

Predicting Violence: Network Dynamics in Nigeria

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Abstract

Canonical studies of civil war examine the conditions that favor conflict across the globe. While predicting the onset of intrastate war has seen great progress, analysis on the occurrence of battles between actors remains obscure. Despite growing interest in the logic of rebel group fighting, empirical assessment of these relationships is underdeveloped. We unmask the interdependent dynamics of civil conflict by conceptualizing actors and battles as nodes and ties in a network. We examine how these relationships change over time and how their evolution in one time period enables precise prediction of conflict in future periods. Our network approach yields theoretical implications for understanding how the entrance of particularly aggressive actors can decisively alter the trajectory of civil conflict.

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[☆]Alphabetical order signifies equal authorship, all mistakes are our own. Replication material and instructions will be made available at <https://github.com/s7minhas/conflictEvolution>.

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Introduction

Who fights whom during civil conflict? Historically, efforts to understand violence between armed actors during civil conflicts have focused on explaining why an armed actor violently mobilizes against the government. But the rebel-government paradigm is limited, as evidenced by the growing number of scholars who now theorize about the implications of multi-party civil wars (Cunningham, 2006; Akcinaroglu, 2012). Still, even these studies have been rooted in a dyadic design, which examines pairs of relationships as independent phenomenon and does not consider conflict between actors as interrelated components that comprise the system as a whole. Current research has yet to provide a full consideration of the interconnected multi-actor dynamics that characterize recent examples of intrastate conflicts; a notable restriction given that by 2003 over 30% of ongoing civil wars involved multiple dyads in conflict with one another (Harbom et al., 2008).

In this study we explain how overlooking interdependence in civil wars misrepresents the full story of who fights whom during a violent conflict. The historical record highlights this reality: in Syria, the entry of ISIS led to an increase in violence between pro-Assad forces and a number of armed actors in the region (Beauchamp, 2014; Schmitt, 2018). In Mexico, the rise and fall of the aggressive and powerful Sinaloa Cartel generated violence between other drug trafficking organizations across the country (La Rosa & Shirk, La Rosa & Shirk). Similarly, understanding the path of violence between the Revolutionary Armed Forces of Colombia (FARC) and government forces is incomplete without a careful examination the FARC's violent clashes with right-wing paramilitary groups (Alesma, 2015). Without research based on both theoretical and empirical considerations of interdependence, we miss how interactions between one pair of actors effect other actors across the political system. Further, as we show in this study, to miss interdependence is to in-

correctly predict the occurrence and intensity of violence and, critically, misunderstand which actors are the perpetrators and recipients of such violence.

We argue that to understand who fights whom in civil wars we must understand the complex social structure of armed actors over time and how new armed actors can generate violence across other conflict dyads. While these ideas are not new to socio-political research more generally, it is new to the study of civil conflict. Accordingly, we conceptualize armed actors and battles as nodes and linkages in a network wherein the actors and their relationships change over time. This framework allows us to estimate the relationships that evolve between actors in a conflict network in order to predict the occurrence of battles between groups within the system. Our network approach, which we employ to investigate civil conflict in Nigeria, significantly outperforms traditional dyad-group approaches at predicting the occurrence of battles between groups in an out-of-sample context. Our findings yield theoretical implications for the study of civilian victimization and conflict occurrence, as well as insights about how the entrance of particularly aggressive actors can decisively alter the trajectory of conflict.

Network Patterns in Intrastate Conflict

In this study, we investigate the formation and evolution of what we term the civil conflict network. This network is the product of strategic actions by both government and armed non-governmental actors. In this section, we discuss how this network emerges, what we gain by treating civil conflict as a network problem, and how civil conflict evolves and shifts when new actors enter the network.

