Predicting Intrastate Conflict: Evidence from Nigeria

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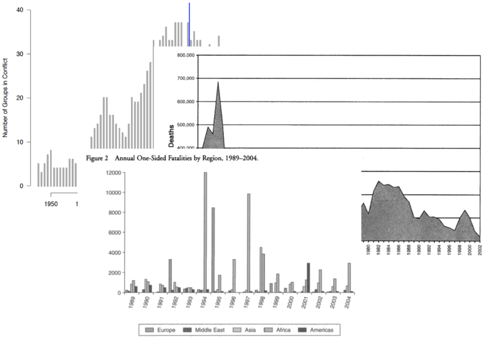
Progress in the field

Extensive literature on the causes and consequences of intrastate conflict

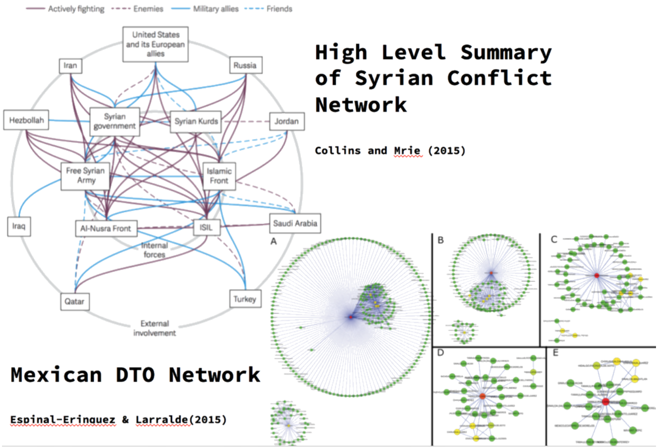
- Hegre et al. (2001)
- Fearon & Laitin (2003)
- Collier et al. (2004)
- Salehyan (2008)
- Cunningham (2013)
- Sambanis & Shayo (2013)
- Lacina (2014)
- Prorok (2016)



Primary modes of analysis: "country-year" and, more recently, the "dyad-year" (Cederman & Gleditsch 2009)

Conflicts are becoming more complex

Roughly a **third** of all intrastate conflict between 1989 and 2003 have been fought with multiple warring parties (UCDP/PRIO 2007).



Role of civilians in conflict

Focus of our project

- The role civilians play in multi-actor civil conflicts
- Network dependencies in civil conflict
- Apply this to the study of intrastate conflict in Nigeria

Civilian victimization & conflict

- Much of the civilian intrastate conflict literature has focused on what causes civilian victimization (e.g., Downes 2006; Salehyan and Wood 2015)
- Relatively, few have explored the role of civilian victimization as it relates to the potential for future conflict
- Those that do use a rebel-dyad design, and their principal argument is based on information flows:

  When insurgents kill civilians, other civilians are more likely to share information with the government.
  Information allows the government to carry out attacks against insurgents, and the lack of information makes insurgent attacks less likely.
  Thus actors are dissuaded from needlessly attacking civilians.

(Kalyvas 2006; Condra & Shapiro 2012; Berman & Matanock 2015)

Civilian victimization & conflict...in a network context

- The literature assumes conflict occurs between just a dyad or independent dyad(s): conditions that enable the government to attack rebels make the rebels less able to attack the government, and vice versa
- In a multi-actor conflict, the choice to respond to victimization by informing on the perpetrators is less clear:
  - Civilians observe that the very existence of multiple challenger groups weakens the government (Fjelde & Nilsson 2012), thus they may not turn to the government
  - Civilians may not be able to safely identify or contact the victimizers' rival rebel group
- As a result, in a multi-actor environment the countervailing effects of targeting civilians are weakened as civilians become less likely to report predation

Expectations on the role of civilians in a multi-actor conflict

- Role of civilians as an information source diminishes, thus actors targeting civilians are not going to be any less likely to initiate conflicts in the future
- Civilians once again become passive actors

