INTERNATIONAL RELATIONS ARE A SOCIAL NETWORK: A LATENT NETWORK APPROACH FOR GLOBAL POLITICS

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ABSTRACT. International relations scholarship is filled with dyads. This includes dyadic hypotheses and propositions, but especially data. These relational data contain information about the interdependencies of various phenomena, including countries, dyads, and even triads. However, most empirical studies of such data do not take into account these dependencies. As a result, the studies are often contradictory and produce results that are not compelling. One reason is that the independence required by the typical methods employed does not exist in the data being studied. We present a different, regression based method, which constructs a latent network which incorporates 1^{st}, 2^{nd}, and 3^{rd}-order dependencies. We replicate five prominent studies in recent IR scholarship and compare the standard approach to the latent factor approach. The additive and multiplicative latent factor approach is shown to produce more precise estimates of covariate effects, and it also dominates standard approaches in terms of out-of-sample cross-validations.

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1. Introduction

Aronow et al. (2015) estimate that over the period from 2010 to 2015, over sixty articles utilizing dyadic data were published in the *American Political Science Review*, *American Journal of Political Science*, and *International Organization*. Most of these studies use a generalized linear model (GLM) to estimate regression coefficients. However, extant approaches to studying dyadic data increase the chance of faulty inferences by treating data as independent and identically distributed (iid) when observations may be highly dependent. Most standard approaches assume that the problems raised by having non-iid relational data can be addressed by recalculating the standard errors of estimated parameters in the link function, so as to reflect the potential clustering of cases. This may work in limited situations, but is not generally effective because these palliatives do not address the fundamental data generating process that remains a threat to inference because of the interdependence of observations or measurements. Namely, it is not just the diagonals of the variance-covariance matrix this affects.

In this article, we discuss a Bayesian approach, the Additive and Multiplicative Effects (AME) model, for directly modeling relational data to reflect the data generating process that yields interdependencies in these types of data structures (Hoff, 2008; Minhas et al., 2016). We focus on three types of interdependencies that can complicate dyadic analyses. First, dependencies may arise within a set of dyads as there may be a particular actor that is more likely to send or receive events such as conflict. Additionally, if the event of interest has a clear sender and receiver, we are likely to observe dependencies within a dyad; specifically, if a rebel group initiates a conflict with a government, the government will likely reciprocate that conflictual behavior. We capture these two dependencies, often referred to as first- and second-order dependencies, respectively, within the additive effects portion of the model. The multiplicative effects capture dependencies that results from groups of actors clustering together or organizing into communities due to *meso-scopic* features of networks, such as homophily and stochastic equivalence. These type of meso-scopic features often arise in relational data because actors possess some latent set of shared attributes that affect their probability of interacting with one another.

We begin by providing a brief review of these dependencies and the AME model. Next, we move to conducting a simulation study to show how this AME approach can recover unbiased and well-calibrated regression coefficients in the presence of network dependencies. Then, we apply this approach to five prominent studies in the international relations (IR) literature and compare results from the current state-of-the-art approach (a GLM with robust standard errors) to those obtained with the AME framework. The latent factor approach (AME) is able to better capture first, second, and third-order interdependencies than the standard approach. It also produces results that are more precise and at times at odds with those found in these studies in particular, and the broader literatures from which they are drawn. As such, this approach offers substantive insights which are often occluded by ignoring the interdependent nature of the relational data that characterize many studies in the field of international relations. Finally, we show that for each replication our network based approach provides substantively more accurate out-of-sample predictions than the models used in the original studies. Thus, the AME approach is one that can be used by scholars in the field to not only generate substantive insights, but it also enables us to better model the data generating process behind events of interest in international relations. It facilitates the concentration on international relations in the field of international relations.

2. Dependencies in Dyadic Data

In working with relational data, scholars in the field begin by structuring it as a set of dyadic observations stacked on top of one another. This makes sense if each observation is independent of the others. Thus, for example, a conflict sent from the United States to Japan, is assumed to be independent of any action that Japan may send to the United States. Additionally, every action sent by Japan to others in the system is considered independent even though each of those interactions involves a common sender, i.e, Japan. As a result, the assumption that most begin with is that each dyadic interaction is taking place in isolation of the others. We know this assumption to be false in theory and in practice because relational data comes with an explicit structure that in general leads to particular types of dependencies. The importance of accounting for underlying structure of our data has been a lesson well understood at least when it comes to time-series cross-sectional data (TSCS) within political science (Beck and Katz, 1995; Beck et al., 1998). As a result, it is now standard practice to take explicit steps to account for the complex data structures that emerge in TSCS applications and the unobserved heterogeneity that they cause.

To uncover the underlying structure that relational data comes with it is helpful to shift towards restructuring dyadic data in the form of a matrix – often called an adjacency matrix – as shown in Figure 1. Rows designate the senders of an event and columns the receivers. In the context of events, the cross-sections in this matrix represent the actions that were sent by an actor in the row to those designated in the columns. Thus y_{ij} designates an action y, such as a conflictual event or trade flows, that is sent from actor i to actor j.

Using the structure of an adjacency matrix, we can visualize the types of first- and second-order dependencies that complicate the analysis of relational data in traditional GLMs. Figure 1 clarifies the types of dependencies that can manifest in these types of data structures. The adjacency matrix on the top left highlights a particular row of an adjacency matrix, to illustrate that these values may be more similar to each other than other values in the adjacency matrix because each has a common sender. Homogeneity in interactions involving a common sender also manifest heterogeneity in how active actors are across the network when compared to each other. Thus in most relational datasets (e.g., trade flows, conflict, participation in international organizations, even networks derived from Twitter or Facebook) we often find that there are some actors which are much more active than others (Barabási and Réka, 1999). Unless one is able to develop a model that can account for the variety of explanations that may play a role in determining why a particular actor may be more active than others, parameter estimates from standard statistical models will be biased.

For similar reasons one also needs to take into account that there is a shared dependence between observations that share a common receiver. The bottom-left panel, illustrates that sender and receiver type dependencies can also blend together. Specifically, actors who are more likely to send ties in a network tend to also be more likely to receive them. As a result, the rows and columns in an adjacency matrix are often correlated. For example, consider that trade flows both from and to many wealthy, developed countries. The bottom-right panel, highlights a second order dependence, specifically, reciprocity. This is a dependency occurring within dyads involving the same actors whereby values of y_{ij} and y_{ji} are correlated. The concept of reciprocity has deep roots in the study of relations between states (Richardson, 1960; Keohane, 1989).

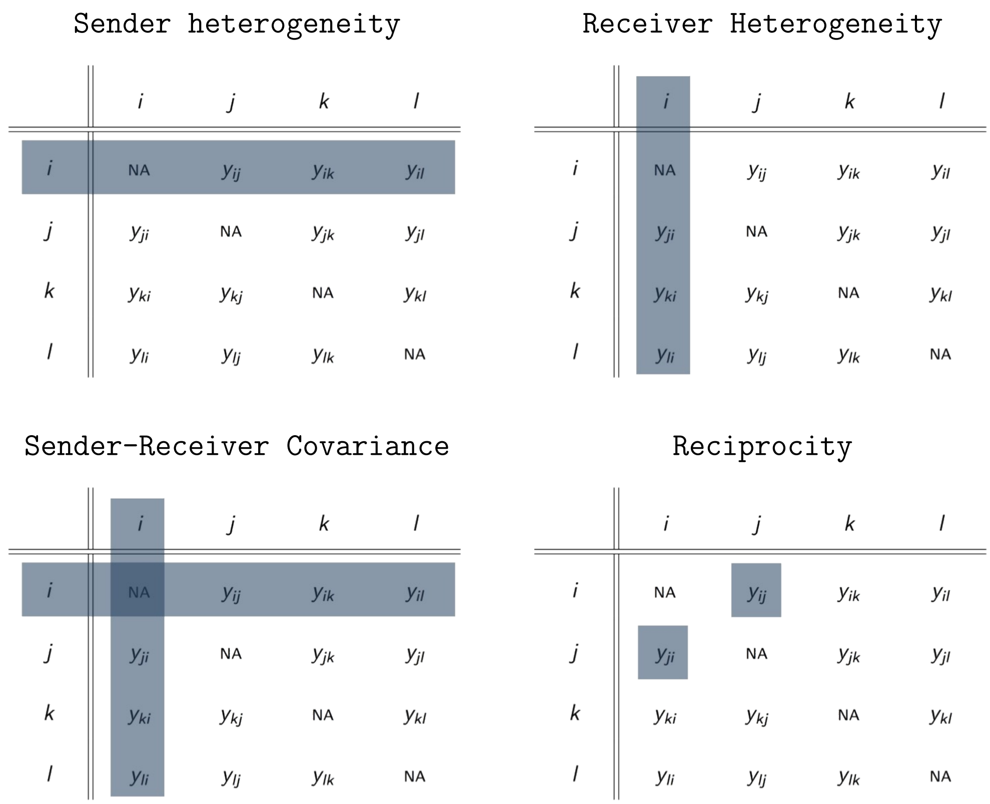


Figure 1. Nodal and dyadic dependencies in relational data.

For most relational data, however, dependencies do not simply manifest at the nodal or dyadic level. More often we find significant evidence of higher order structures that result from dependencies between multiple groups of actors (Poast, 2010). These dependencies arise because there may be a or some set of latent attributes between actors that affects their probability of interacting with one another (Zinnes, 1967; Wasserman and Faust, 1994). In Figure 2 we provide a visualization of a hypothetical relational dataset wherein the nodes designate actors and edges between the nodes indicate that an interaction between the two took place. To highlight third order dependence patterns, nodes with similar latent attributes are colored similarly.

The visualization illustrates that the actors belonging to the same group have a higher likelihood of having an interaction with each other, whereas interactions across groups are more rare. A prominent example of a network with this type of structure was found in American Politics by Adamic and Glance (2005), who visualized the ways in which right and left leaning political blogs linked to one another in the 2004 United States Election. Adamic and Glance find that the degree

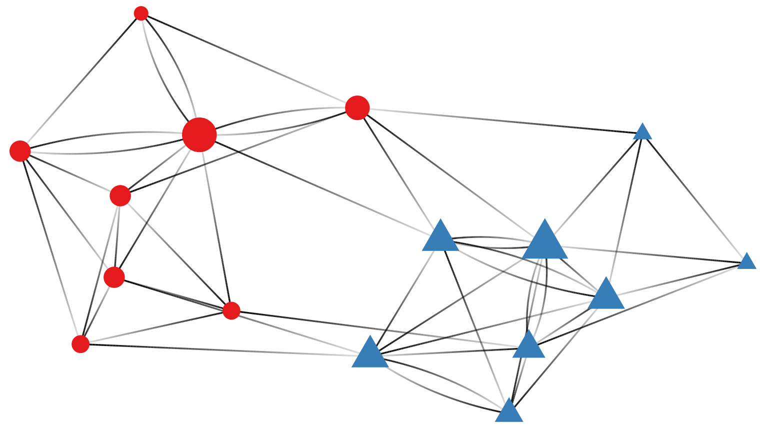


Figure 2. Visualization of network with meso-scopic features.

of interaction between right and left leaning blogs was minimal, and that most blogs just linked to others that were political similar. This showcases the types of higher-order dependencies that can emerge in relational data. First, the fact that interactions was determined by a shared attribute, in this case political ideology, is an example of what is known as *homophily*. Homophily can be used to explain the emergence of patterns such as transitivity ("a friend of a friend is a friend") and balance ("an enemy of a friend is an enemy"), which also have a long history in international relations. The other major type of meso-scopic feature that emerges in relational data is community structure (Mucha et al., 2010), which is often formalized through the concept of stochastic equivalence (Anderson et al., 1992). This concept simply refers to the idea that groups of nodes that act similarly in the network are stochastically equivalent. In the example we have laid out above each of the left leaning blogs would be considered stochastically equivalent to one another.