To understand the generation of the conflict network, it is useful to start by looking at the motivations of the actors that make up this network – the government and rebel groups. We follow Collier & Hoeffler (2004) in claiming that rebel actions are driven by a combination of material factors (sometimes referred to as greed) or the desire to gain

additional resources, rents, or otherwise enrich the group and its leaders; and ideological factors (often called grievances) or the desire to change public policy and shift the benefits towards particular economic, social, ethnic or religious groups (see also Gurr (1970); Regan & Norton (2005); Bodea & Elbadawi (2007)). Conversely, the government is motivated principally by the desire to remain in power and secondarily to enrich themselves and their winning coalition Bueno de Mesquita et al. (2005); Goemans (2000); Acemoglu & Robinson (2001).

These motivations provide incentives for different groups to attack other armed groups. A rebel group that is motivated by greed might attack not just the government, but other rebel groups in order to increase their abilities to control rents or lootable resources. Ideological motivation could drive groups to attack the government in hopes of either toppling the government and changing policy themselves, driving the government out of territory in order to impose policies in that territory, or simply to impose costs and obtain policy concessions. Ideologically motivated groups might also attack rebel groups that draw support from different sections of society in order to shift support away from challenger groups in a territory. The government also has a number of incentives to attack rebel groups – attacking strong rebel groups reduces the likelihood those groups can defeat the government, but governments also attack to control resources and suppress challengers’ abilities to interact violently (through predation) or nonviolently (through public goods provision) with the civilian population.

In order to attack other groups, rebels rely on the ability to mobilize resources. They can do this by mobilizing or taxing the civilian population Kalyvas (2006), through the sale of so called “lootable” goods like alluvial diamonds, narcotics, or tropical timber Ross (2004); Lujala et al. (2005); de Soysa (2000), or they can gain resources from foreign supporters, generally those that are rivals of the central government Gleditsch (2007); Regan (2002b,a).

Armed actors and their actions, driven by their motivations and sources of resources, constitute what we call the “civil-conflict network.” In this network the nodes are the different armed groups – both rebel and government – and the links are battles between armed groups. This network is not static over time. New groups are created, groups split into rivals, and groups demobilize and leave the network. Similarly, groups are not constant in their behavior over time, and groups might fight each other in one time period, and a common enemy in another.

First Order Dependencies

In the conflict network, some actors are more likely to fight than others due to their group-level characteristics. In the studies of networks, these are called first-order dependencies, and much of the study of rebel group behavior focuses on these kinds of factors.¹ In particular, *ceteris paribus*, certain groups are going to be more likely to *attack* other groups, and certain groups are going to be more likely to *be attacked*.

Many of these first order dependencies stem from a group’s motivations or their resources. For example, if a group is ideologically motivated where most other groups are ideologically different, then this group is in a target rich environment, where they will have many opportunities to advance their ideology through violence. Similarly, groups that adhere to an exclusionary ideology, or an ideology that is center-seeking, as opposed to one that can be satisfied by secession, are going to be more likely to attack across the network. Another example of first order dependence is when a contextual feature of the group makes it more likely to be a target. For example, when a group possesses territory with valuable natural resources, they are more likely to be attacked by groups that are

¹For just a few examples see Weinstein (2007) on organizational structure leading to different levels of violence, Wucherpfennig et al. (2012) on how ethnic power relations makes certain rebel groups more cost tolerant, Buhaug et al. (2009) on rebel capacity and goals.

motivated by greed.

While some of these factors can be controlled for in the context of a standard regression model, many of them are either contextual or difficult to observe (measure). This creates serious challenges for understanding who fights whom and when. If two groups fight, it might be because one of the groups is particularly aggressive, or the other group is a particularly appealing target, and failing to account for these first order dependencies will lead to inappropriately assigning credit for the confrontation, and a biased understanding of the sources of conflict. A network approach allows for us to both appropriately account for actor-level effects, or first-order dependencies, without directly measuring whether ideology or religion or resources are driving these effects. While measuring this is undoubtedly important and relevant to the study of conflict, testing hypotheses on these characteristics has already been a primary focus of existing theoretical and empirical work. Our aim is to move one step beyond these factors to explore other dimensions of the conflict system.