From dyads to networks

Dyadic data consists of a set of:

- nodes (e.g., rebel group actors)
- measurements specific to a pair of actors (e.g., the occurrence of a battle)

Sender	Receiver	Event
i	j	y_{ij}
$\vdots$	k	y_{ik}
	l	y_{il}
j	i	y_{ji}
$\vdots$	k	y_{jk}
	l	y_{jl}
k	i	y_{ki}
$\vdots$	j	y_{kj}
	l	y_{kl}
l	i	y_{li}
$\vdots$	j	y_{lj}
	k	y_{lk}

$\longrightarrow$

	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

$\downarrow$

Dyadic data assumptions

GLM: $y_{ij} \sim \beta^T X_{ij} + e_{ij}$

Networks typically show evidence against independence of $e_{ij} : i \neq j$

Not accounting for dependence can lead to:

- biased effects estimation
- uncalibrated confidence intervals
- poor predictive performance
- inaccurate description of network phenomena

We've been hearing this concern for decades now:

Thompson & Walker (1982)	Beck et al. (1998)	Snijders (2011)
Frank & Strauss (1986)	Signorino (1999)	Erikson et al. (2014)
Kenny (1996)	Li & Loken (2002)	Aronow et al. (2015)
Krackhardt (1998)	Hoff & Ward (2004)	Athey et al. (2016)

What network phenomena? Sender heterogeneity

Values across a row, say $\{y_{ij}, y_{ik}, y_{il}\}$, may be more similar to each other than other values in the adjacency matrix because each of these values has a common sender i

	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

What network phenomena? Receiver heterogeneity

Values across a column, say $\{y_{ji}, y_{ki}, y_{li}\}$, may be more similar to each other than other values in the adjacency matrix because each of these values has a common receiver i

	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

What network phenomena? Sender-Receiver Covariance

Actors who are more likely to send ties in a network may also be more likely to receive them

	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

What network phenomena? Reciprocity

Values of y_{ij} and y_{ji} may be statistically dependent

	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

Social Relations Model (The "A" in AME)

Additive effects portion of AME (Warner et al. 1979; Li & Loken 2002):

$$
\begin{aligned}
y_{ij} &= \mu + e_{ij} \\
e_{ij} &= a_i + b_j + \epsilon_{ij} \\
\{(a_1, b_1), \ldots, (a_n, b_n)\} &\sim N(0, \Sigma_{ab}) \\
\{(\epsilon_{ij}, \epsilon_{ji}) : \; i \neq j\} &\sim N(0, \Sigma_\epsilon), \text{ where}
\end{aligned}
$$

$$
\Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \qquad \Sigma_\epsilon = \sigma_\epsilon^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}
$$

- μ baseline measure of network activity (for the purpose of regression we turn this into $\boldsymbol{\beta}^T \mathbf{X}_{ij,t}$)
- e_{ij} residual variation that we will use the SRM to decompose

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- row/sender effect (a_i) & column/receiver effect (b_j)
- Modeled jointly to account for correlation in how active an actor is in sending and receiving ties

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$$

- σ_a^2 and σ_b^2 capture heterogeneity in the row and column means
- 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)

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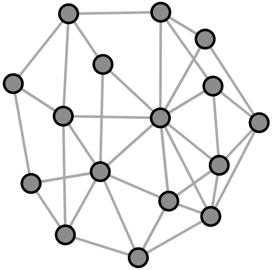
\Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \qquad \Sigma_\epsilon = \sigma_\epsilon^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}
$$

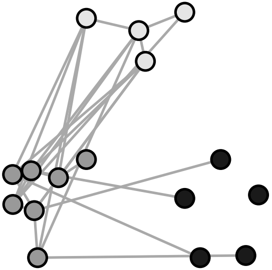
- ϵ_{ij} captures the within dyad effect
- Second-order dependencies are described by σ_ϵ^2
- Reciprocity, aka within dyad correlation, represented by ρ