The presence of these dependencies in relational data points to the fact that there is a complex structure underlying the dyadic events that we observe, and that accounting for this structure is necessary if we are to adequately represent the data generating process. Of course, if one is able to specify each of the nodal, dyadic, and triadic set of attributes that influence interactions then one can be assured that the conditional independence assumption underlying standard approaches will be satisfied. However, it is rarely the case that we can do this even for TSCS data, thus we more than often make certain modeling decisions to account for that structure. Failing to account for the underlying structure in either TSCS or dyadic data leads to a number of well-known challenges: a) biased estimates of the effect of independent variables, b) uncalibrated confidence intervals, and c) poor predictive performance. Further by ignoring these potential interdependencies, we often ignore substantively interesting features of the problem under study. The study of international relations is founded on the relations among actors. Why ignore the interdependencies that led to the study of IR in the first place?

3. Additive and Multiplicative Effect Models for Networks

To account for the dependencies that are prevalent in dyadic data, we turn to the AME model. The AME approach can be used to conduct inference on cross-sectional and longitudinal networks with binary, ordinal, or continuous linkages. It is flexible and easy to use for analyzing the kind of relational data often found in social science. It accounts for nodal and dyadic dependence patterns, as well as higher-order dependencies such as homophily and stochastic equivalence. Hoff (2015); Minhas et al. (2016) provide a detailed introduction to this framework, and the latter piece details how it contrasts with alternative network based approaches. Here we just provide a brief review and then move onto presenting a simulation exercise.

The AME model combines the social relations regression model (SRRM) to account for nodal and dyadic dependencies and the latent factor model for third order dependencies.[1] The AME model is specified as follows:

$$
\begin{aligned}
& y_{ij} = f(\theta_{ij}), \text{ where} \\
& \theta_{ij} = \\
& \boldsymbol{\beta}_d^\top \mathbf{X}_{ij} + \boldsymbol{\beta}_s^\top \mathbf{X}_i + \boldsymbol{\beta}_r^\top \mathbf{X}_j + \\
& a_i + b_j + \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j + \epsilon_{ij}
\end{aligned} \tag{1}
$$

where $y_{ij,t}$ captures the interaction between actor i (the sender) and j (the receiver). We use a Bayesian probit framework, in which we model a latent variable, θ_{ij}, using first a set of exogenous dyadic ($\boldsymbol{\beta}_d^\top \mathbf{X}_{ij}$), sender ($\boldsymbol{\beta}_s^\top \mathbf{X}_i$), and receiver covariates ($\boldsymbol{\beta}_r^\top \mathbf{X}_j$); and then parameters from the

[1] For details on the SRRM see: for details on this model see Li and Loken (2002); Dorff and Minhas (2016). Additionally, an earlier version of the latent factor model (LFM) used in AME is presented in Hoff and Ward (2004). This approach is more limited in the types of dependence patterns that it can capture and has not been generalized to studying longitudinal networks in a cohesive manner.

SRRM and LFM. a_i and b_j in Equation 1 represent sender and receiver random effects incorporated from the SRRM framework:

$$\begin{aligned} \{(a_1, b_1), \ldots, (a_n, b_n)\} &\overset{\text{iid}}{\sim} N(0, \Sigma_{ab}) \\ \{(\epsilon_{ij}, \epsilon_{ji}) : \; i \neq j\} &\overset{\text{iid}}{\sim} N(0, \Sigma_{\epsilon}), \text{ where} \\ \Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \quad & \Sigma_{\epsilon} = \sigma_{\epsilon}^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \end{aligned} \tag{2}$$

The sender and receiver random effects are modeled jointly from a multivariate normal distribution to account for correlation in how active an actor is in sending and receiving ties. Heterogeneity in the the sender and receiver effects is captured by σ_a^2 and σ_b^2, respectively, and σ_{ab} describes the linear relationship between these two effects (i.e., whether actors who send [receive] a lot of ties also receive [send] a lot of ties). Beyond these first-order dependencies, second-order dependencies are described by σ_{ϵ}^2 and a within dyad correlation, or reciprocity, parameter ρ.

The LFM contribution to the AME comes in the multiplicative term: $\alpha(\mathbf{u}_i, \mathbf{v}_j) = \mathbf{u}_i^{\top} \mathbf{D} \mathbf{v}_j$. This model posits a latent vector of characteristics $\mathbf{u_i}$ and $\mathbf{v_j}$ for each sender i and receiver j. The similarity or dissimilarity of these vectors will then influence the likelihood of activity, and provides a representation of third order interdependencies (Minhas et al., 2016). The representation of third order interdepedencies is accomplished by a process similar to computing the singular value decomposition (SVD) of the observed network. When taking the SVD we factorize our observed network into the product of three matrices: $\mathbf{U}, \mathbf{D},$ and $, \mathbf{V}$. This provides us with a low-dimensional representation of our original network in terms of third order dependence patterns arising in the network.[2] Specifically, values in **U** provide a representation of how stochastically equivalent actors are as senders in a network, or more simply put how similar actors are in terms of who they are initiating, for example, conflict with. $\hat{\mathbf{u}}_i \approx \hat{\mathbf{u}}_j$ would indicate that actor i and j initiate battles with similar third actors. **V** provide a similar representation but from the perspective of how similar actors are as receivers. The values in **D**, a diagonal matrix, represent levels of homophily in the

[2]The dimensions of **U** and **V** are $n \times K$ and **D** is a $K \times K$ diagonal matrix.

network.[3] Parameter estimation in the AME takes place within the context of a Gibbs sampler in which we iteratively sample from the posterior distribution of the full conditionals for each parameter.

Given initial values of $\{\boldsymbol{\beta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho,$ and $\sigma_\epsilon^2\}$, the algorithm proceeds as follows:

- sample $\boldsymbol{\theta} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)
- sample $\boldsymbol{\beta} \mid \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)
- sample $\mathbf{a}, \mathbf{b} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)
- sample $\Sigma_{ab} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \rho,$ and σ_ϵ^2 (Inverse-Wishart)
- update ρ using a Metropolis-Hastings step with proposal $p^*|p \sim$ truncated normal$_{[-1,1]}(\rho, \sigma_\epsilon^2)$
- sample $\sigma_\epsilon^2 \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab},$ and ρ (Inverse-Gamma)
- For each $k \in K$:
  - Sample $\mathbf{U}_{[,k]} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}_{[,-k]}, \mathbf{V}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)
  - Sample $\mathbf{V}_{[,k]} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}_{[,-k]}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)
  - Sample $\mathbf{D}_{[k,k]} \mid \boldsymbol{\beta}, \mathbf{X}, \boldsymbol{\theta}, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho,$ and σ_ϵ^2 (Normal)[4]

4. Simulation study

To highlight the ability of AME to capture

Here we consider inference for a regression parameter β of a linear or generalized linear model for a network in the case where there is an omitted variable. The true data-generating models we consider are of the form

$y_{i,j} \sim \mu + \beta x_i x_j + \gamma w_i w_j + \epsilon_{i,j}$

where $Y = \{y_{i,j}\} \in \mathbb{R}^{n \times n}$ is an observed sociomatix, $x = \{x_i\} \in \mathbb{R}^n$ is a vector of observed node-specific characteristics, and $w = \{w_i\} \in \mathbb{R}^n$ is a vector of unobserved node-specific characteristics. We compare inference for β using three models:

- A naive regression model assuming independent errors;
- A latent factor model;
- An "oracle" regression model that includes both $x_{i,j} = x_i x_j$ and $w_{i,j} = w_i w_j$.

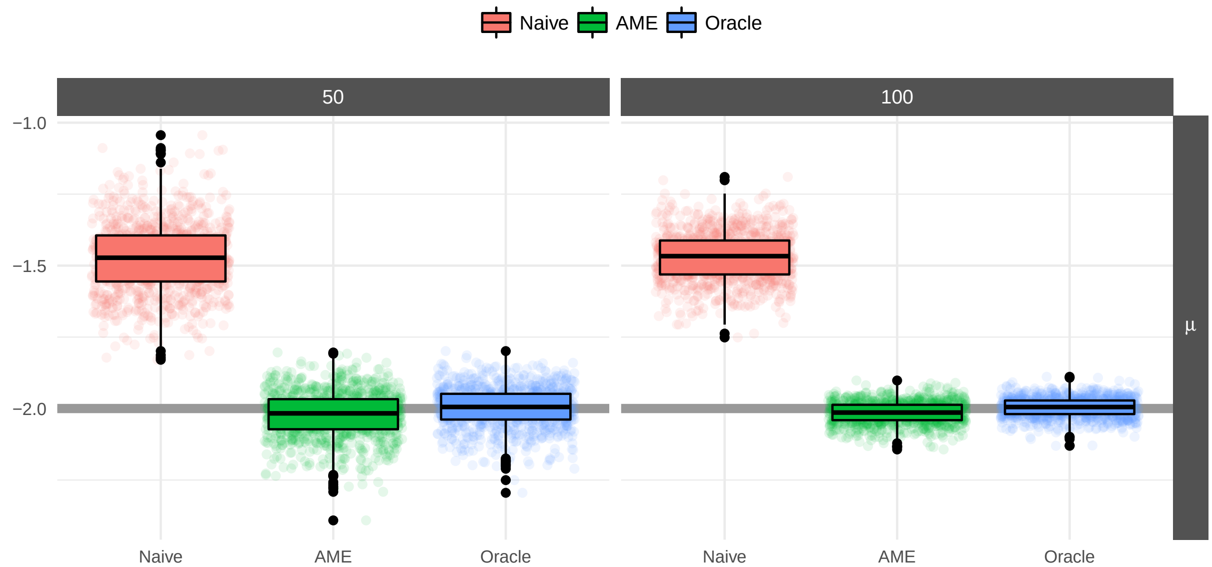
[3]Unlike traditional SVD, in the latent factor model, the singular values are not restricted to be positive, thus allowing us to account for both the presence and absence of homophily.
[4]Subsequent to estimation, **D** matrix is absorbed into the calculation for **V** as we iterate through K.