Second Order Dependencies

Networks of civil conflict are not created only by the attributes of armed groups, they are also a consequence of armed groups' actions. Condra & Shapiro (2010) and Lyall (2009) have explored how armed groups affect the tendency of their targets to be violent in the future, and many scholars have looked at how rebel groups retaliate against violence, leading to more violence Kathman & Wood (2015), but few studies have fully explored the consequences of armed group actions (and interactions) to explain fighting during civil wars.

One of the most important ways that conflicts evolve is through reciprocity and retaliation. If one armed group attacks another, it is more likely to be attacked itself. Some of this behavior is not causal. If a latent characteristic of groups leads actor A to attack

B, it is also more likely to lead B to attack A. At the same time, dynamics of support can also encourage reciprocity. If a group does not respond to attacks against it, it risks being seen as weak and which can lead to a loss of support from civilians or foreign sponsors. For groups relying on civilians, the need for retaliation can be especially stark, as one of the reasons civilians might support an armed group is for protection from other armed groups (Kalyvas, 2006; Valentino et al., 2004).

Accounting for reciprocity in a conflict network improves our ability to understand many dynamics of civil conflict. It becomes difficult to parse the factors that cause groups to attack and to be targeted if we ignore the fact that some attacks are retaliatory in nature. More generally, understanding reciprocity during civil conflict underscores that conflicts are not static: the actions and reactions passed between groups play a crucial role in shaping the contours of civil conflict.

Third Order Dependencies

We posit that another form of dependency is relevant to explain conflict in the conflict network. Importantly, there are ways in which the motivations, resources, and actions of groups effect not just their targets, but also unrelated pairs of actors. In the network literature, this is termed “third-order dependencies,” where the relationship between A and B are linked with the relationship between B and C, and the relation between A and C. Two particular ways in which this instantiate are homophily and stochastic equivalence.

Armed actors’ motivations often lend themselves to homophily or heterophily – the tendency of groups that share a latent trait to interact more or less. Homophily (and heterophily) themselves cause networks to have greater (lesser) levels of transitivity and clusterability. Groups that are ideologically motivated are more likely to attack armed actors that are not ideologically similar (the same holds for ethnic or religious motivations). Similarly, groups that are motivated by greed are more likely to fight geographically prox-

imate groups rather than distant ones. Accordingly, we should also observe that groups with similar resource bases fight each other in an effort to monopolize access to those resources.

The second type of third order dependency that we expect to influence conflict is stochastic equivalence. Stochastic equivalence captures the tendency for actors to behave similarly in the conflict network. A very straightforward example of this is when groups are sponsored by the same foreign actor. In this case, groups are going to be unlikely to fight each other and more likely to fight the government (Bapat & Bond, 2012). A similar dynamic occurs when rebel groups have actual alliances, whether competitive or otherwise (Zeigler, 2016). When groups have similar ideological motivation, they are not only unlikely to fight each other, but they are also incentivized to select similar targets. Finally, when ideological groups have secessionist aims, they could be expected to be stochastically equivalent since they would be most likely to fight the central government and not geographically proximate groups.

Taken in concert, we have argued that these types of social structure – actor effects, reciprocity, homophily and stochastic equivalence – influence the likelihood of violence between actors in the conflict network. Importantly, these first, second, and third order effects intuitively reflect theoretical perspectives found in the existing scholarship on civil war and rebel group behavior. Our study unites these two literatures and demonstrates the importance of combining substantive theories of violent behavior with network estimation strategies.

Actor Entry

An important and under discussed aspect of civil conflict is that actors are not static. Armed groups can enter or exit the civil conflict network at any given time. As Kathman & Wood (2015, p. 168) have argued “conflict systems are fluid, and competition varies

in response to the arrival or exit of violent combat groups...”, thus the entry of particularly strong or aggressive groups can have violent ripple effects across the entire conflict network. We argue that the presence of a group (call them group A) can increase the likelihood of conflict between two separate groups (group B and C). The two main ways that an actor’s entry influences the behavior of other groups is by effecting the capabilities and actions of the government and altering the system-wide distribution of resources.

