

# PREDICTING VIOLENCE: NETWORK DYNAMICS IN NIGERIA

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Cassy Dorff (University of New Mexico),  
Max Gallop (University of Strathclyde),  
and Shahryar Minhas (Michigan State University)

OCTOBER 9, 2017

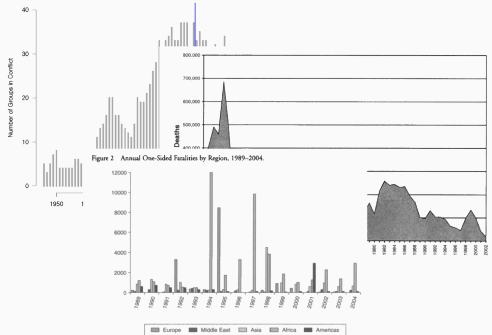
# Motivation

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# Intrastate War

Extensive literature on the causes and prediction of intrastate conflict

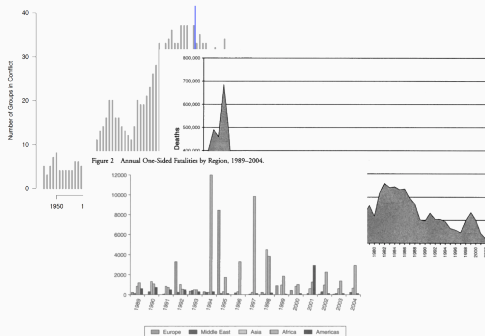
Hegre et al. (2001)  
Fearon & Laitin (2003)  
Collier et al. (2004)  
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Fearon & Laitin (2003) has been cited over 6,000 times!

# Conflicts are complex: unpacking social structure

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

Conflicts involve multiple actors with changing relationships overtime

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Conflicts involve multiple actors with changing relationships overtime

- Coordination (Bakke et al 2012; Findley & Rudloff, 2012)
- Spoiler groups and veto-players (Cunningham, 2006)
- Disaggregating actors (Shellman et al, 2010)

*“Existence of **multiple rebel groups** means we can no longer understand civil wars with a sole focus on state attributes. In fact, the government’s strategies leading to victory, defeat, or continuation of war can only be understood **in relation to** the rebel group/groups it is fighting.”*

Akcinaroglu (2012)

Conflict processes are driven by the evolution of relationships overtime.

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**Conflict processes are driven by the evolution of relationships overtime.**

1. Intrastate conflicts → single complex system composed of multiple actors in conflict
2. Armed actors & battles = nodes and ties in a network
3. Novel model captures relationships endogenous to the conflict system
4. Our approach provides precise estimates, & out performs standard approaches
5. Uncovers important patterns of conflict with substantive implications for the study of conflict processes

# Networks & Conflict Processes

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# From dyads to networks

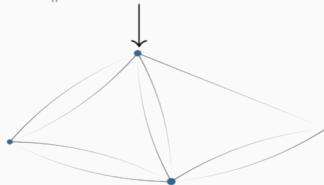
Dyadic data consists of a set of:

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

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



	$i$	$j$	$k$	$l$
$i$	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



How does evolution in the structure of relationships influence conflict over time?

- 1st-order: Sender effects
- 2nd-order: Reciprocity
- 3rd-order: Homophily & Stochastic equivalence
- System level: Changing actor composition

# 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



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

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

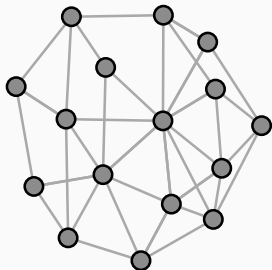
# Network phenomena: reciprocity

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

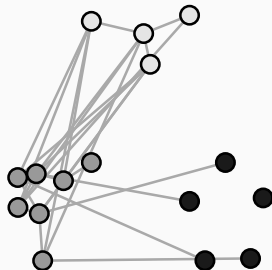
	$i$	$j$	$k$	$l$
$i$	NA	$y_{ij}$	$y_{ik}$	$y_{il}$
$j$	$y_{ji}$	NA	$y_{jk}$	$y_{jl}$
$k$	$y_{ki}$	$y_{kj}$	NA	$y_{kl}$
$l$	$y_{li}$	$y_{lj}$	$y_{lk}$	NA