Third Order Dependencies

HOMOPHILY



STOCHASTIC EQUIVALENCE



To account for these patterns we can build on the SRM framework and find an expression for γ:

$$y_{ij} \approx \beta^T X_{ij} + a_i + b_j + \gamma(u_i, v_j)$$

Latent Factor Model: The "M" in AME

Each node i has an unknown latent factor

$$\mathbf{u}_i, \mathbf{v}_j \in \mathbb{R}^k \quad i, j \in \{1, \ldots, n\}$$

The probability of a tie from i to j depends on their latent factors

$$\begin{aligned} \gamma(\mathbf{u}_i, \mathbf{v}_j) &= \mathbf{u}_i^T D \mathbf{v}_j \\ &= \sum_{k \in K} d_k u_{ik} v_{jk} \end{aligned}$$

D is a $K \times K$ diagonal matrix

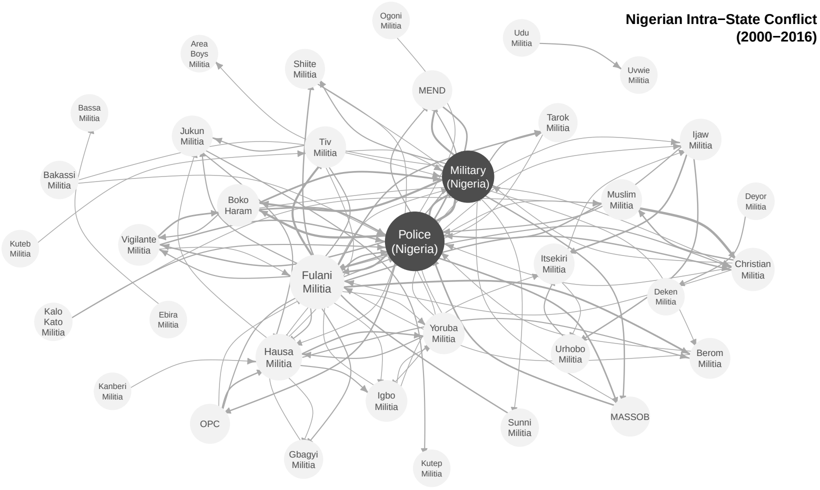
Accounts for both stochastic equivalence and homophily (Hoff 2008)

Additive and Multiplicative Effects (AME) Model

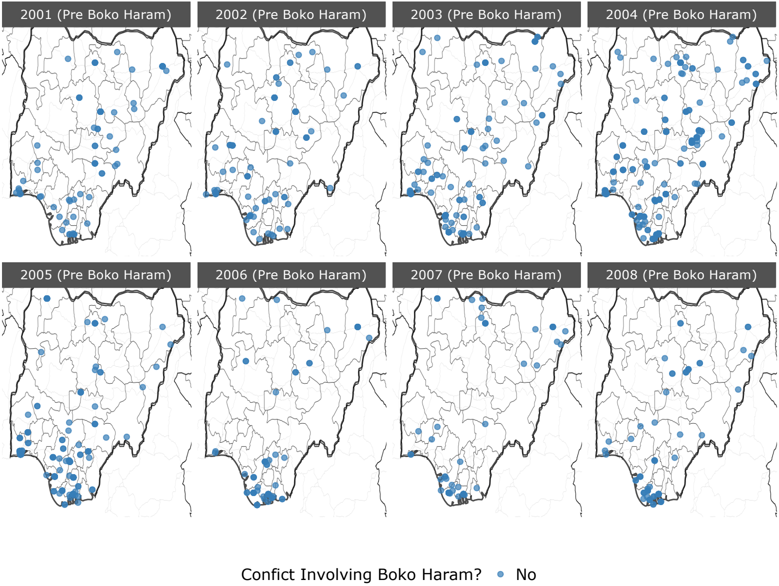
$$
\begin{aligned}
y_{ij,t} &= g(\theta_{ij,t}) \\
\theta_{ij,t} &= \boldsymbol{\beta}^T \mathbf{X}_{ij,t} + e_{ij,t} \\
e_{ij,t} &= a_i + b_j + \epsilon_{ij} + \alpha(\mathbf{u}_i, \mathbf{v}_j) \text{ , where} \\
\alpha(\mathbf{u}_i, \mathbf{v}_j) &= \mathbf{u}_i^T \mathbf{D} \mathbf{v}_j = \sum_{k \in K} d_k u_{ik} v_{jk}
\end{aligned}
$$