We make these comparisons in the context of a binary network outcome with a probit regression model.

One way to compare inferences across models is with bias and variance of the parameter estimates. Both of these quantities are combined to get the MSE.

Alternatively, bias and precision can be summarized by confidence interval coverage and width. Coverage should ideally be at the nominal level. If two methods have the same actual coverage rate, the one with the narrower intervals is preferred.

Figure 3. Bias in parameter when homophily is ignored.



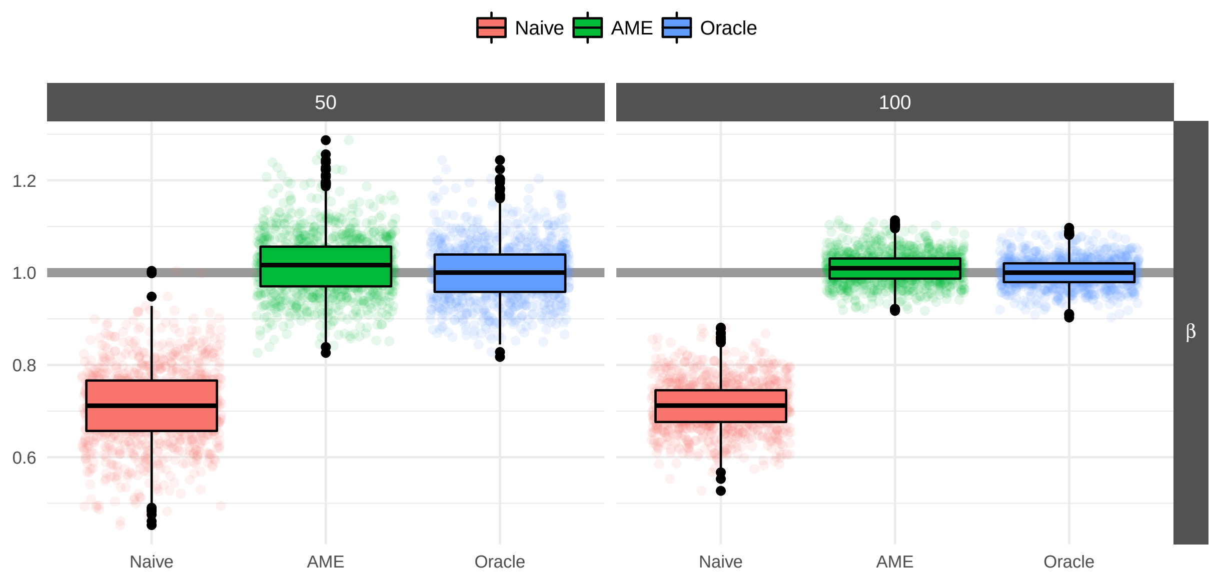
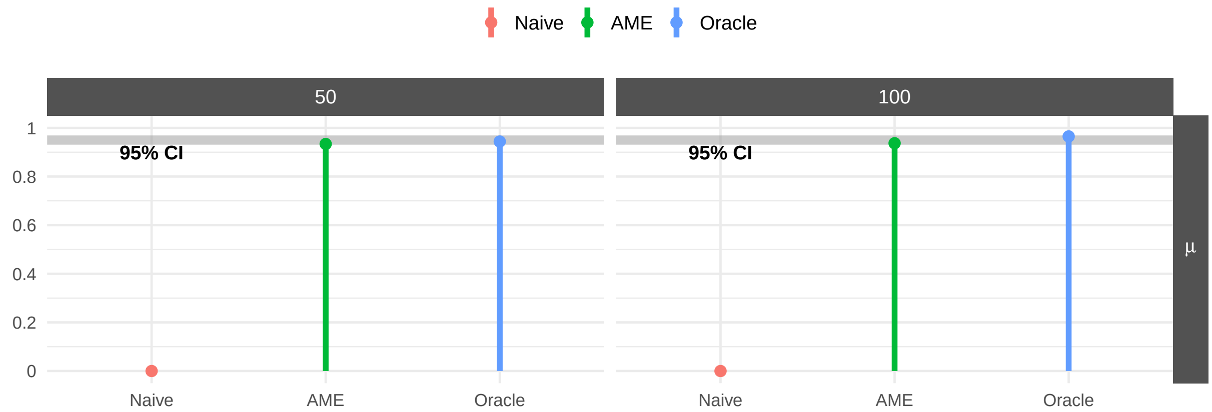


Figure 4. Coverage in parameter when homophily is ignored.



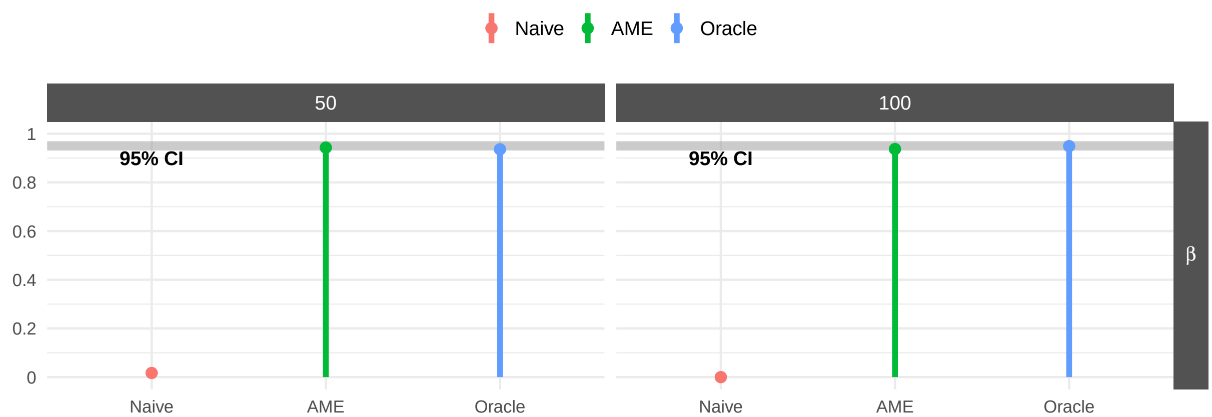
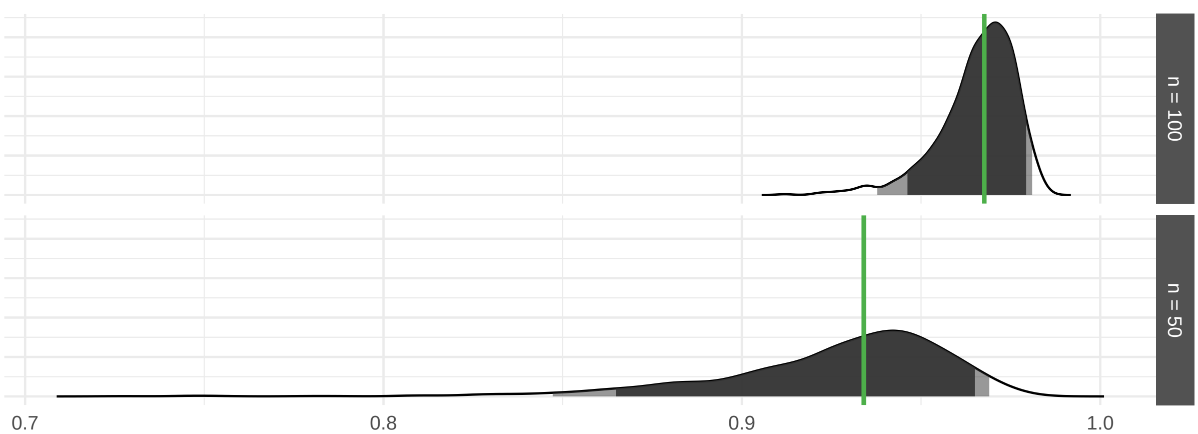


Figure 5. Correlation between missing variable and multiplicative random effect in AME.



5. Replications

5.1. **Design.** For the purpose of this study, we choose five prominent studies from the broad field of international relations and international political economy that utilize relation data (McDonald, 2004; Reiter and Stam, 2003; Rose, 2004; Weeks, 2012; Gibler, 2017). We chose to replicate studies that were written fairly recently, since 2000, and that have been cited over 100 times. Each of these pieces was published in a prominent journal and is well-known in the literature. They all used the standard approach in political science, which is to employ some form of general linearized regression that ignores dyadic interdependencies. Post estimation, standard errors are often adjusted in an attempt to account for clustering of observations.

We obtained the data for each of these studies from their replication archives and replicated the main results of each of the articles.[5] We examine each of the models using the AME framework described above. Our goal is to ascertain whether the ignored interdependencies—the non-iid structure of the relational data—would result in different model estimates when they were addressed in an AME framework, and more importantly to see if there were substantive opportunities that were presented with the dynamic factor approach.

Finally, we assess whether there is any substantive finding that emerges or indeed if any disappear once the interdependencies in the data are modeled.

The broader goal, beyond introducing the use of the AME framework in an applied setting, is to examine the extent to which interdependencies within typical dyadic data make much difference in what we have learned about international relations from empirical studies over the past decade or so. We believe that it does, and that the dynamic latent factor model provides a step forward.

[5]Without exception this was straightforward to accomplish, thanks to an increasing norm in the social sciences of open data sharing.

Table 1. Features of the Studies Replicated.

	Model	# of Actors	Years	# of Dyads	Type of Dyads	Clustered $\sigma_{\hat{\beta}}$
Weeks (2012)	Logit			$901,540$	Directed	Robust
Reiter & Stam (2003)	Logit			$753,456$	Directed	Robust
McDonald (2004)	Logit			$92,354$	Undirected	Robust
Gibler (2017)	Logit			$650,557$	UnDirected	no
Rose (2004)	OLS			$234,597$	Directed	Robust

	Central Finding	Does it Replicate in a Network Model?
Weeks (2012)	Bosses, Juntas and Strongmen are more Aggressive, Machines are Not	**Fails to Replicate**
Reiter & Stam (2003)	Personalist Regimes Attack Democracies, Not Vice Versa	Replicates
McDonald (2004)	Lower Trade Barriers and Higher Trade Lead to Peace	**Fails to Replicate**
Gibler (2017)	Power Parity at time of Entry to International System Inceases Conflict	**Fails to Replicate**
Rose (2004)	WTO Membership Does not Effect Trade	Replicates

Table 2. Here we provide a brief summary of the key variable in each of the five replications and a note about whether or not the finding is replicated when using our network based approach. Cases in which the finding is not replicated are highlighted in bold.

We also examine the accuracy of the predictions made with each approach. Out of sample cross validation strategy.