# Network phenomena: third order dependencies

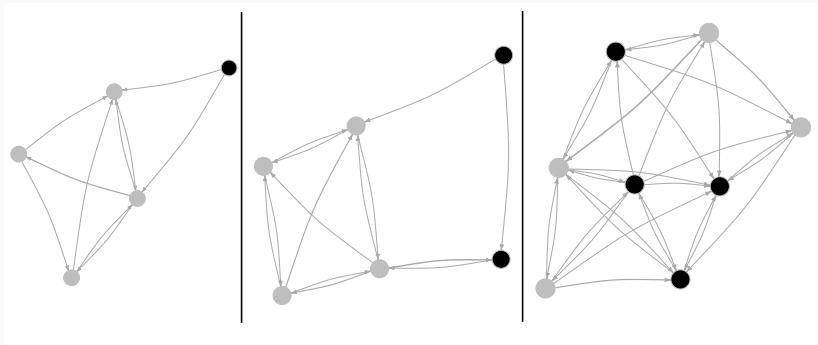
HOMOPHILY



STOCHASTIC EQUIVALENCE



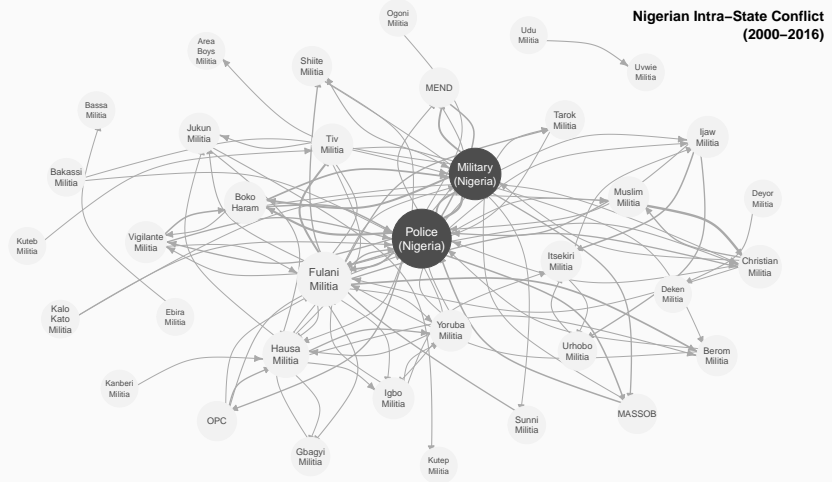
# Network phenomena: changing actor composition