The entry of a new group that clashes with the government can significantly increase the level of conflict in the network. Obviously, this is in part because the new violent group is directly involved in conflict, but this group can also spur violence between other armed groups. The entry of a new violent group that targets the government has two possible effects on the conflict network. First, the new group’s entry could strain, and ultimately decrease, government resources and capabilities. This harms the government’s ability to provide security and deter violence from other armed groups. Secondly, when a new armed group successfully defeats government actors in a given region or battle, this harms the government’s reputation and makes them appear more vulnerable. Thus, if the government does not want to incite other challengers (Walter, 2006) it will try to overcompensate for it’s loss and demonstrate strength by fighting heavily against armed actors.

The entry of a new group can also effect the actions of other rebels based on those rebels’ sources of support. In particular, the entrance of a new group might displace existing groups. This potentially leads groups into conflict with each other over scarce resources and lootable goods. At the same time, the entry of a new group might ignite a process of outbidding for the support of the civilian population who could be drawn to support the aggressive and “successful” new group.

The entrance of powerful or violent rebel groups into the conflict network can radically change the status quo. These groups influence perceptions and capabilities of the govern-

ment and they also force other rebel groups to be increasingly aggressive in chasing scarce resources. Thus, even when we account for new groups' first order tendencies towards violence, we expect to see their entry associated with a higher level of violence in the overall system.

The Conflict[s] in Nigeria

Over the past decade and a half, the people of Nigeria have experienced violence through ethnic and religious group tensions, organized insurgency, and government repression. In this section, we describe Nigeria's conflict landscape and summarize the nature of warfare between multiple armed actors, government agents, and civilians. This overview highlights the complex nature of Nigeria's conflict(s) and the sustained toll on human life that results from such hostilities.

The year 2000 marks the beginning of a critically tense transition period in Nigeria. Following the 1999 presidential election of Olusegun Obasanjo, Nigeria's 15-year long military dictatorship ends. Meanwhile, a resurgent Islamic political movement consolidates influence in Nigeria's predominantly Muslim northern states. Sharia Law, a penal code in effect for hundreds of years in Nigeria but disbanded in 1960, is re-implemented following the 2000 elections. The implementation of Sharia law then leads to numerous riots and clashes, largely between Muslims and Christians (one clash, in Nigeria's second largest city of Kano, ends with over 100 dead in October of 2001).²

President Obasanjo faces many more violent episodes during his first term. As Christian-Muslim disputes continue in the Northern regions, a tribal war fomented in the eastern-central state of Benue. Thousands of people are forced to flee the area, and troops reportedly target unarmed civilians in retaliation for the abduction of nearly 20 soldiers.

²See <http://articles.latimes.com/2001/oct/16/news/mn-57819>.

Continuing Christian-Muslim clashes in the north mark Obasanjo's second term (beginning in 2003) as well as deepening violence in the Niger Delta where militants vie for control of oil production centers. Fighting in the Okere district of Warri occurs between Itsekiris and Urhobos over contentious primary elections held for the Delta South district. Reports state that government forces attempt to suppress violence through execution-style killings. The Nigerian Red Cross reports that more than 6,000 people are displaced as result of the fighting.³

Mohammed Yusuf emerges in the early 2000s as the radical leader of the religious extremist group, the Boko Haram.⁴ Yusuf spreads an anti-state, anti-elite ideology couched in Sunni Muslim teachings. Conflict in the northern region of Nigeria continues along religious lines, and by 2008 Boko Haram has grown increasingly well organized, operating as a mini-state with institutions, a welfare system, and religious police. Clashes between Boko Haram and state security forces gain momentum as the 2009 uprising begins in the state of Bauchi and spreads to Borno, Yobe, and Kano. These battles are the first sustained conflict between Boko Haram and the government; these clashes culminate in the death of scores of police officers, more than 700 members of Boko Haram, and the capture of Mohammed Yusuf.⁵

Vice President Goodluck Jonathan succeeds to the presidency following the death of his predecessor in 2010. The death of Yusuf, killed by police in a raid, leads to an intensification of tactics by Boko Haram, including greater violence against civilians. Demonstratively, in December of 2010, Boko Haram bombs kill an estimated 80 people

³See <https://www.hrw.org/reports/2003/nigeria1103/3.htm> for more details.