(Hoff 2005; Hoff 2008; Hoff et al. 2013; Minhas et al. 2016)

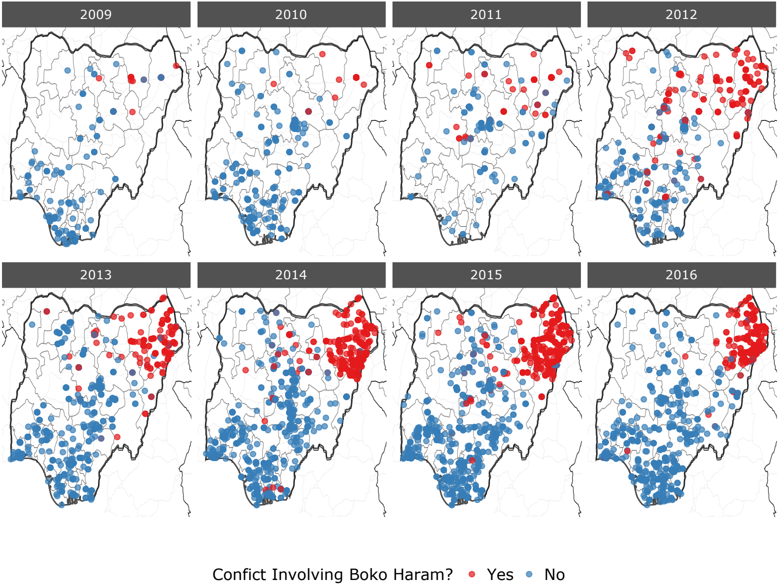
Application case: Nigerian intrastate conflict system



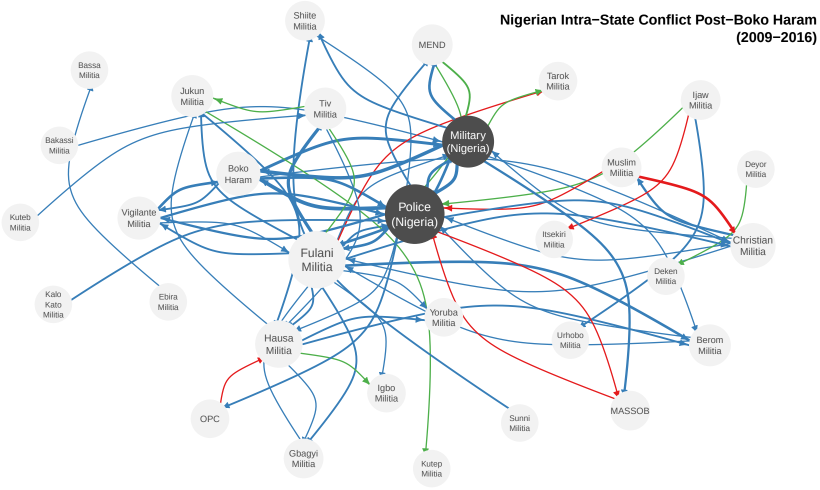
Spatial Distribution of Conflict Pre Boko Haram



