Me

# Predicting Intrastate Conflict: Evidence from Nigeria

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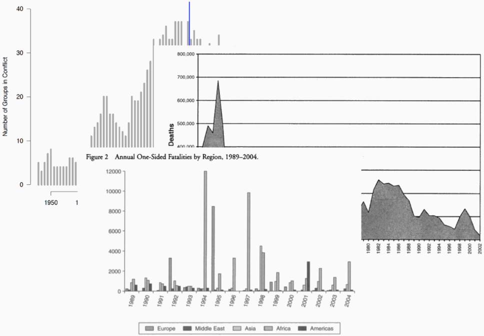
# Motivation

# Intrastate War

Extensive literature on the causes and prediction of intrastate conflict

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



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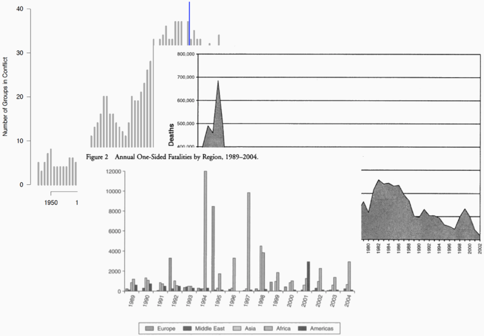


Fearon & Laitin (2003) has been cited over 6,000 times!

# Conflicts are complex

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

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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)

# Pairing Empirical Analysis to Theory

*"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)

# Our Project

Conflict processes are driven by the evolution of relationships overtime.

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# Our Project

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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

# 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 |

$\downarrow$

# Network Effects

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 $i$

| | $i$ | $j$ | $k$ | $l$ |
|---|---|---|---|---|
| $i$ | 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: 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 | $y_{kl}$ |
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# 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 | $y_{kl}$ |
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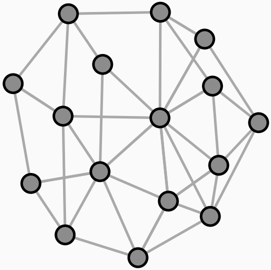
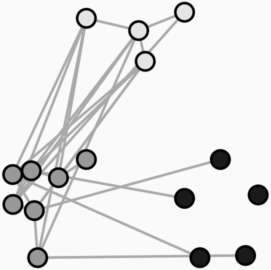
# Network phenomena: third order dependencies

