Predicting Violence: Network Dynamics in Nigeria

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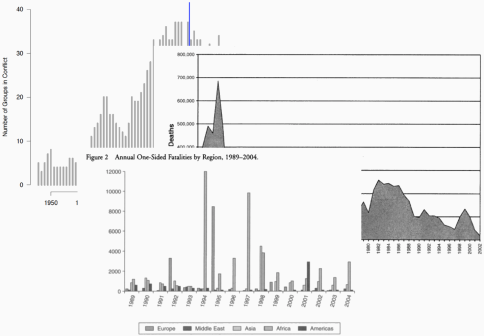
Motivation

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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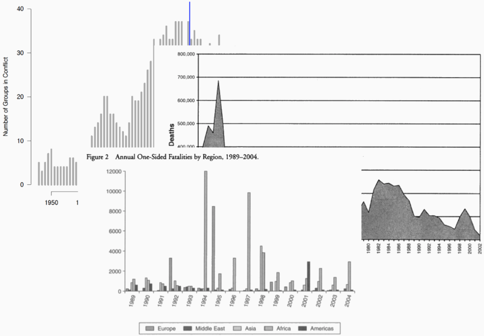

Fearon & Laitin (2003) has been cited over 6,000 times!

Conflicts are Complex: 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 (Weinstein 2007, 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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2. Armed actors & battles = nodes and ties in a network
3. Novel model captures relationships endogenous to the conflict system
4. Our approach provides unbiased parameter estimates & out performs standard approaches

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1. Intrastate conflicts $\rightarrow$ 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 relational 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

Network Effects & Social Structure

Missing information in previous work: 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

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

Network Phenomena: Second-order effect (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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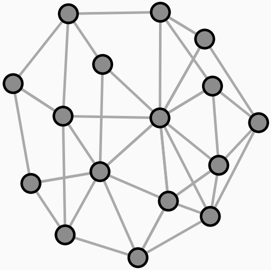
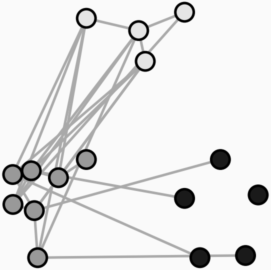
Network Phenomena: Third Order Dependencies

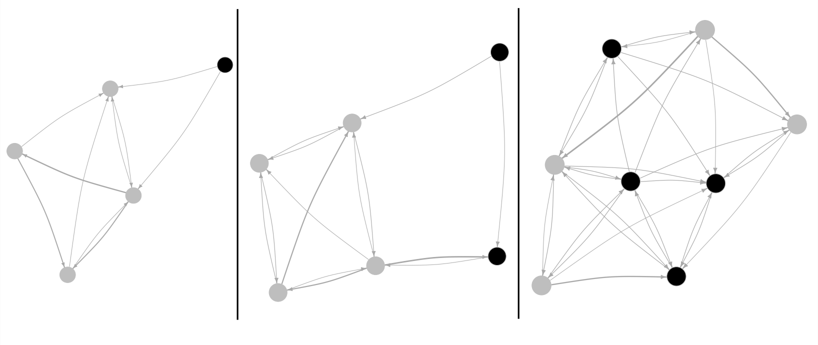
Homophily



Stochastic Equivalence



Network Phenomena: Changing Actor Composition



Model: The Latent Factor Model

Social Relations Model (The "A" in AME)

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

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

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

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

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

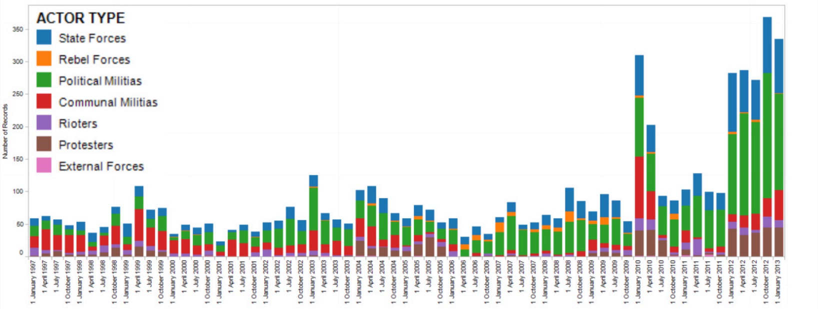
(Hoff 2005; Hoff 2008; Hoff et al. 2013; Minhas et al. 2016)
R software: AMEN