By accounting for exogenous and network dependent patterns that give rise to conflict systems we are able to better account for the data generating process underlying relational data structures. To show that this is the case, we examine whether our approach achieves better predictive performance in an out of sample context than traditional dyadic models. To evaluate our model, we randomly divide the $\binom{n}{2} \times T$ data values into $k = 30$ sets, letting $s_{ij,t}$ be the set to which pair ij, t is assigned. Then for each $s \in \{1, \ldots, k\}$, we:

(1) estimate model parameters with $\{y_{ij,t} : s_{ij,t} \neq s\}$, the data not in set s,
(2) and predict $\{\hat{y}_{ij,t} : s_{ij,t} = s\}$ from these estimated parameters.

The result of this procedure is a set of sociomatrices $\hat{Y}$, in which each entry $\hat{y}_{ij,t}$ is a predicted value obtained from using a subset of the data that does not include $y_{ij,t}$.

We set a number of benchmarks for comparison. First we compare the AME model to a GLM model using the same covariates to show the effect of accounting for network dependencies on predicting conflict. We supplement this with an alternative GLM that includes not just these covariates, but also a lagged dependent variable and a lagged reciprocity term. The lagged dependent variable is the equivalent of saying that conflict and peace are relatively likely to persist between dyads, while the inclusion of a lagged reciprocity term in a GLM framework is a simple way to account for retaliatory strikes.

We utilize three performance criterions to compare the models: Receiver Operator Characteristic (ROC) curves, Precision Recall (PR) curves, and separation plots. ROC curves look at the trade-off between true positive rates and false positive rates at different thresholds of classification. An issue with an ROC Curve when looking at conflict, is that it is relatively rare at the dyadic level: in most years only 3% of possible dyads are in conflict with one another. If peace is common, even a poor model will have a very low False Positive Rate.

To better assess which models predict the presence of conflict, not just its absence, we look at PR Curves. These examine the trade-offs between the percentage of conflicts a model predicts, and the percentage of predicted conflicts which occur. Lastly, we examine separation plots (Greenhill et al., 2011). These provide an intuitive visualization of the accuracy of our predictions by juxtaposing a line showing the predicted probability of conflict with whether conflict actually occurs for all cases (where the cases are sorted by the predicted probability and then colored to indicate the outcome). Here a perfect model would have all cases where conflict actually exists on the right with a predicted probability of 1, and would predict 0 in all other cases. All of the models' performance out of sample by these metrics are displayed in figure **??**. The AME model with covariates is the best performing model out of sample in all cases. This model outperforms each of the GLM variants by a notable margin.

		GLM	AME
Weeks (2012)	Area Under ROC Curve (AUC-ROC)	0.64	**0.97**
	Area Under PR Curve (AUC-PR)	0.00	**0.15**
Reiter & Stam (2003)	AUC (ROC)	0.92	**0.96**
	AUC (PR)	0.08	**0.15**
McDonald (2004)	AUC (ROC)	0.92	**0.99**
	AUC (PR)	0.13	**0.28**
Gibler (2017)	AUC (ROC)	0.52	**0.91**
	AUC (PR)	0.00	**0.08**
Rose (2004)	Root Mean Squared Error (RMSE)	3.23	**1.99**
	Root Median Squared Error (RMDSE)	2.01	**1.06**

Table 3. Here we provide a summary of the out-of-sample performance based on our cross-validation strategy for each of the five replications when using the standard dyadic approach and our network based approach. Four of the five studies involved a binary dependent variable, so for those measures we provide area under the curve (AUC) statistics. The fifth involved a gaussian dependent variable and for that we use the root mean squared error (RMSE) and root median squared error (RMDSE). Cases in which our network based approach outperformed the standard approach are highlighted in bold.

5.2. **Replication of Weeks (2012).** Weeks (2012) examines the influence of domestic institutions on the initiation of military conflicts by autocratic leaders. She argues that in some circumstances autocrats are held accountable for their foreign policy decisions. She adds the nuance that autocratic audiences are not homogeneous. When the autocratic regime is nonmilitary, the domestic audience do not favor military actions, but in military autocracies this is not the case. Further she argues that in personalistic regimes without a military or civilian domestic audience, the leaders tend to be more likely to employ military force in their foreign policy. To study this question, she uses a dyadic design in which the dependent variable is "whether country A in a directed dyad initiated military conflict against country B during year t" (page 337). These data come from the Militarized Interstate Disputes database (Maoz, n.d.). One major innovation in her study resides in the nuanced way in which she conceptualized and coded regime type into four types: a) Machine, b) Junta, c) Boss, and d) Strongmen. She also includes a variety of putative control variables focusing on capabilities for both sides of the dyad, alliances, geography, trade dependence, regime instability, and the regime type of "side B." She uses a logistic regression, but follows Beck et al. (1998) and includes splines to capture temporal covariation in the dependent variable along with fixed, unit effects. The analysis is done for dyads, but is considered to be from the perspective of the actor that initiated the dispute. Her time frame is from 1946-1999. The basic finding is that a) juntas, bosses, and strongmen are more likely to initiate conflict than machines (and maybe democracies) and that b) machines are no more belligerent than democracies. These insights are mainly determined by looking at coefficients and their putative significance in Tables 1 and 2 (pages 339–340). She makes the argument that ignoring important nuances between different types of autocracies hinders our understanding of the initiation of military conflict by autocracies.

The replication of Weeks (2012) likely has the sharpest divergence between the General Linear Model results and those of the AME Model. In Weeks's initial models, as detailed in figure 6 she finds that machines are less prone to initiate conflict than the reference category, whereas Juntas, Bosses and Strong-men are more conflict-prone, in line with her theoretical expectations. When we look at the posterior distribution of these coefficients in the AME results, we find that none of these values are distinguishable from zero. We similarly find less pronounced effects for military capabilities. One explanation for this divergence is the AME model's ability to account for third order effects. Inspection of the multiplicative effects in figure 8 reveals a number of clusters of states which exhibit structural equivalence – in the top right corner we see states like the US, the UK, and Israel who often send conflict to similar targets. In particular, we observe a cluster of "rogue states," who are receivers of conflict, in the top right (Iran, Iraq, Syria, Libya, North Korea). In the bottom corner we see a cluster of authoritarian senders including Iraq, Russia, Syria, North Korea and China. In general, these clusters have similar governmental types (Iraq, Syria, Libya, and North Korea all fell under the "boss" category), and similar conflict behavior. So, in the GLM, which ignores these third order dependencies, much of these results might have been attributed to regime type. The AME model, on the other hand, finds that it is more efficient to attribute this behavior to the multiplicative effects. In terms of out of sample performance, shown in figure 7(a), the AME model performs markedly better than the GLM out of sample, lending credence to the possibility that these third order dependencies cause spurious effects for regime type.

5.3. **Replication of Reiter & Stam (2003).** Reiter and Stam (2003) examine the relationship between democracy, dictatorship and the initiation of militarized disputes. They use directed dyads and find that dyads involving a democratic leader on the one hand and a personalist dictator on the other tend to be violent. They also discover that dictators are likely to challenge democracies,

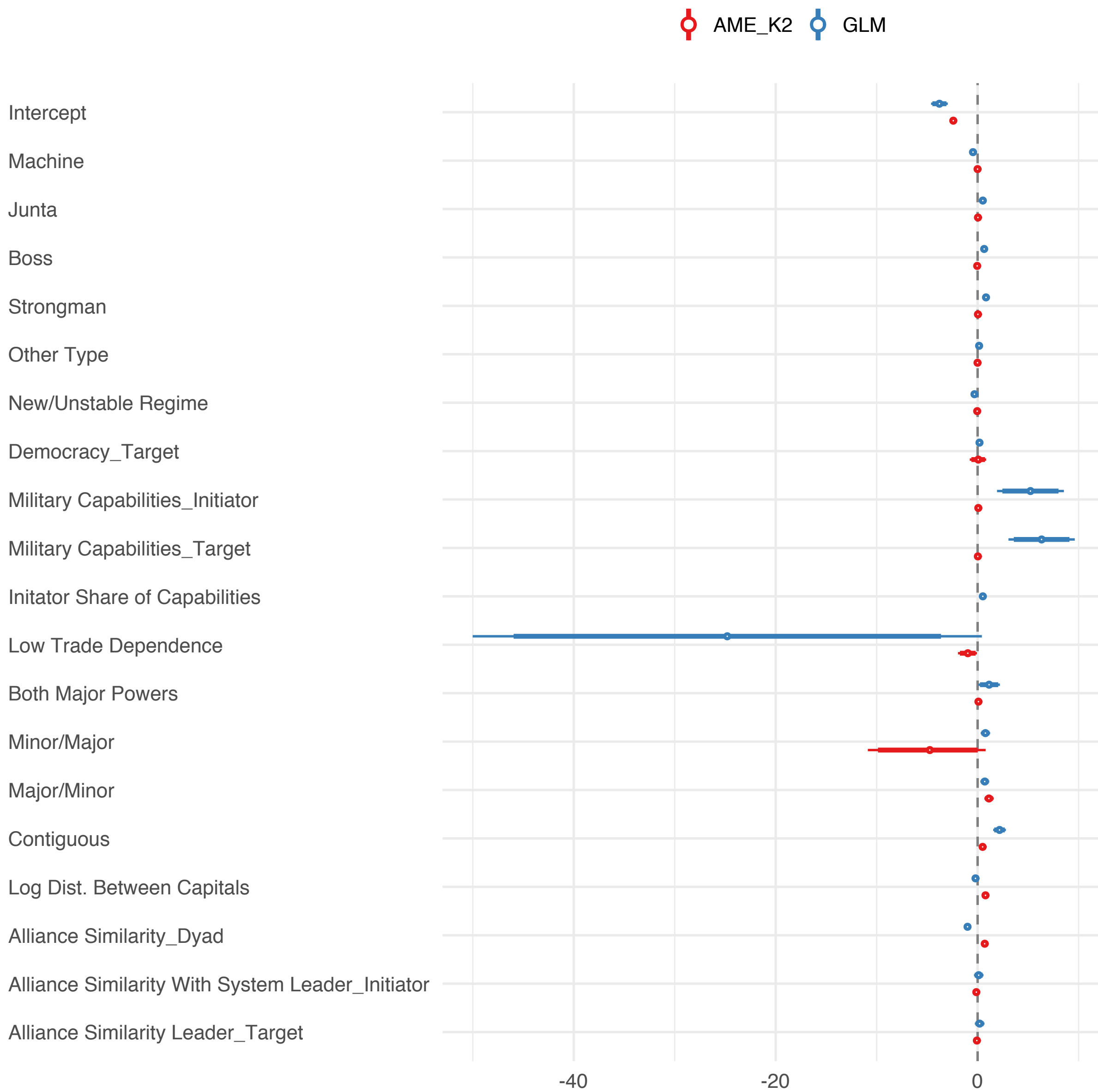
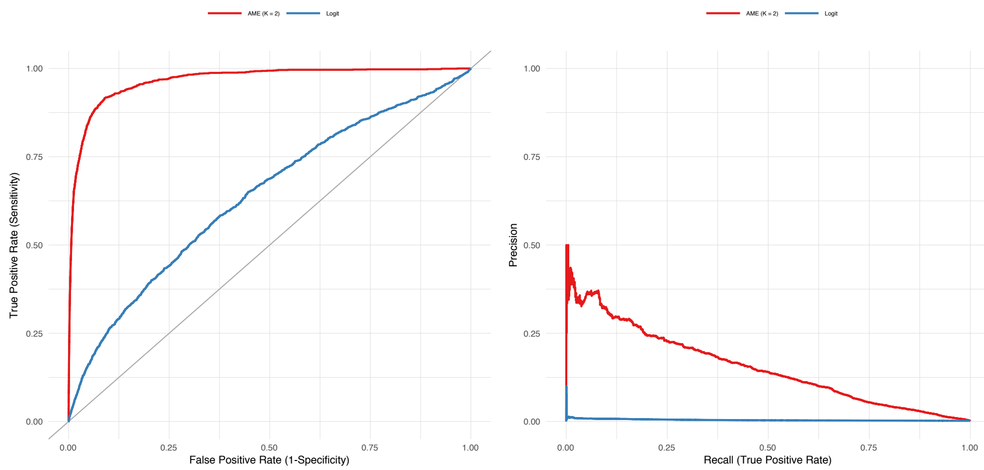