⁴There is evidence that the early leadership of the movement formed around 2000 or 2002, though in many reports the fully armed, organized, radical group forms closer to the year 2008 following a clash with government forces. See Walker (2016) for details.

⁵See <http://edition.cnn.com/2014/06/09/world/boko-haram-fast-facts/>.

in the central city of Jos. This event sparks a response from opposing Christians leading to roughly 200 more deaths.⁶ Attacks on civilians continue and in April of 2014 Boko Haram chooses a target that sparks international condemnation: 276 Chibok schoolgirls. Though this is not the first time that civilians organize against the insurgency's violent tactics, high levels of protest and vigilantism ensue following the children's kidnapping.

Violence against civilians, both on behalf of insurgent and government actors, continues to displace and disappear civilians. In March 2014, the Director-General of the Nigerian National Emergency Management Agency (NEMA) reported that more than 250,000 people were displaced as a result of the fighting in north-eastern Nigeria. Battles between Boko Haram, local militant groups, and security forces continue today. While Boko Haram has evolved as perhaps the most well known armed insurgent movement in Nigeria, there are major ethnic militias such as the Urhobo Ethnic Militia that engage in localized battles and groups such as MEND which battle with other armed actors and the government over natural resources. MEND is one of the largest militant groups in the Niger Delta region. The militant organization is expressly concerned with the public and private production of oil in the local area. Despite these important armed actors, Boko Haram's entrance into the conflict network in 2009 has had unique consequences on the stability of the entire region.

Figure 1 shows the spatial distribution of violence in Nigeria from 2001 to 2016, points in red represent Armed Conflict Location and Event Data Project (ACLED) battle events in which Boko Haram is involved (either as the initiator or target) while points in blue designate events that do not involve Boko Haram. Boko Haram's entrance into the system corresponds to an increase in both the level and spread of conflict. The increase in conflict is not attributable to just the violent actions of Boko Haram, instead other actors

⁶See <http://www.aljazeera.com/news/africa/2013/09/201397155225146644.html>.

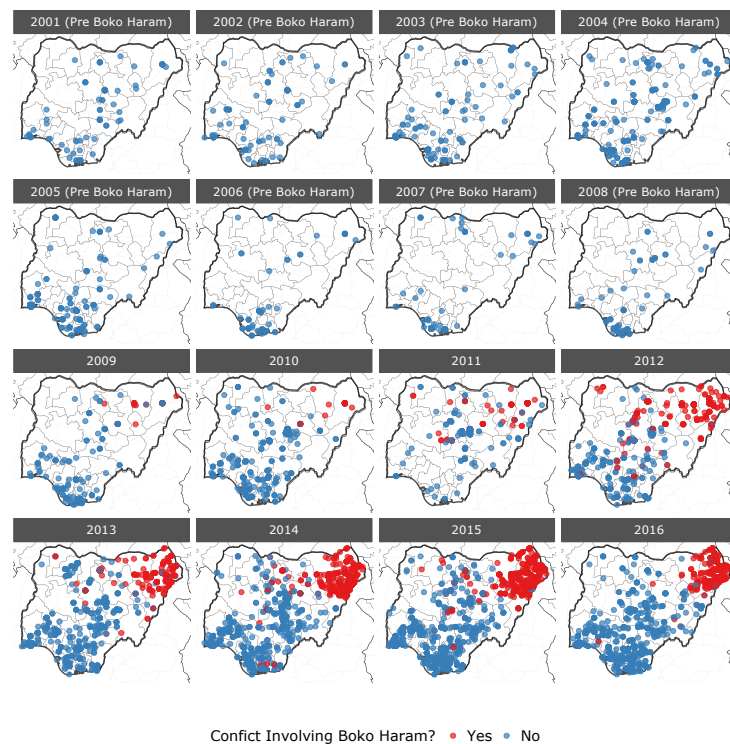


Figure 1: Spatial distribution of conflict in Nigeria from 2001 to 2016. Points colored in blue represent conflict events between sets of actors not including Boko Haram, and points in red events that do involve Boko Haram as either the initiator or target of conflict.

engage in more conflictual events. Figure 2 further highlights the complexity of Nigeria's conflict and the relevance of relationships between actors: the Fulani Militia is central to the network, as is (understandably) the Nigerian police and military forces. Reciprocal conflictual relations are also visible, such as between the Boko Haram and the Military.