Nigeria

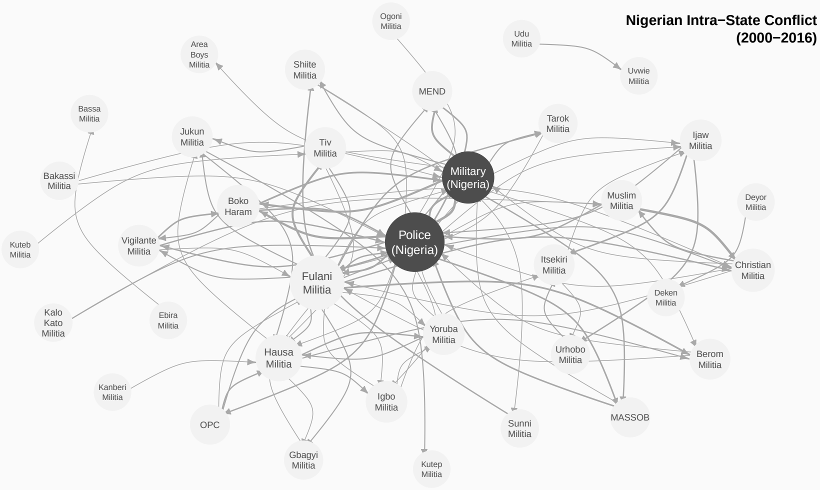
Intrastate Conflict: Nigeria's Intrastate Conflict System

Complex, multi-actor conflict

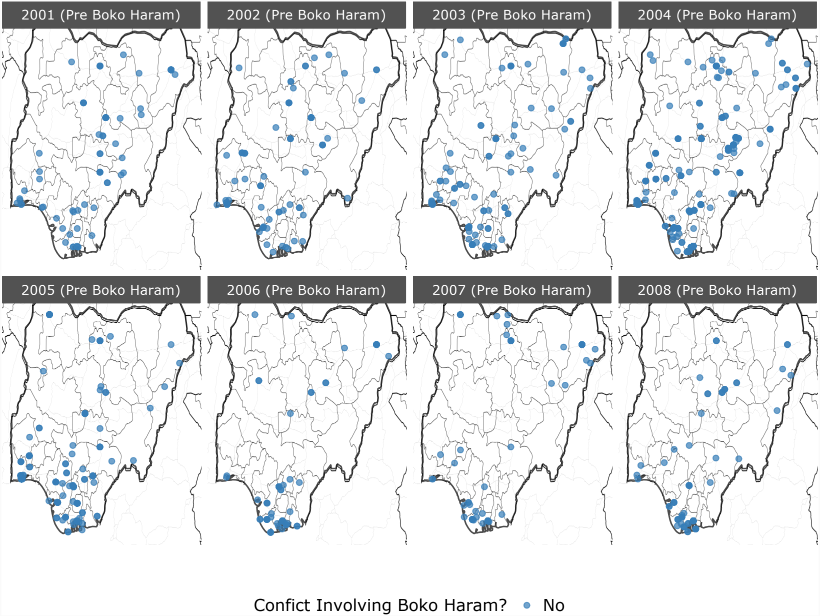
- numerous violent political groups including ethnic militias, militant regional groups and Islamist insurgents
- political violence of all types has risen substantially since 2011 with violence against civilians seeing the most dramatic increase.



