

PREDICTING INTRASTATE CONFLICT: EVIDENCE FROM NIGERIA

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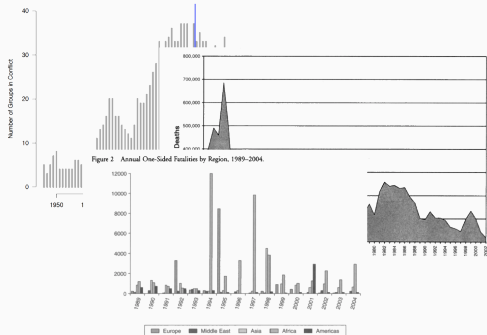
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Motivation

Intrastate War

Extensive literature on the causes and prediction of intrastate conflict

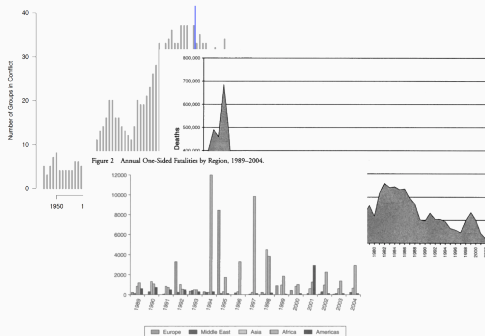
Hegre et al. (2001)
Fearon & Laitin (2003)
Collier et al. (2004)
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Fearon & Laitin (2003) has been cited over 6,000 times!

Conflicts are complex

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

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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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

From dyads to networks

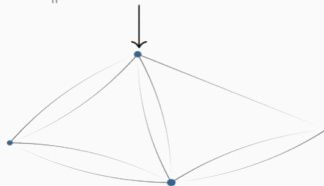
Dyadic data consists of a set of:

- 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}
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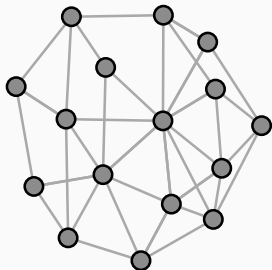
Network phenomena: reciprocity

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

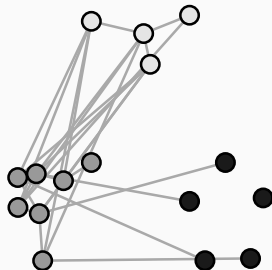
	i	j	k	l
i	NA	y_{ij}	y_{ik}	y_{il}
j	y_{ji}	NA	y_{jk}	y_{jl}
k	y_{ki}	y_{kj}	NA	y_{kl}
l	y_{li}	y_{lj}	y_{lk}	NA