Figure 6. Coefficient plot of Weeks' (2012) original model (blue) compared to AME model (red).

but that this is not reciprocal. In addition, military regimes and single-party regimes are more prone to initiate disputes with democracies, than the other way around. They use the MID data, but note that "We code a state as having initiated a dispute if it is on 'side A' of a MID, the conventional approach to coding initiation. This means that the state was on the side that took the first action in the dispute, whether that action was the threat, display, or use of force. We code



(a) AUC (b) Precision and Recall

Figure 7. Assessments of out-of-sample predictive performance for Weeks (2012) using ROC curves and PR curves.

joiners as initiators or targets, though the results do not change if we do not code joiners as initiators or targets. . . . Though coding initiation will always be difficult, the 'side A' variable has been widely used in past conflict scholarship (page 334)." Independent variables are largely taken from an earlier study and focus on various encodings of regime types, contiguity, alliance, and capability measures. As is prevalent in these kinds of studies, Reiter & Stam employ a logistic regression that includes an indicator of the time since the last dispute as well as three cubic splines. The database for this study is constructed using EUGene (Bennett and Stam, 2000) and comprises approximately three-quarters of a million stacked dyads. Based on their statistical analysis, they conclude that institutional constraints affect the propensity of democratic and non-democratic leaders to engage in military conflict.

In the original model, the variable "Pers/Democ Directed Dyad" (which represents a Personalist $\rightarrow$ Democractic directed dyad) is clearly positive while the variable "Democ/Personalist Directed Dyad" is zero and the difference between the two coefficients is clearly distinct from zero. In our replication using the AME framework, we also find that Pers-Democ directed dyad has a positive effect with zero excluded from the 95% confidence interval while Democ-Pers directed dyad is indistinguishable from zero. Using this model, however, we can no longer conclusively say that the Pers/Democratic coefficient is larger than the Democ/Personalist one. Our replication using the

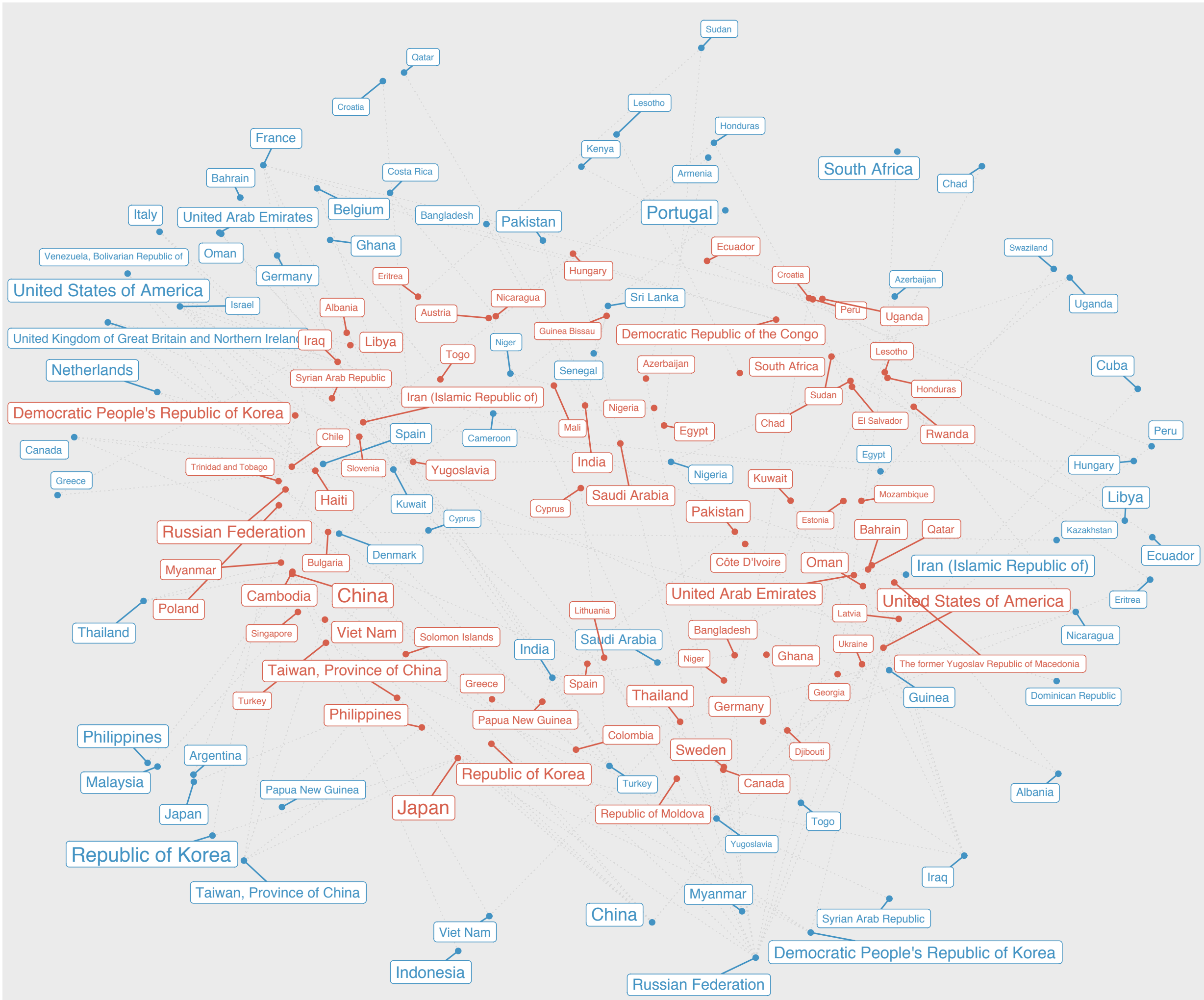


Figure 8. Visualization of multiplicative effects for Weeks (2012). Blue represents groups with common sending patterns and red represents groups with common receiving patterns.

AME approach therefore cast doubt on Reiter & Stam's key claim that MIDs initiated by personalist dictatorships against democracies are more likely than MIDS initiated by democracies. Further, the effect of most of the covariates in the literature thought to predict interstate MIDs are much closer to zero when using the AME framework, as seen in Figure 9. Finally, our modeling approach outperforms the original model by better, and more accurately, predicting MIDs out-of-sample (Figure 10(a) and Figure 10(b)).

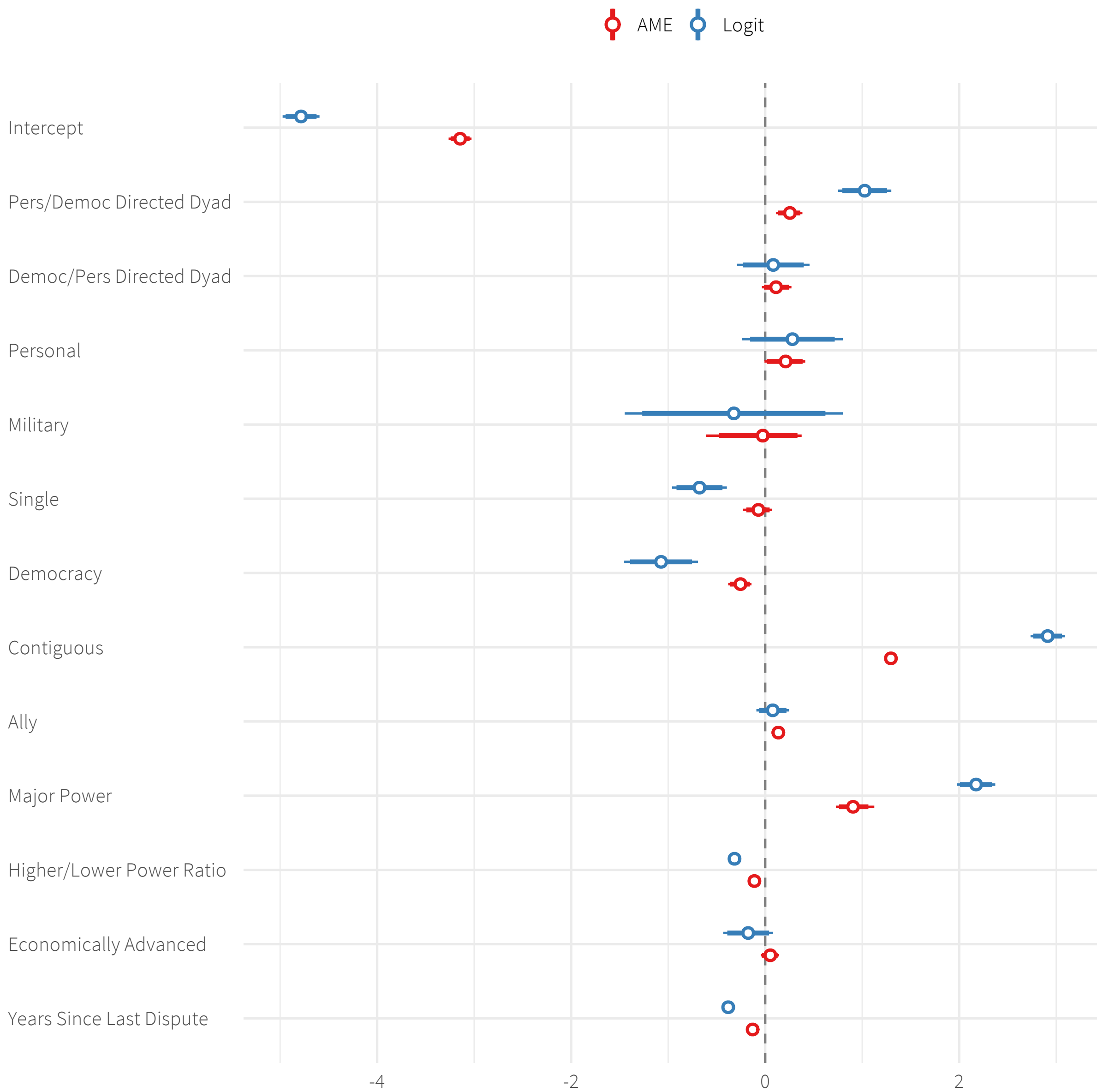
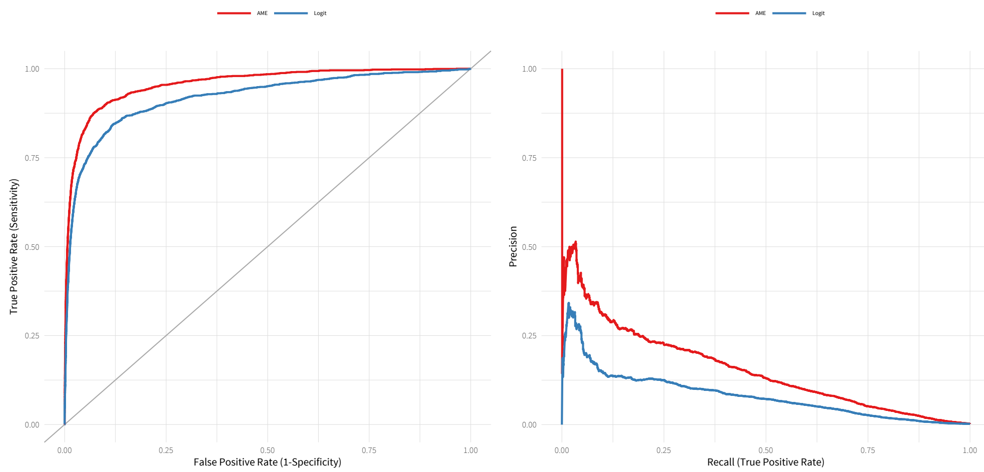