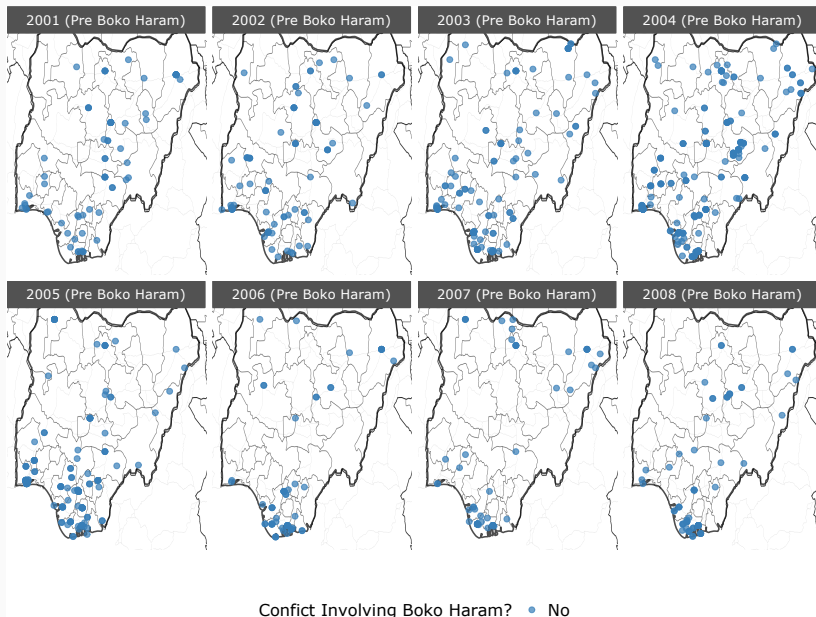
# Nigeria

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## Intrastate Conflict Case: Nigerian intrastate conflict system

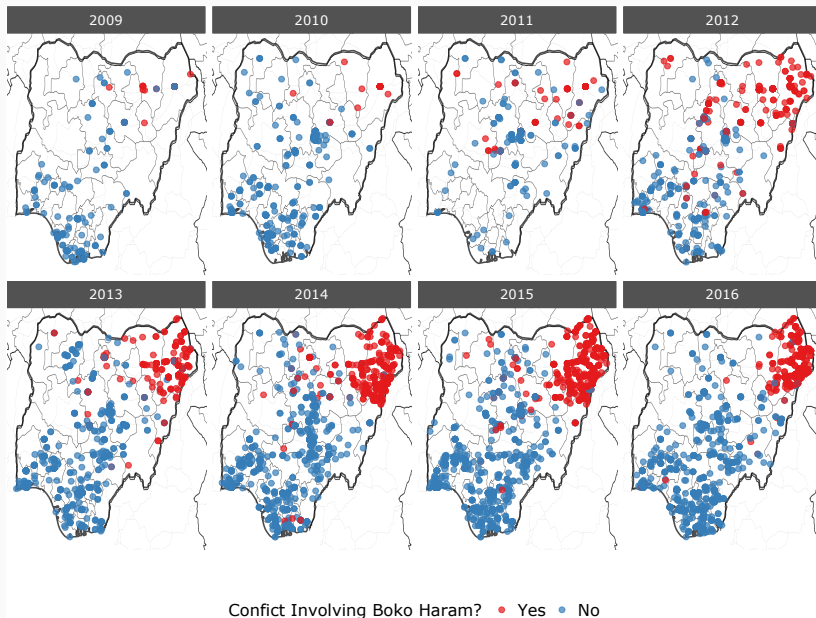


# Spatial Distribution of Conflict Pre Boko Haram





# Spatial Distribution of Conflict Post Boko Haram



## Modeling Approach & Results

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# Social Relations Model (The “A” in AME)

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

$$y_{ij} = \mu + e_{ij}$$

$$e_{ij} = a_i + b_j + \epsilon_{ij}$$

$$\{(a_1, b_1), \dots, (a_n, b_n)\} \sim N(0, \Sigma_{ab})$$

$$\{(\epsilon_{ij}, \epsilon_{ji}) : i \neq j\} \sim N(0, \Sigma_{\epsilon}), \text{ where}$$

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

- $\mu$  baseline measure of network activity (for the purpose of regression we turn this into  $\beta^T \mathbf{x}_{ij,t}$ )
- $e_{ij}$  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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- $\sigma_a^2$  and  $\sigma_b^2$  capture heterogeneity in the row and column means
- $\sigma_{ab}$  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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$$y_{ij} = \mu + e_{ij}$$

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- $\epsilon_{ij}$  captures the within dyad effect
- Second-order dependencies are described by  $\sigma_{\epsilon}^2$
- Reciprocity, aka within dyad correlation, represented by  $\rho$

# Latent Factor Model: The “M” in AME

Each node  $i$  has an unknown latent factor

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

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

$$y_{ij,t} = g(\theta_{ij,t})$$

$$\theta_{ij,t} = \beta^T \mathbf{x}_{ij,t} + e_{ij,t}$$

$$e_{ij,t} = a_i + b_j + \epsilon_{ij} + \alpha(\mathbf{u}_i, \mathbf{v}_j), \text{ where}$$