Network phenomena: third order dependencies

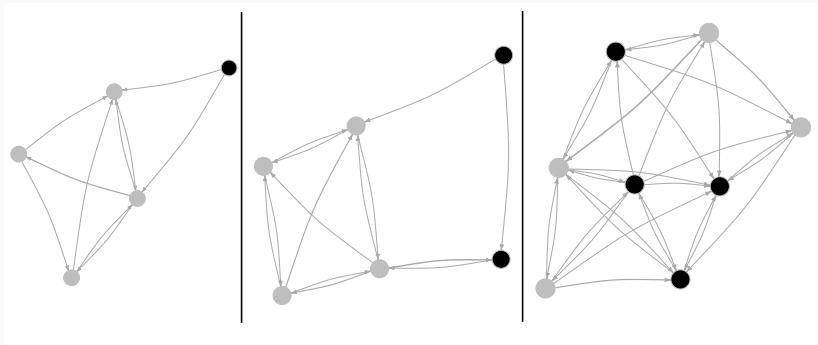
HOMOPHILY



STOCHASTIC EQUIVALENCE



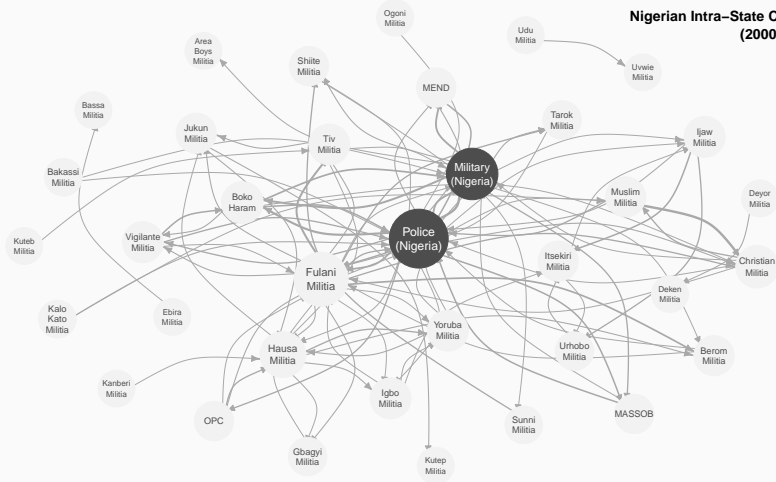
Network phenomena: changing actor composition



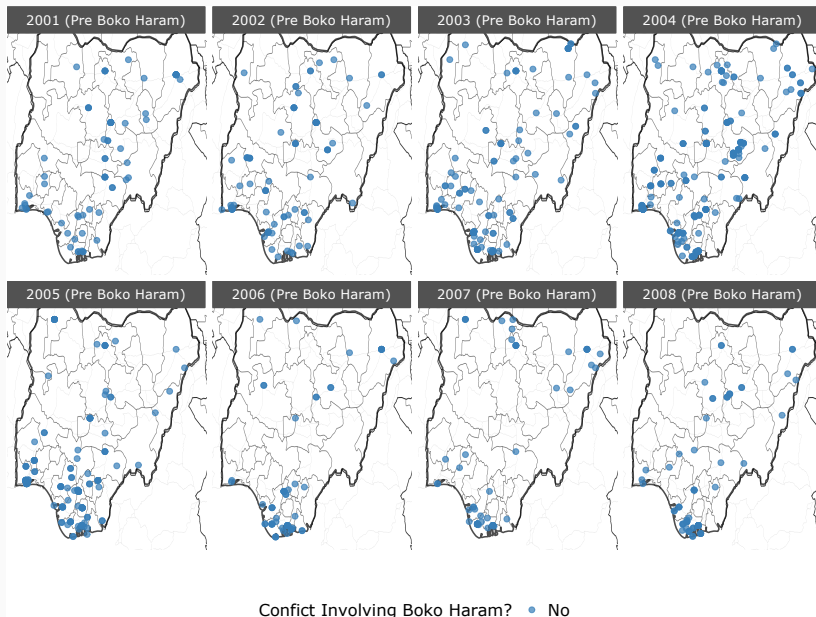
Nigeria

Intrastate Conflict Case: Nigerian intrastate conflict system

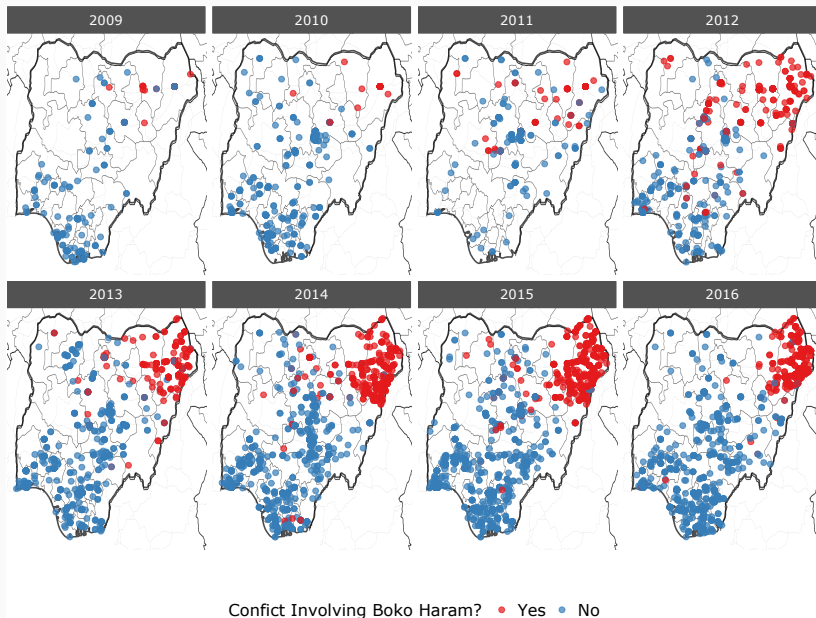
**Nigerian Intra-State Conflict
(2000–2016)**