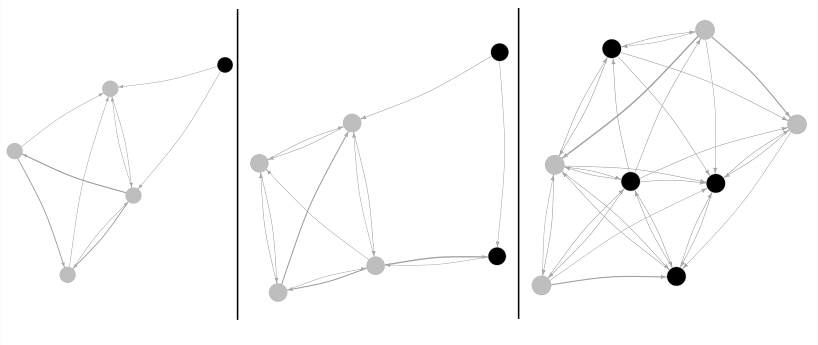
Homophily



Stochastic Equivalence

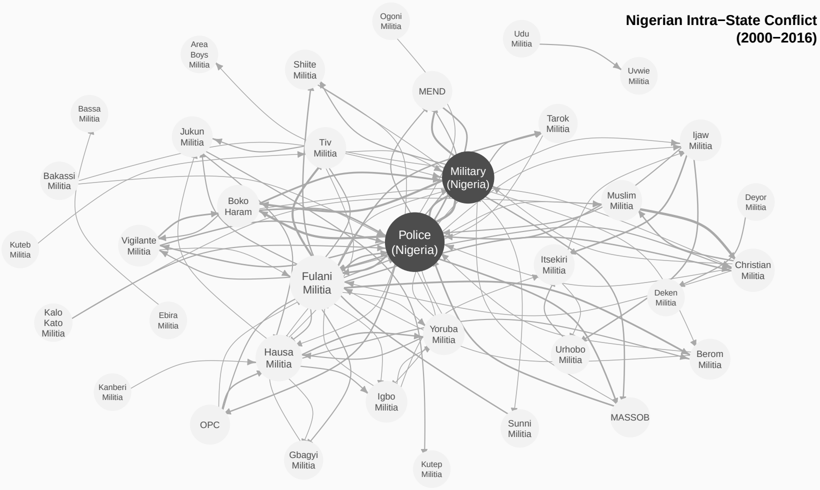


# Network phenomena: changing actor composition

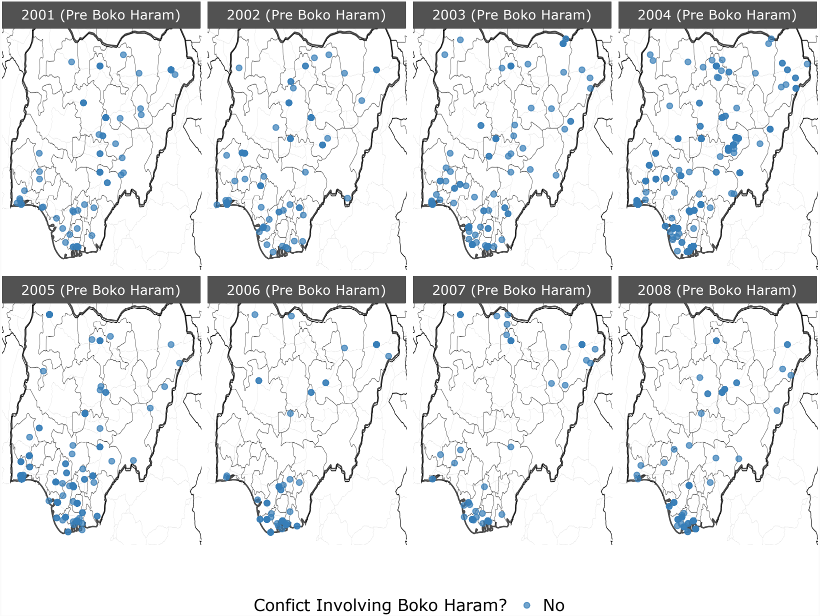


# Nigeria

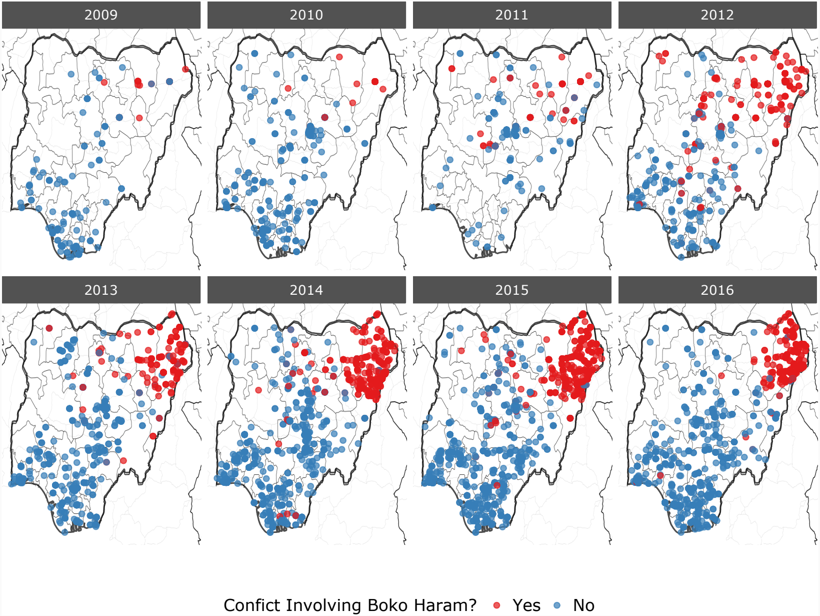
# Intrastate Conflict Case: Nigerian intrastate conflict system



# Spatial Distribution of Conflict Pre Boko Haram



# Spatial Distribution of Conflict Post Boko Haram



# Modeling Approach & Results

# Social Relations Model (The "A" in AME)

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

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

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

- $\mu$ 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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$$

- $\sigma_a^2$ 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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\end{aligned}
$$

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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}
$$

- $\epsilon_{ij}$ 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

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

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)