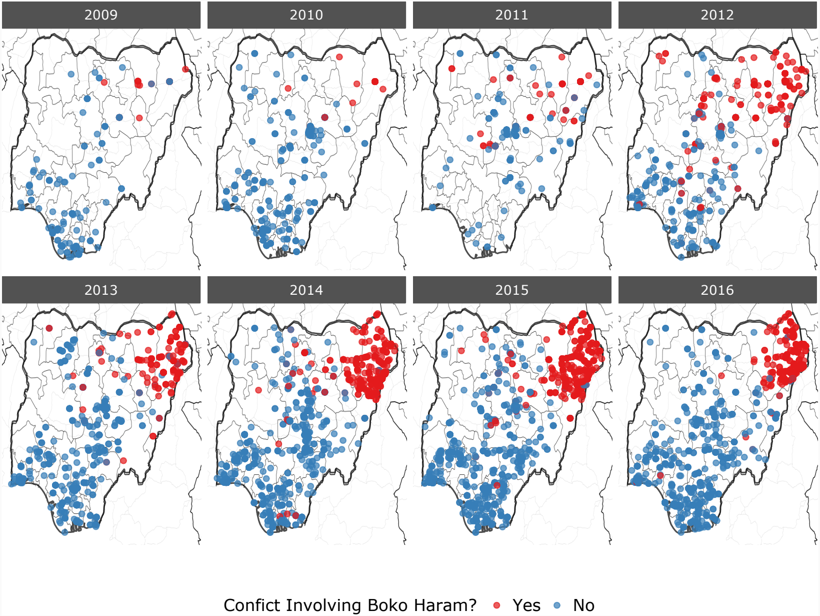
Intrastate Conflict: Nigeria’s Intrastate Conflict System



Spatial Distribution of Conflict Pre Boko Haram



Spatial Distribution of Conflict Post Boko Haram



Recap: Expectations for the Nigerian Case

How do network dynamics influence the likelihood of conflict?

- Sender/reciever effects
- Reciprocity
- Homophily & stochastic equivalence
- Key Actor entry: aggressive new actors signal government weakness

Data

Data

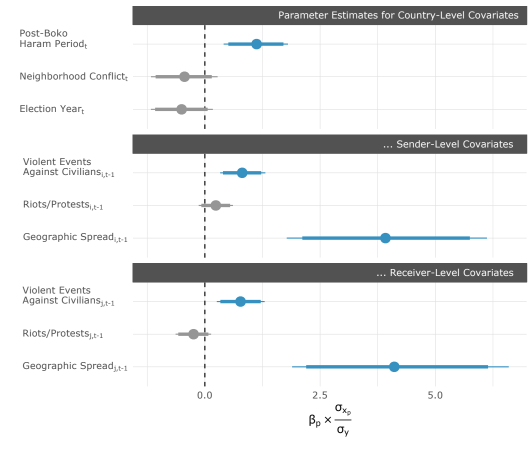
Armed Conflict Location and Event Data Project (ACLED) developed by Raleigh et al. (2010)

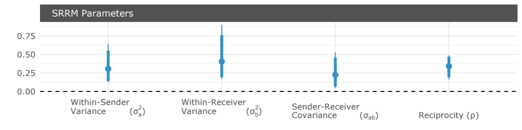
- ACLED records armed conflict and protest events in over 60 developing countries
- We use ACLED *battles* data for Nigeria to generate a measure of conflict where:
  - $y_{ij,t} = 1$ indicates that a conflict occurred when actor i attacked actor j at time t
  - $y_{ij,t} = 0$ if no conflict occurred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

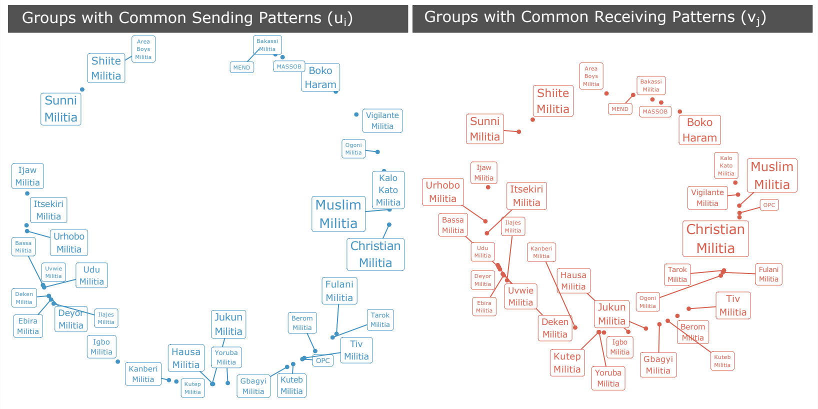
- Country-Level covariates:
    - Post Boko-Haram
    - Neighborhood conflict
    - Election year
- Sender and Receiver-Level Covariates:
    - Violence against civilians
    - Riots/Protests directed against actor
    - Geographic spread

