robustness of our coefficient estimates when estimated on different subsamples of our

[22]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.

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 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.[23] 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.[24]

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

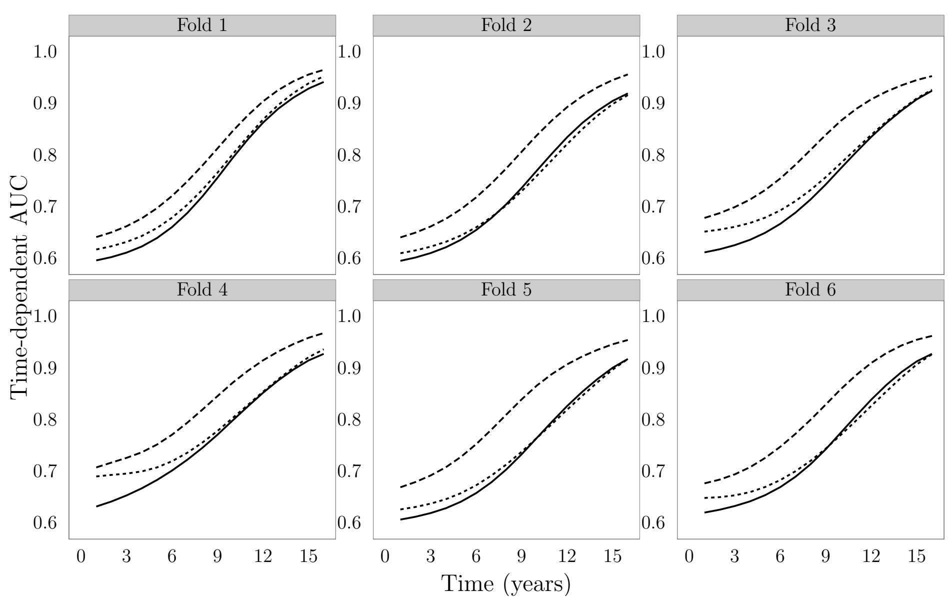


[23]Beck (2008)

[24]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.

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 15 years.[25] 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 Model 2, and the dashed line represents Model 3.



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

Conclusion

International 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 United States are both launching sanction initiatives 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 little examined aspect of sanction behavior and show that countries whom have sanctioned each other in the past without complying to one another are not likely 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.

While much of the research on international sanctions has focused on explaining how individual, formalized linkages between states–such as trade or ally agreements–drive sanction outcomes, our study challenges researchers to more deeply consider interstate politics as a nuanced networked phenomenon wherein relations between states develop overtime as a function of continued informational and behavioral exchange.

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.

Regression results on the original 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$_{j,t-1}$			0.545^{**}
			(0.112)
Sanction Reciprocity$_{j,t-1}$			-0.235^{**}
			(0.061)
Number of Senders$_{j,t}$		0.282^{**}	0.251^{**}
		(0.055)	(0.055)
Distance$_{j,t}$		0.814^{**}	0.775^{**}
		(0.212)	(0.215)
Trade$_{j,t}$		-3.4	-2.566
		(5.944)	(4.978)
Ally$_{j,t}$		-0.045	0.004
		(0.181)	(0.182)
Polity$_{i,t-1}$	0.014	0.029^{*}	0.017
	(0.016)	(0.017)	(0.017)
Ln(GDP per capita)$_{i,t-1}$	-0.265^{**}	-0.274^{**}	-0.213^{**}
	(0.061)	(0.063)	(0.066)
GDP Growth$_{i,t-1}$	-0.002	0.003	-0.002
	(0.015)	(0.015)	(0.015)
Population$_{i,t-1}$	-0.207^{**}	-0.212^{**}	-0.114^{*}
	(0.053)	(0.056)	(0.06)
Internal Conflict$_{i,t-1}$	0.024^{*}	0.022	0.016
	(0.014)	(0.014)	(0.014)
n	5342	5279	5279
Events	150	148	148
Likelihood ratio test	46.93 (0)	83.77 (0)	109.96 (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.

Summary Statistics.

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$_{j,t}$	6183	1.51	1	1.24	1	5
Distance$_{j,t}$	6183	0.14	0	0.34	0	1
Trade$_{j,t}$	6183	0.01	0.01	0.02	0	1
Ally$_{j,t}$	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	5279	0.03	0	0.17	0	1
Compliance Reciprocity$_{j,t-1}$	5279	0.56	-0.01	1.07	-0.81	4.15
Sanction Reciprocity$_{j,t-1}$	5279	3.61	1.96	4.35	-1.1	21.19
Number of Senders$_{j,t}$	5279	1.45	1	1.17	1	5
Distance$_{j,t}$	5279	0.14	0	0.34	0	1
Trade$_{j,t}$	5279	0.01	0.01	0.02	0	1
Ally$_{j,t}$	5279	0.48	0	0.5	0	1
Polity$_{i,t-1}$	5279	15.53	19	6.32	0	20
Ln(GDP per capita)$_{i,t-1}$	5279	8.45	8.49	1.67	3.86	10.94
GDP Growth$_{i,t-1}$	5279	3.55	3.48	4.37	-42.45	34.8
Population$_{i,t-1}$	5279	17.68	17.77	1.49	13.49	20.99
Internal Conflict$_{i,t-1}$	5279	3.18	2	5.46	0	87

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

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