# Data

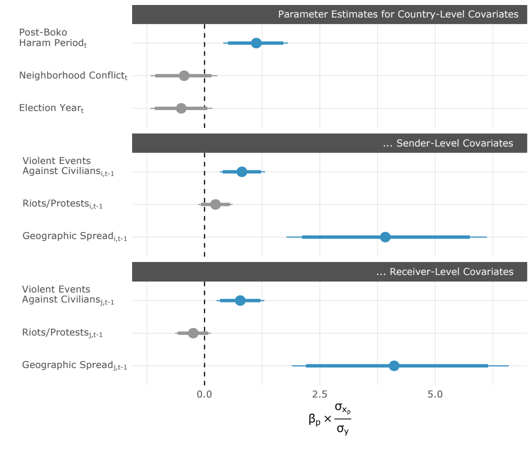
Armed Conflict Location and Event Data Project (ACLED) developed by Raleigh et al. (2010)

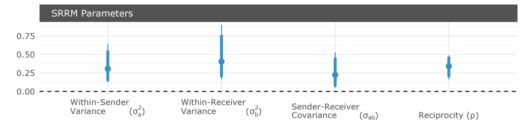
- ACLED records armed conflict and protest events in over 60 developing countries
- We use ACLED *battles* data for Nigeria to generate a measure of conflict where:
    - $y_{ij,t} = 1$ indicates that a conflict occurred when actor $i$ attacked actor $j$ at time $t$
    - $y_{ij,t} = 0$ if no conflict 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

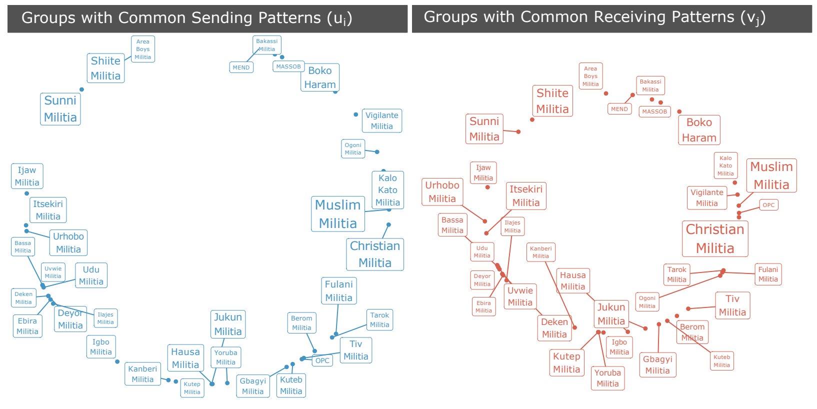
- Country-Level covariates:
  - Post Boko-Haram
  - Neighborhood conflict
  - Election year
- Sender and Receiver-Level Covariates:
  - Violence against civilians
  - Riots/Protests directed against actor
  - Geographic spread