Model Results

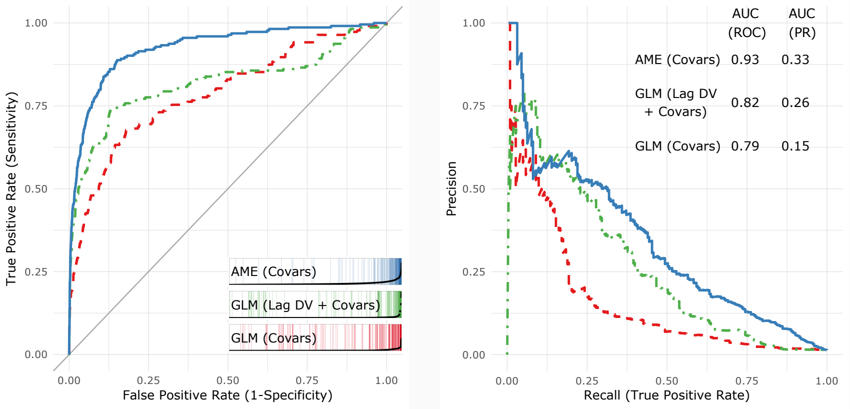




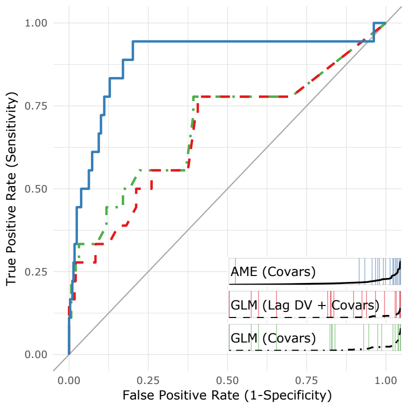
Multiplicative Effects

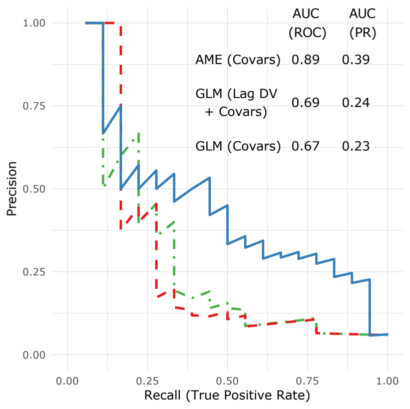


Out of Sample Cross-Validation



Out of Sample Forecast





Key Take-Aways

CONFIRMED: Intrastate conflict is a network process! Structure of relationships influences violence between actors (reciprocity and warring communities characterize social patterns in the data).

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

CONFIRMED: Network model of conflict out performs standard approaches.