Spatial Distribution of Conflict Post Boko Haram



Boko Haram's Entrance in Network



Data

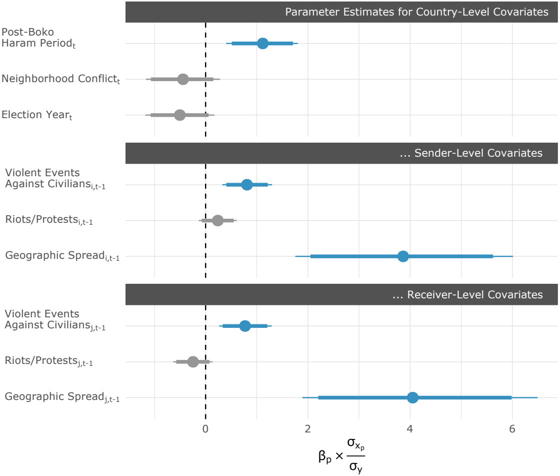
Armed Conflict Location and Event Data Project (ACLED) developed by Raleigh et al. (2010)

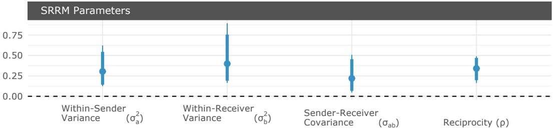
- ACLED records armed conflict and protest events in over 60 developing countries
- We use ACLED *battles* data for Nigeria to generate a measure of conflict where:
  - $y_{ij,t} = 1$ indicates that a conflict occurred when actor i attacked actor j at time t
  - $y_{ij,t} = 0$ if no conflict occurred
- We focus only on modeling the interactions between armed groups that are engaged in battles for at least 5 years during the 2000-2016 period, which results in a total of 37 armed groups

Covariates

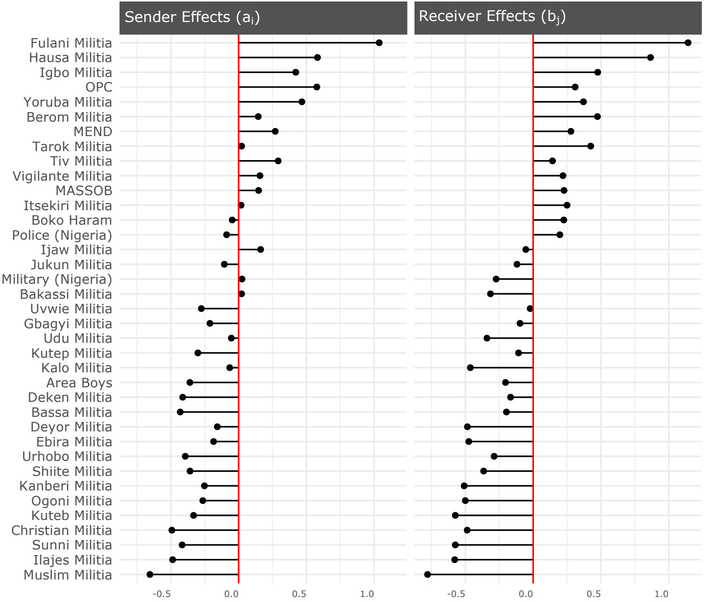
- Country-Level covariates:
  - Post Boko-Haram
  - Neighborhood conflict
  - Election year
- Sender and Receiver-Level Covariates:
  - Violence against civilians
  - Riots/Protests directed against actor
  - Geographic spread