# Model Results

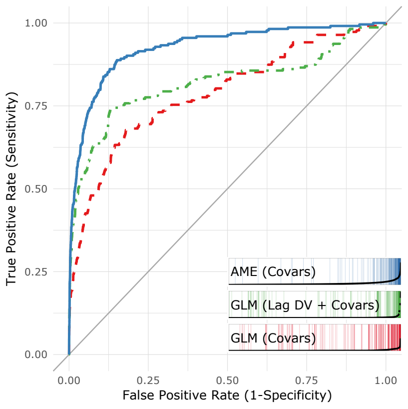


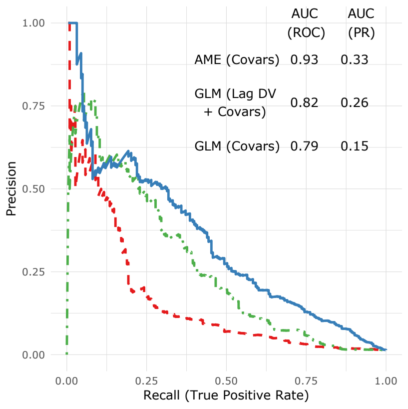



# Multiplicative Effects

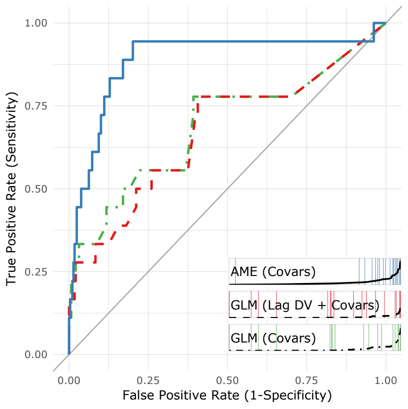


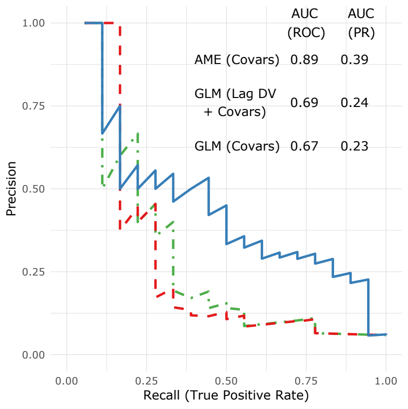
# Out of Sample Cross-Validation



# 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?

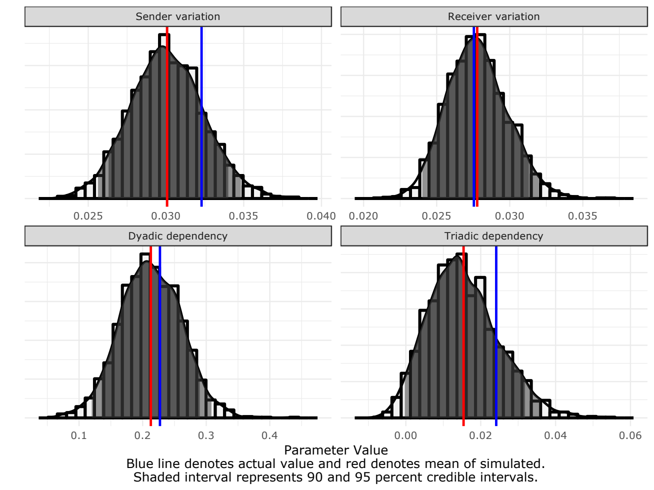
Why does violence against civilians increase an actor’s conflictual behavior towards armed groups?

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

# Thanks!

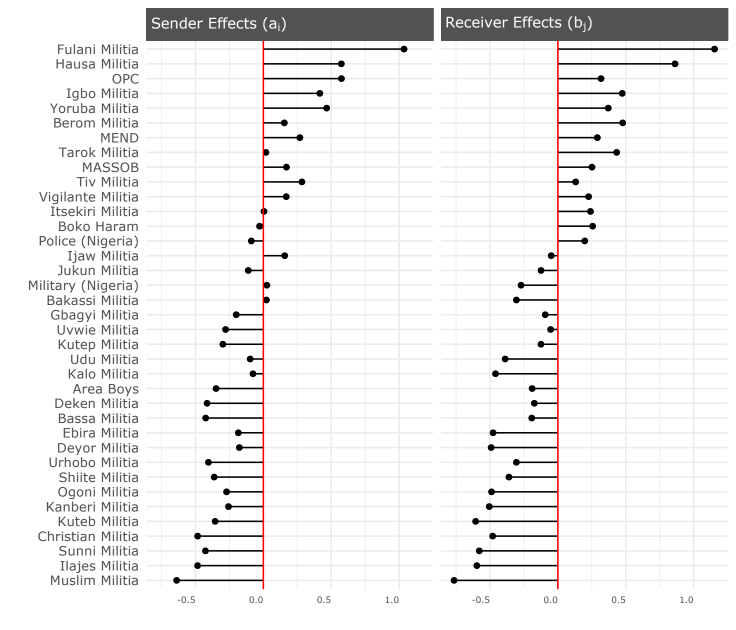
CASSYDORFF.COM

# Network GOF



Sender variation
Receiver variation
Dyadic dependency
Triadic dependency
0.025
0.030
0.035
0.040
0.020
0.025
0.030
0.035
0.1
0.2
0.3
0.4
0.00
0.02
0.04
0.06
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)
Frank & Strauss (1986)
Kenny (1996)
Krackhardt (1998)
Beck et al. (1998)
Signorino (1999)
Li & Loken (2002)
Hoa & Ward (2004)
Snijders (2011)
Erikson et al. (2014)
Aronow et al. (2015)
Athey et al. (2016)

# Boko Haram's Entrance in Network