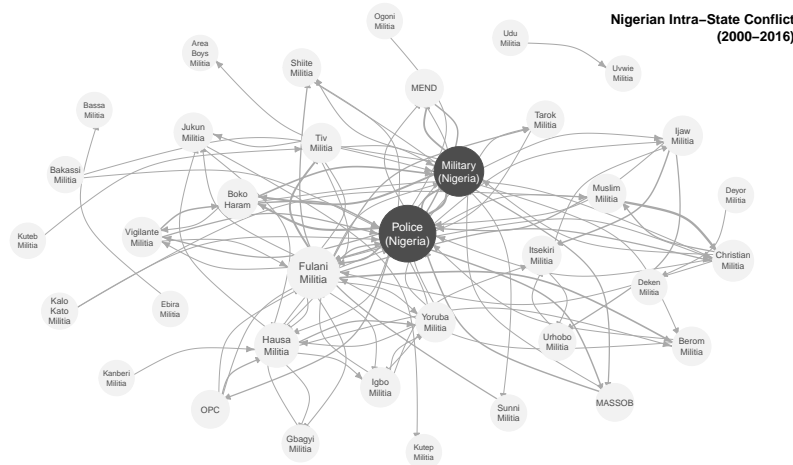


Figure 2: Network graph depicting battles between actors for the entire 2000-2016 time period. Pairs of actors experiencing more conflict have thicker links and arrows indicate direction of ties.

Data

To study intrastate conflict patterns in Nigeria we utilize the ACLED data initiated by Raleigh et al. (2010). This dataset records armed conflict and protest events in over 60 developing countries. ACLED's *battles* data is used to generate our 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).^{7,8} We focus only on 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.

The groups included in our battle-data analysis are politically violent actors as defined by the ACLED codebook. Such actors include rebels, militias, and ethnic groups.⁹ Ad-

⁷In the appendix, we show results when only including battles from ACLED that resulted in at least one battle death. The results when using a fatality threshold and not are similar, thus we focus on the latter for the remainder of this paper.

⁸Some scholars have noted that the ACLED conflict data should be understood as defining symmetric events, since who started a particular battle can at times be difficult to entangle. In the appendix, we show that the results presented in the paper are robust to utilizing a directed or undirected formulation.

⁹For detailed definitions of these actors, see the on-line ACLED Africa data codebook maintained at

ditionally, we use secondary resources to confirm the existence of each actor in the data. Overall, the data capture several key types of actors: government armed forces (military and police), insurgent groups (Boko Haram), and ethnic militias (including the Yoruba and Fulani Militias).

The ACLED data also allows us to explore civilians' role in shaping conflict within the Nigerian system. Building on the research agenda motivated by macro-level studies (Tarrow, 1994; Tucker, 2007; Chenoweth & Stephan, 2011), we investigate the link between civilian mobilization and violence between armed actors at the local level by creating a count of the number of protests/riots led by civilians against a given actor at time $t - 1$. While there is a robust debate over what causes civilian victimization,¹⁰ discussion of the consequences of civilian victimization, particularly as they relate to the potential for future conflict has been more limited (Hultman, 2007; Raleigh, 2012). Berman & Matanock (2015) argue that when rebels groups [governments] kill civilians, other civilians are more [less] 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. Condra & Shapiro (2012) find support for this relationship in Iraq. To account for both these dynamics we create a count of the number of violent actions that an actor committed against civilians at time $t - 1$ and nodal covariates to explain both the probability of an actor sending and receiving a conflictual tie.

Additionally, we attempt to account for spatial effects in modeling the likelihood of conflict between a particular pair of actors. First, we add a measure of how dispersed a rebel group's activity is across the country. Armed groups whose actions are more dispersed across Nigeria are more likely to come into conflictual contact with others. We

www.acleddata.com.