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

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

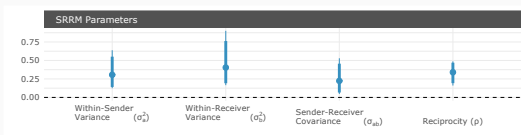
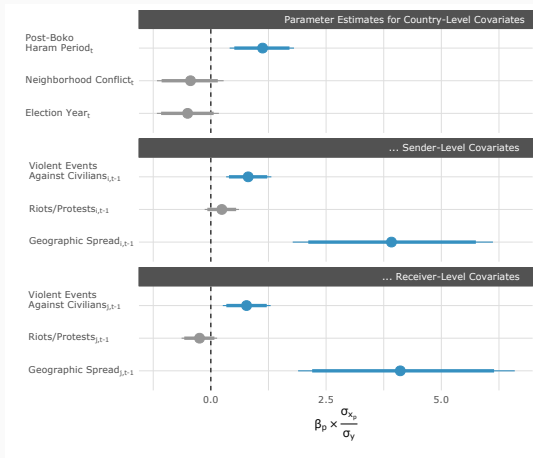


Armed Conflict Location and Event Data Project (ACLED) developed by Raleigh et al. (2010)

- 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

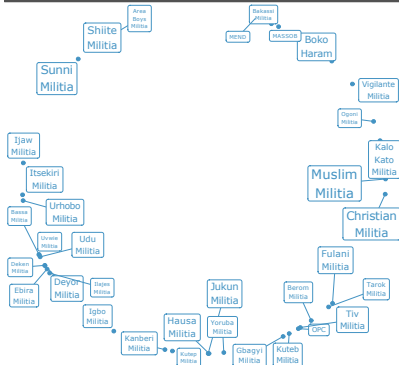
- Country-Level covariates:
  - Post Boko-Haram
  - Neighborhood conflict
  - Election year
- Sender and Receiver-Level Covariates:
  - Violence against civilians
  - Riots/Protests directed against actor
  - Geographic spread

# Model Results

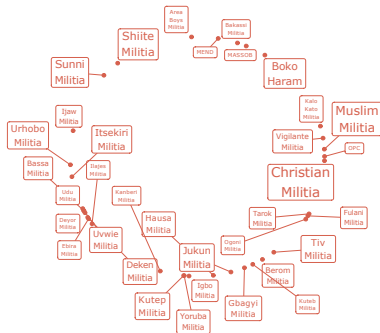


# Multiplicative Effects

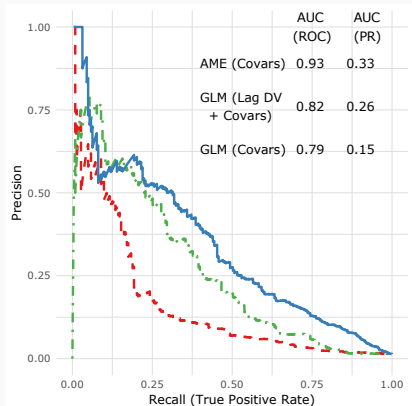
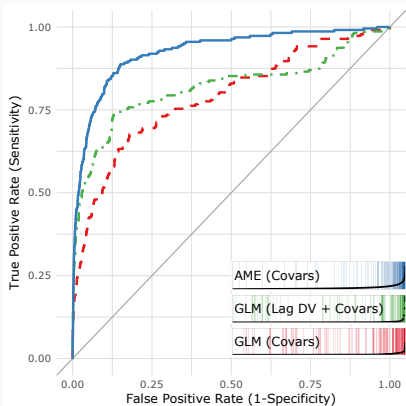
Groups with Common Sending Patterns ( $u_i$ )