Future Work: Conflict Processes Revealed

Are “people-power” movements less effective 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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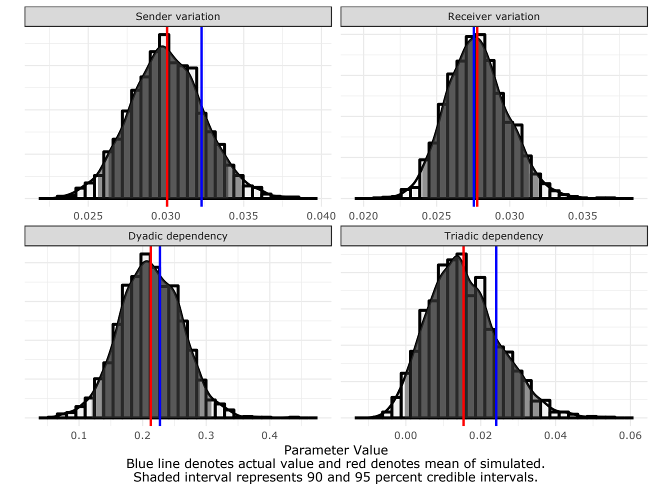
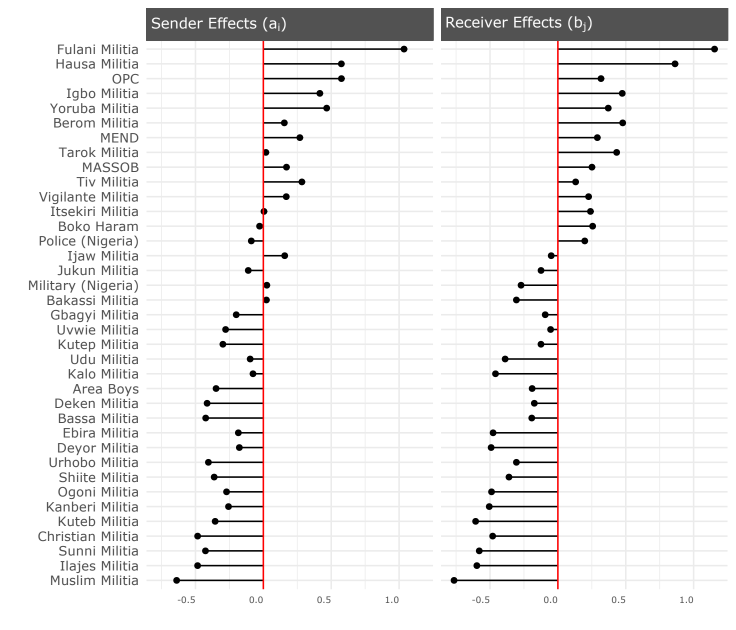
Network GOF


Sender variation
Receiver variation
0.025
0.030
0.035
0.040
0.020
0.025
0.030
0.035
Dyadic dependency
Triadic dependency
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:

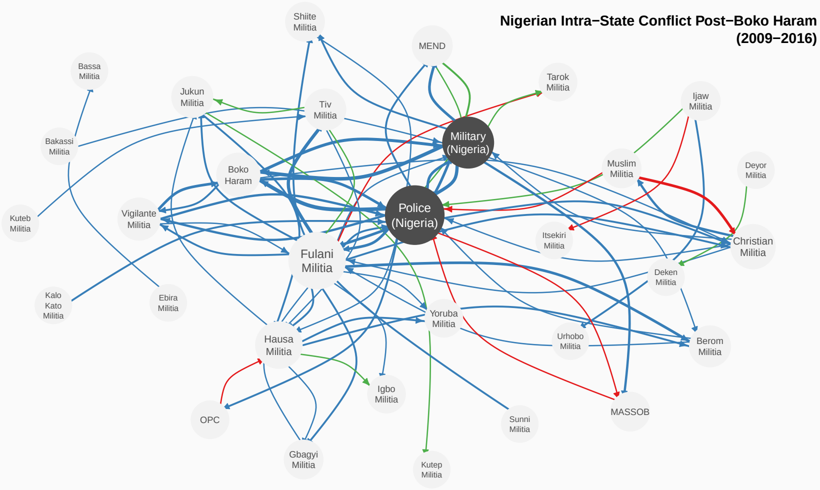
Thompson & Walker (1982)	Beck et al. (1998)	Snijders (2011)
Frank & Strauss (1986)	Signorino (1999)	Erikson et al. (2014)
Kenny (1996)	Li & Loken (2002)	Aronow et al. (2015)
Krackhardt (1998)	Hoa & Ward (2004)	Athey et al. (2016)

ACLED Data - Nigeria

Data collection

- Battles are violent clashes between at least two armed groups.
- Battles make up approximately one third of the dataset.
- Data types: civic society (reports, NGOs), media (newspapers), Analysts (specialists' reports), governing bodies (UN reports), "Local source project" (ACLED is connected with local sources)
- Analysis of data does not reveal urban bias

Boko Haram’s Entrance in Network



ERGMs

ERGMs are useful when researchers are interested in the role that a specific list of network statistics have in giving rise to a certian network. (Such as: number of transitive triads in a network, balanced triads, reciprocal pairs, etc.)

- ERGMs provide a way to find the probability of a network given the patterns it exhibits
- the researcher must specify which network statistics should give rise to a particular network of interest