Figure 9. Coefficient plot of Reiter & Stam (2003)'s original model (blue) compared to AME model (red).

5.4. **Replication of Rose (2004).** In 2004, Andrew Rose published a study in the *American Economic Review* that proved to be quite controversial in terms of macroeconomic trade theory and in terms of trade policy in a variety of nations. It also provoked a number of responses in the international political economy literature Tomz et al. (2007); Ward et al. (2013). Rose's basic argument is that despite longstanding arguments made by trade theorists and the World Trade Organization



(a) AUC

(b) Precision and Recall

Figure 10. Assessments of out-of-sample predictive performance for Reiter & Stam (2003) using ROC curves and PR curves.

that WTO membership fosters greater cooperation and thereby more trade among its members, the empirics do not bear out such claims. He uses a standard gravity model with dyadic data on bilateral merchandise trade (not services) for 175 countries over a period of five decades. Estimating this model using OLS within many differing contexts, his conclusion was that: "An extensive search reveals little evidence that countries joining or belonging to the GATT/WTO have different trade patters from outsiders... (2004, page 98, abstract)." The data for this study have been widely used in replications by many searching for the missing effects of the WTO—as well as preferential trade agreements, bilateral investment theories, and other aspects of modern trade theory.

When we compare the results of Rose's original OLS model to our model that accounts for network dependencies, the results are generally similar. As you can see in Figure 11, the main result of the model – the null effect of membership in the WTO, as represented by the "One-In" and "Both-In" variables – remains when we move from an OLS to a Gaussian AME model. The most striking difference between the models is that, while in the original model there was a clear positive relationship between Real GDP and Trade, most of this effect vanishes in the AME model. The random effects shown in Figure 12 reveal the cause of much of this divergence. Here, the states with the most positive random effects are also states with high GDP, though not necessarily high

GDP/capita.[6] Thus, the effect of GDP in the original model was, in part, an artifact of first-order dependencies. Most of the other results of the model are constant across each model, though some geographic features, such as islands and landlocked states, have a more clear effect on trade once we account for these network dependencies. Excitingly, when we account for network interdependencies, we observe a markedly lower Root Mean Squared Error out of sample – 3.23 for the OLS model and 1.77 for the AME model.

[6]Note: Qatar exhibits strongly negative random effects.

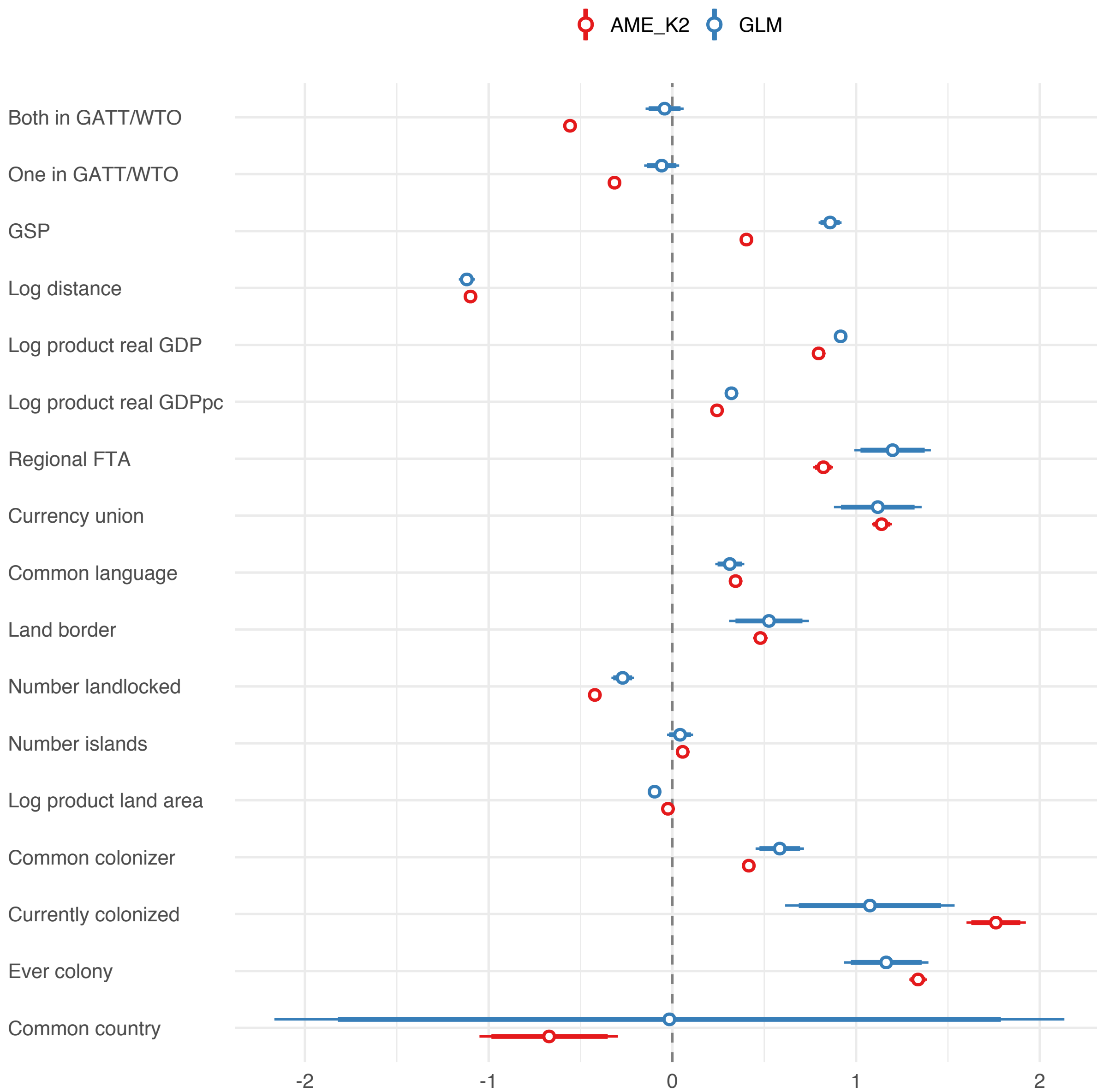


Figure 11. Coefficient plot of Rose (2004)'s original model (blue) compared to AME model (red).

5.5. **Replication of McDonald (2004).** McDonald (2004) studies whether trade promotes peace between nations. He observes that knowledge about the link between conflict and trade is indeterminate in the field of international relations, noting that competing explanations persist. He calls for more precise empirical tests. Importantly, McDonald (2004) includes the interdependence

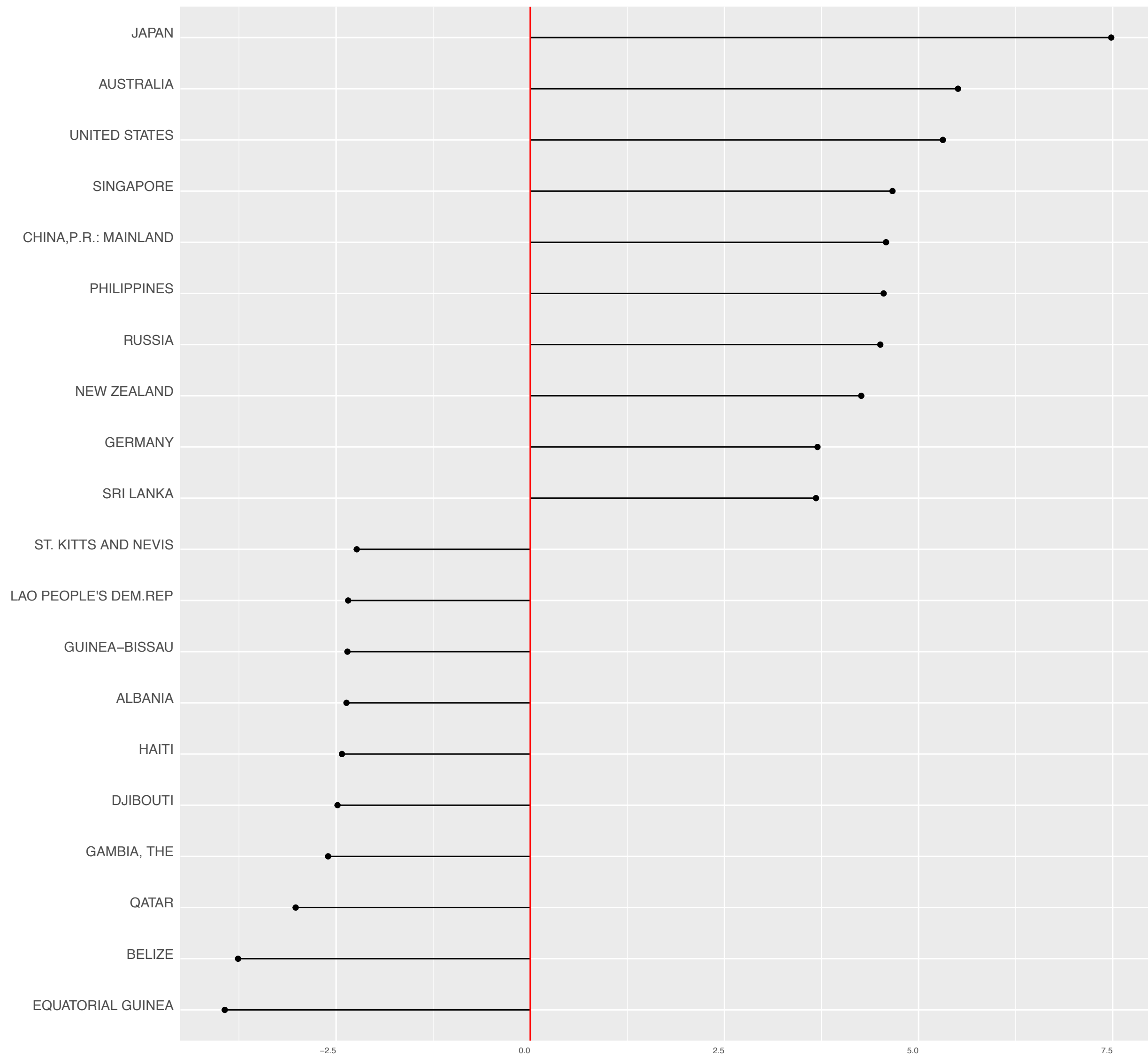


Figure 12. Nodal Random Effects for AME estimation of Rose (2004).