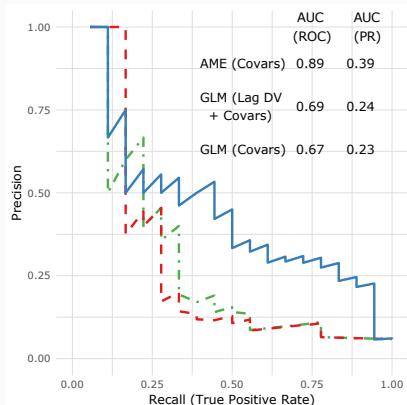
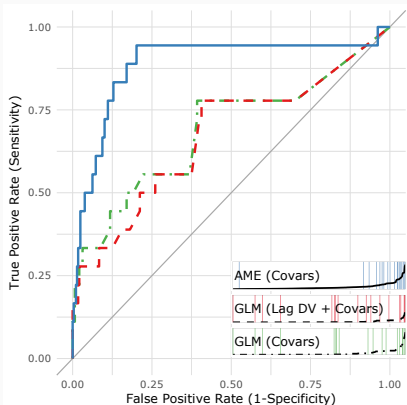
Groups with Common Receiving Patterns ( $v_j$ )



# Out of Sample Cross-Validation



# Out of Sample Forecast



## Key take-aways & future work

CONFIRMED: Structure of relationships influences violence between actors

CONFIRMED: Key players can alter violence in the conflict system, even in warring dyads the key player is not directly involved in.

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Do “people-power” movements matter in multi-actor civil conflicts?

Why does violence against civilians increase an actor’s conflictual behavior towards armed groups?

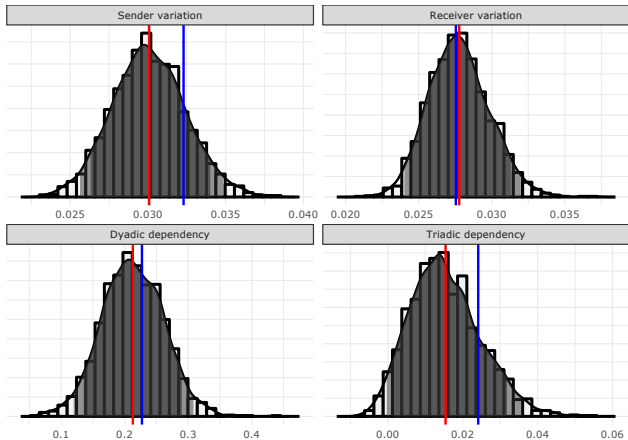
Does our “key player” effect matter in other conflict settings?

Thanks!

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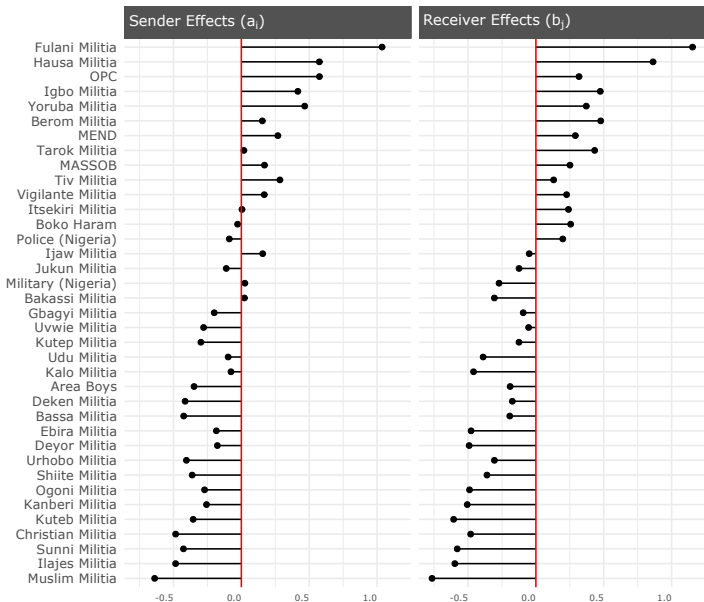


# Network GOF



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

# Additive Sender/Receiver Random Effects



# Dyadic data assumptions

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

Networks typically show evidence against independence of dyadic interactions

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)

Hoa & Ward (2004)

Athey et al. (2016)

# Boko Haram's Entrance in Network