Model Results



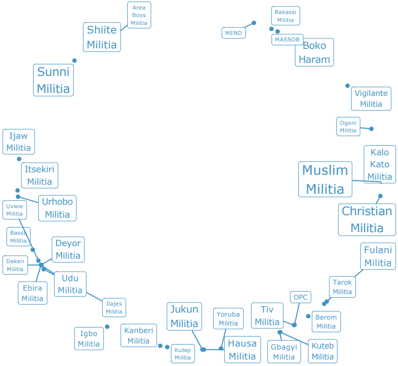


Additive Sender/Receiver Random Effects

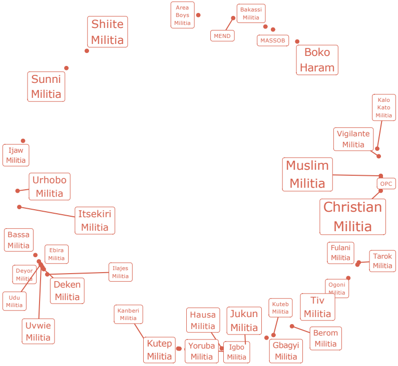


Multiplicative Effects

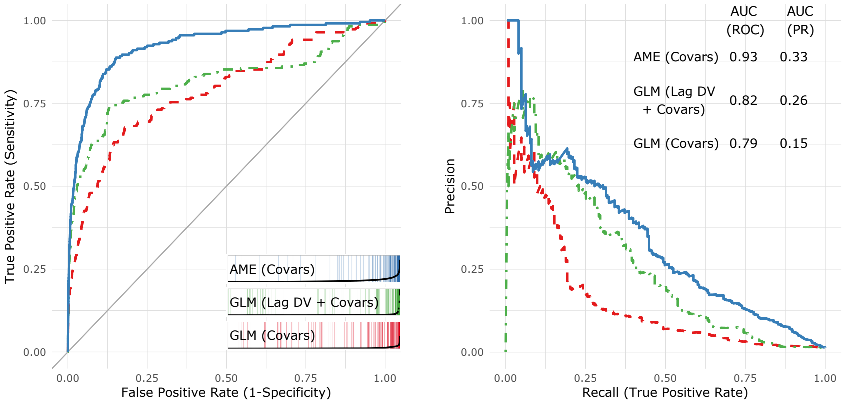
Groups with Common Sending Patterns (u_i)



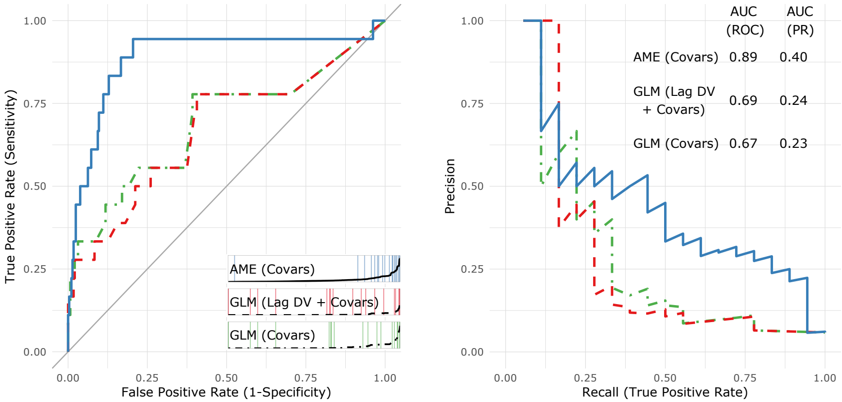
Groups with Common Receiving Patterns (v_j)



Out of Sample Cross-Validation

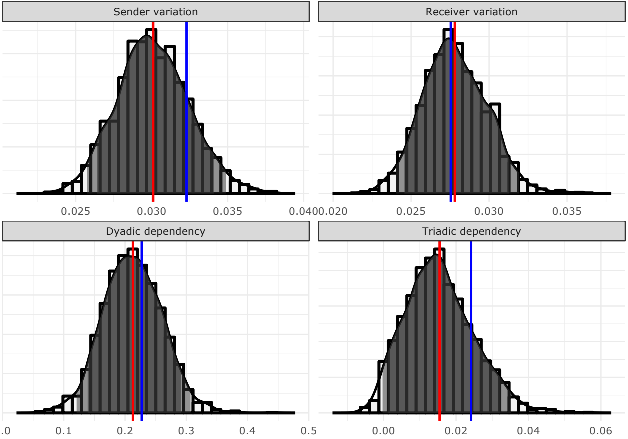


Out of Sample Forecast



Thanks.

Network GOF



Blue line denotes actual value and red denotes mean of simulated.
Shaded interval represents 90 and 95 percent credible intervals.