argument—that interdependence between states "makes conflict less likely because of its efficiency over conquest in acquiring resources. . . (547)" in his overview of underdeveloped hypotheses.

Accordingly, the primary contribution of the study is to provide evidence challenging the generalized linkage between peace and trade and to offer a new measurement of the key independent variable, trade. To do so, McDonald (2004) refines the trade variable, arguing that *free* trade, rather than trade alone, reduces the likelihood of conflict between states. His key hypothesis that greater levels of protection increase the probability of interstate conflict, an argument that builds on the work of classic liberalism and connects free trade to the power of domestic audiences. McDonald (2004) measures free trade in two ways. The first captures the idea that larger protected sectors generate greater societal pressures resulting in pockets of support for war. This protection variable measures the proportion of customs revenue divided by total imports in the state that possesses the greater such ratio in each dyad. This measure captures the score of the state in the dyad that possesses higher barriers to trade (560). McDonald (2004) also includes a measure of economic integration calculated as "the lower proportion of total dyadic trade (imports plus exports) divided by state i's GDP or total dyadic trade divided by state j's GDP." (560). Finally, the binary, dependent variable is the onset of a new militarized interstate dispute within a given dyad. McDonald (2004) employs logistic regression to examine the putative statistical significance of these variables. The models include a spline correction for time-series data as well as robust standard errors clustered on each dyad.

Our replication reveals that trade relations are highly interdependent and exhibit important patterns of transitivity. Or, in other words, if countries i and j are highly dependent and countries j and k are also highly dependent, then we are likely to observe high dependency between countries i and k. Our findings support those of Traag and Lupu (2013) which argue that indirect trade relations reduce the probability of conflict. This indicates that conflict is less likely between members of a trade community. Once we control for these dependencies, we can more clearly interpret the positive link between trade and conflict. Figure 13 shows the coefficients for both the original and replicated model and Figure 14 demonstrates the predictive performance of each model. Figure 15 represents the multiplicative effects of the model. This plot enables us to consider actors with similar sending and receiving patterns resulting from stochastic equivalence and homophily. In the upper arch for senders, there is a clear clustering of United States' allies (the United Kingdom, Netherlands, and Japan). We also observe an African cluster in the top right segment for receivers (Egypt, Niger, and Zambia for example). These countries both trade amongst themselves and have similar conflict behavior – stochastic equivalence is present among the first group, homophily among the second – and so once we account for these clusters using the multiplicative effects, the residual effect of trade actually increases the likelihood of conflict.

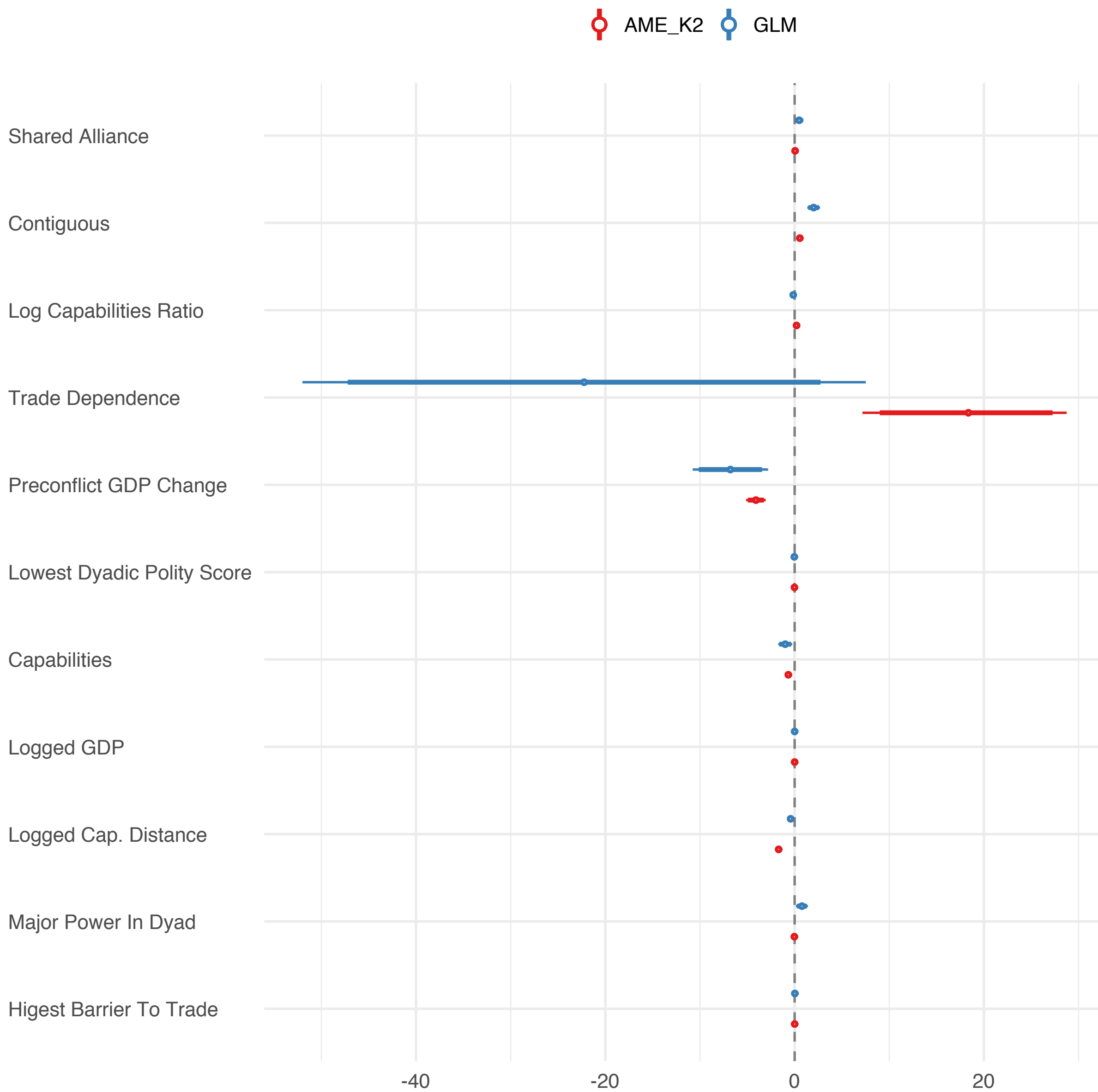
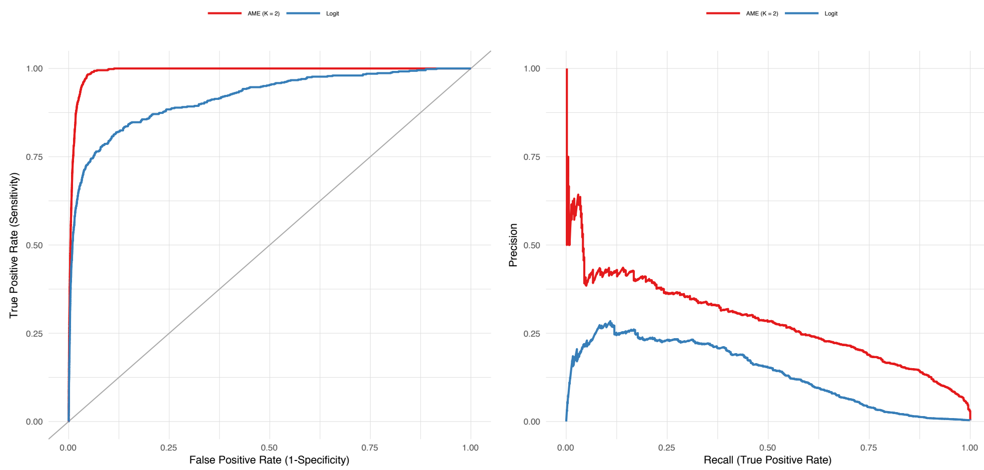


Figure 13. Coefficient plot of McDonald (2004)'s original model (blue) compared to AME model (red).

5.6. **Replication of Gibler (2017).** The replications we have undertaken are all from articles over the past fifteen years. A more recent example is Gibler (2017) which examines the onset of militarized disputes using capabilities, joint democracy, alliances, and power parity in a undirected dyadic study using logistic regression and dyad clustered standard errors. In addition to this, Gibler shows that the long-standing relationship between the relative parity of capabilities and initiation



(a) AUC (b) Precision and Recall

Figure 14. Assessments of out-of-sample predictive performance for McDonald (2004) using ROC curves and PR curves.

of international conflict is almost completely mediated by the initial conditions for the members of the dyad when they joined the international system as sovereign members. This finding calls into question many IR theories about the role of balance in terms of generating international conflict (Organski, 1958).

We re-estimated model 6 from Table 6 (2017,34). The results are presented in Table 4 in order to facilitate explicit comparison. The results obtained with `amen` stand in stark contrast to those found with a logistic regression (with dyad clustered, robust standard errors). Most importantly, the primary variable from the Gibler study, parity of the members of a dyad at the year in which they entered the international system, is shown to be unimportant in the amen results. Not only is the value of the this parameter small, but it has a very large relative standard error, over a magnitude larger than the parameter itself ($z = 0.038$). In addition, joint democracy follows the same pattern of importance in the logistic results, but this disappears once interdependencies are modeled. As might be expected the strong geographic clustering in the original study is about one-quarter as strong in the `amen` estimations. Similarly, rivalry coefficients are about one-third the size in the `amen` formulation, but a great deal more precisely measured ($z = 18.116$).