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):

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

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

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

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

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

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

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

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

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

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

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

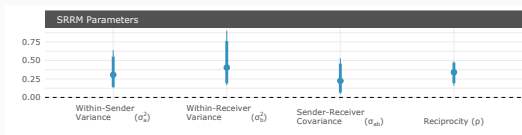
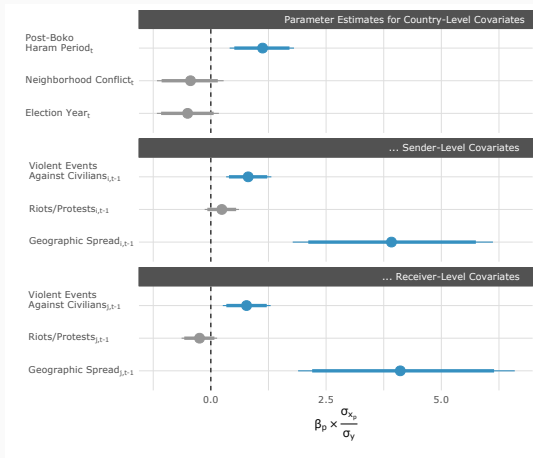
(Hoff 2005; Hoff 2008; Hoff et al. 2013; Minhas et al. 2016)

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

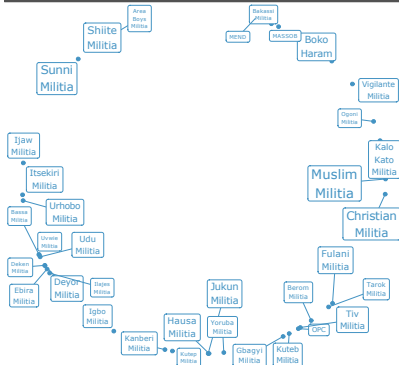
- Country-Level covariates:
 - Post Boko-Haram
 - Neighborhood conflict
 - Election year
- Sender and Receiver-Level Covariates:
 - Violence against civilians
 - Riots/Protests directed against actor
 - Geographic spread

Model Results

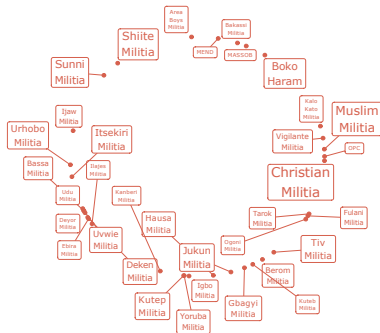


Multiplicative Effects

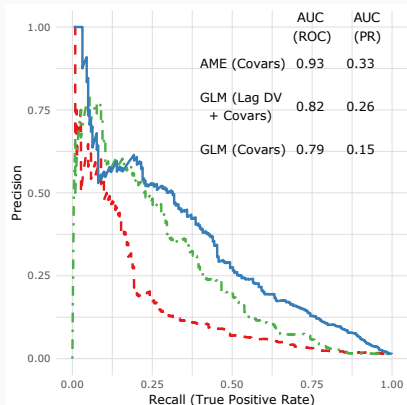
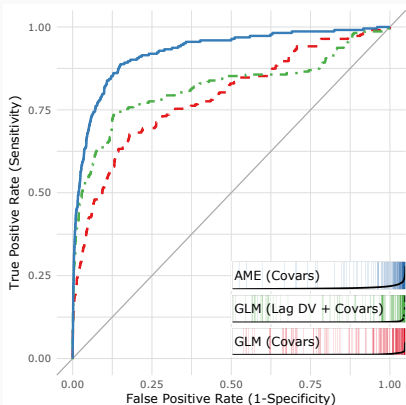
Groups with Common Sending Patterns (u_i)



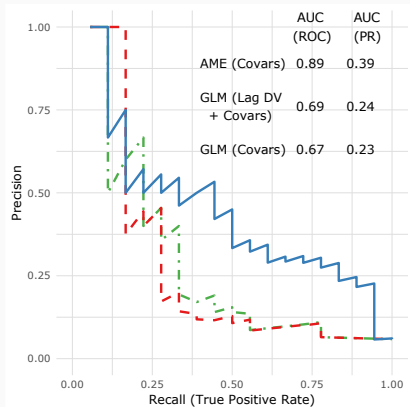
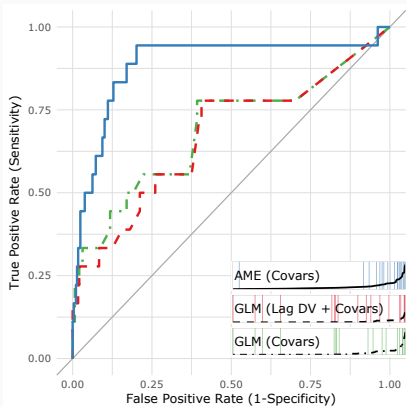
Groups with Common Receiving Patterns (v_j)



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.

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

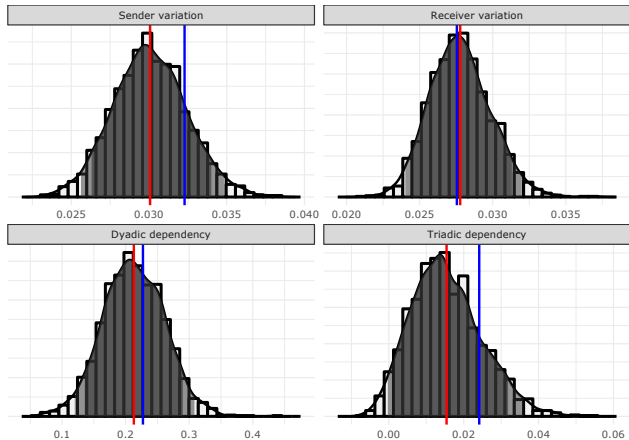
Why does violence against civilians increase an actor’s conflictual behavior towards armed groups?

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

Thanks!

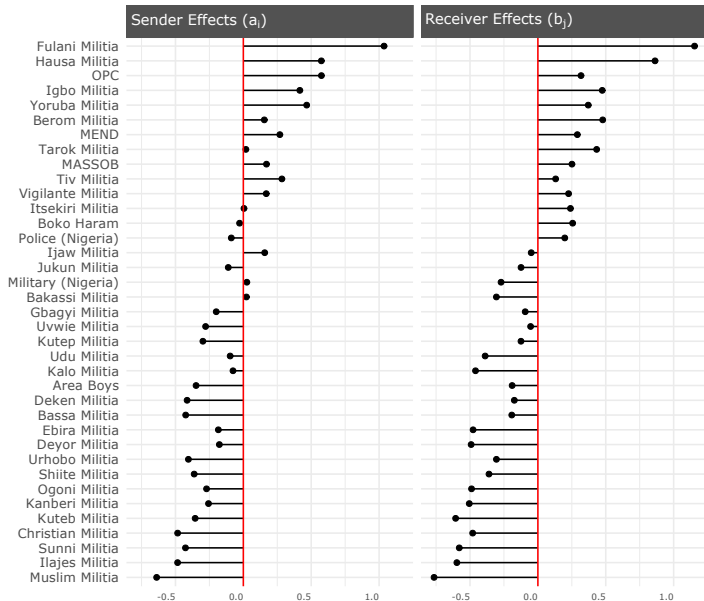
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Network GOF



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