Beyond more informative fixed effect coefficients, the `amen` approach also provides information about the interdependencies that were modeled. The most pertinent of these may be the dyadic

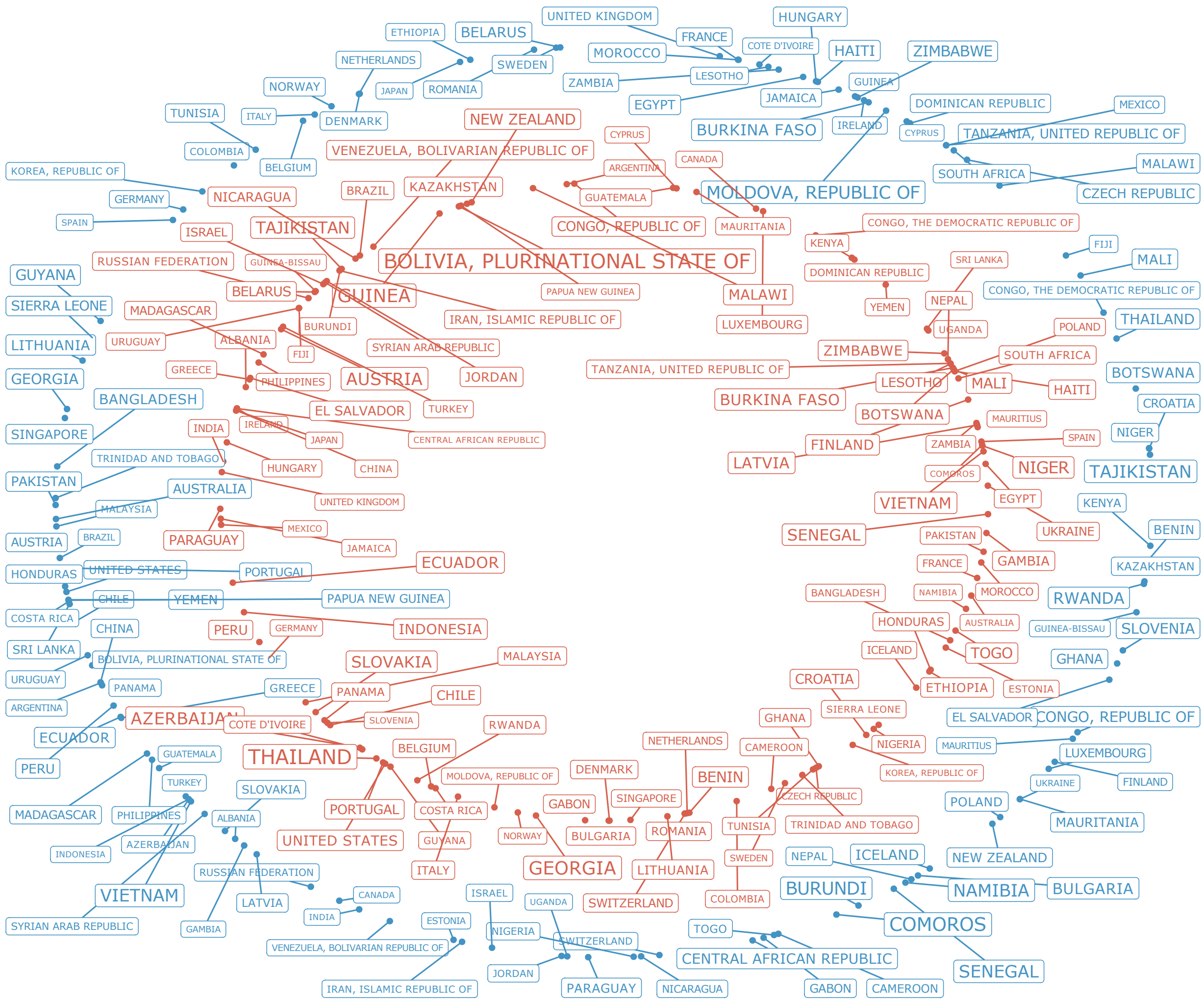


Figure 15. Visualization of multiplicative effects. Blue represents groups with common sending patterns and red represents groups with common receiving patterns.

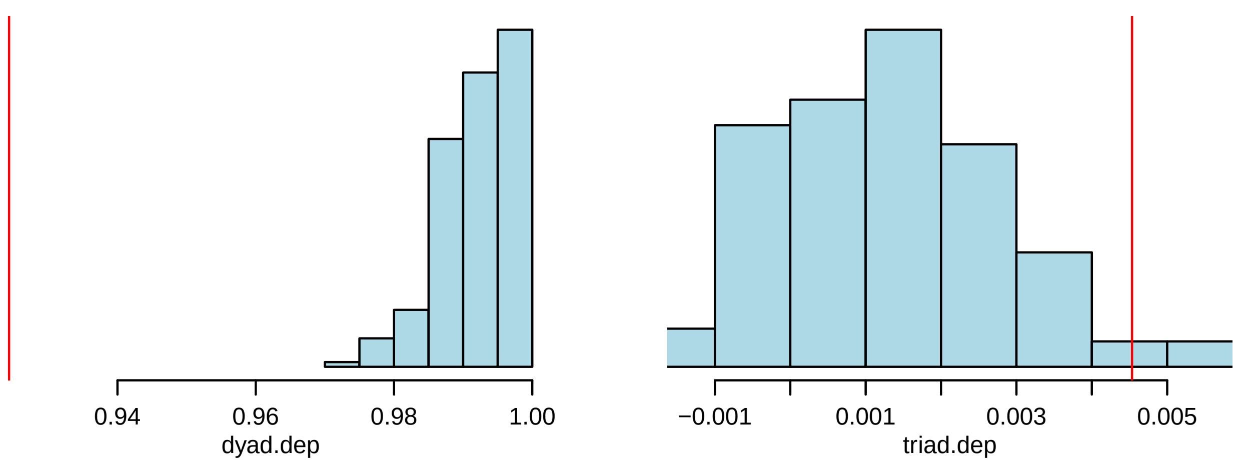
and triadic dependencies which are presented in Figure 16, which further reveal that the assumption of independence among the dyadic data in this study can be strongly rejected. Perhaps most importantly, the main substantive conclusions of the 2017 Gibler study do not seem warranted from the perspective of the results obtained with the `amen` estimation that explicitly models 1st-2nd-, and 3rd-order interdependencies. Not only do the estimated coefficients tell a different story, but the assumptions under which the original results would hold are shown to be violated by the data.

Table 4. Comparison of Gibler (2017) Model 6 results with AME results. This was run over a chain of $10,000$ iterations.

	$\hat{\beta}$ Estimates	
Variable	`logit`	`amen`
Allied	0.142	0.023
Joint Democracy	**-0.507**	0.045
Peace Years	-0.260	**-0.060**
Spline 1	**-0.001**	**0.00**
Spline 2	**-0.000**	**0.00**
Spline 3	-0.000	**0.00**
Contiguity	**2.412**	**0.640**
Parity	0.075	-0.013
Parity at entry year	**0.868**	0.002
Rivalry	**2.031**	**0.721**
Constant	**-5.526**	**-2.581**

Note: **Bold** indicates conventional statistical significance at $p < 0.05$ or less in Gibler (2017). For comparative purposes, only, we have employed the same criterion to the results from the `amen` estimation.

Figure 16. The left panel is a plot of the dyadic dependencies in the Gibler model 6; the right panel shows the triad dependencies. Note that the red line represents the null hypothesis of no dependencies, indicating that the standard logistic approach is far from what is uncovered with this analysis.



6. Conclusion

International relations is generally about the interactions and dependences among a set of countries or other important actors such as international governmental organizations (IGOs, such as the WTO) and non-governmental organizations (NGOs, such as the Gates Foundation). Some approaches focus on only looking a at small number of these actors, but many scholars examine a large number of actors at a time. This is particularly true of those scholars who work in the tradition of the Correlates of War Project, but is by no means limited to them.[7] Many scholars have debated the use and abuse of dyadic data. One recent on-line symposium can be found at http://bit.ly/2wB2hab. It is clear from a survey of the literature and from work in this area published as recently as 2017 that many find dyadic data to be an important touchstone in the study of international relations Erikson et al. (2014); Aronow et al. (2015).

At the same time, we know that research designs which focus on the statistical analysis of dyadic data quickly go astray if the dyadic data are assumed to be independent and identically distributed (iid). Virtually all of the standard statistical models–ordinary least squares, logistic and probit regressions, to name a few–fail if the data are not iid. By definition dyadic data are not iid and thus the standard approaches can not be used cavalierly to analyze these data. Signorino (1999) showed why this is true of models of strategic interaction, but it is more broadly true of models that employ dyadic data. We show that latent networks can be employed to defeat this vulnerability of dyadic data in the realm of international relations. These approaches have been developed for a while, but are not yet widely used in international relations scholarship. The statistical model of the latent network captures first-order (example or restatement), second-order (example or restatement), and third-order (example or restatement) dependencies in dyadic data using a familiar regression framework that has been adapted for relational data–such as dyadic data–which are not independent nor identically distributed. There is an available, open source computer packages that implements this approach.

To explore this approach in the context of international relations we conduct two broad analyses. The first is a simulation of XCLKFJDSLF. The second is a replication of five prominent studies that have been published recently using a broad range of dyadic data to draw inferences about international relations. These five studies have been replicated with the original research designs, each of which used a statistical method that assumes the dyadic data are all independent from one another. We then reanalyzed each study using the latent network approach which captures that additive and multiplicative aspects of interdependencies among the dyadic data. In every

[7]See Singer (1972) for an early description of the project and also see the project's Web site for an history and more recent efforts http://www.correlatesofwar.org/.

case, we found that the AME approach provided a) increased precision of estimation, b) better out-of-sample fits, c) evidence of 1st-, 2nd-, and 3rd-order dependencies that were overlooked in the original studies. In several cases, the new approach overturns the basic findings of the original research. This leads us to speculate that many of the findings in the international relations literature may be fragile in the sense that they only obtain under stringent assumptions that can not possibly be valid. This in turn leads to a certain arbitrariness in some research findings, which might lead to puzzles that are more apparent than real (Zinnes, 1980). At the same time, the latent factor model we present and demonstrate herein provides a way to easily examine and if necessary defeat these assumptions.

It is no longer necessary to assume that the interesting, innate interdependencies in relational data about international relations can be ignored. Nor do they have to be approximated with *ad hoc*, incomplete solutions that purport to control for dependencies (such as modifying the post-estimation standard errors of the estimated coefficients (King and Roberts, 2014)). Instead, the interdependencies may be addressed directly with additive and multiplicative effects in the context of a generalized linear model that provides more reliable inferences and better out-of-sample predictive performance, along with new substantive insights.

Appendix

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