¹⁰See Humphreys & Weinstein (2006); Downes (2006); Kalyvas (2006); Prorok & Appel (2014).

include a “Geographic Spread” variable as both a sender and receiver covariate.¹¹ Second, we add a measure of neighboring conflict to account for the notable literature that has developed explicating the mechanisms through which civil conflict can diffuse between countries.¹² To account for this effect, we use the ACLED dataset to count the number of conflict events occurring within Nigeria’s contiguous neighbors.

We add three other covariates to the model. First, we create a control for whether both actors are a part of the government (the Police and Military). We include this control to account for the fact that the probability of an interaction between these two is minimal relative to the other potential dyads in this system. Second, we include a binary variable that takes on the value of one if the following year is an election year and zero otherwise. This is to account for the fact that elections in Nigeria are rarely waged peacefully in the ballot box, but instead are typically followed or preceded by episodes of conflict. Most importantly, to examine the affect that Boko Haram’s entrance has had on the level of conflict in this system we include a binary variable that takes on the value of one after the Boko Haram insurgency has begun (in 2009) and zero beforehand.¹³

Modeling Approach

To estimate conflict in this system in a way that explicitly models interdependencies between actors, we rely on a network based approach that combines the social relations regression model (SRRM) – for details on this model see Dorff & Minhas (2017) – and the latent factor model (LFM). Together the SRRM provides a set of additive effects to

¹¹For example, to model the spread of group i in period t , we calculate this by taking all the events involving group i in the 3 years prior to t and estimate the variance.

¹²See Salehyan & Gleditsch (2007); Metternich et al. (2017); Braithwaite (2010); Beardsley (2011).

¹³We choose this date both because 2009 is considered the beginning of the Boko Haram insurgency in most media reports.

capture first and second order dependencies, and the latent factor model provides a set of multiplicative effects to model third order dependencies (Minhas et al., 2016). This estimator is referred to as the additive and multiplicative effects (AME) model:

$$\begin{aligned}
 y_{ij,t} &= g(\theta_{ij,t}) \\
 \theta_{ij,t} &= \beta_d^\top \mathbf{X}_{ij,t} + \beta_s^\top \mathbf{X}_{i,t} + \beta_r^\top \mathbf{X}_{j,t} + e_{ij,t} \\
 e_{ij,t} &= a_i + b_j + \epsilon_{ij} + \alpha(\mathbf{u}_i, \mathbf{v}_j), \text{ where} \\
 \alpha(\mathbf{u}_i, \mathbf{v}_j) &= \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j = \sum_{k \in K} d_k u_{ik} v_{jk}
 \end{aligned} \tag{1}$$

where $y_{ij,t}$ represents whether or not conflict occurred between actor i (the sender) and actor j (the receiver) at time t . To model our binary dependent variable we employ a latent variable representation of a probit regression framework, in which we model a latent variable, θ_{ij} , using a set of time varying dyadic $(\beta_d^\top \mathbf{X}_{ij,t})$, sender $(\beta_s^\top \mathbf{X}_{i,t})$, and receiver covariates $(\beta_r^\top \mathbf{X}_{j,t})$.

To be able to assess the effect that the entrance of actors such as Boko Haram have on the Nigerian conflict network, we extend the AME framework to handle networks in which the composition of actors change over time.¹⁴ Typically, when employing a latent variable framework to longitudinal networks one assumes that the composition of actors is uniform across time, and if the composition is not truly uniform the authors arbitrarily make it so by choosing a select group of actors to study. This is obviously problematic in general and especially in the case of intrastate conflict as rebel groups often emerge and

¹⁴This extension is one reason why we choose not to use the Exponential Random Graph Model (ERGM). The ERGM framework requires that the set of actors remain constant over time, and so using that framework would require us to either ignore important actors in the network, or treat them as if they were present and non-violent for long periods of time.

dissolve – meaning that in time t we may have actors $\{i, j, k\}$ in the network, and in time $t + 1$ actors $\{i, j, k, l\}$ or just a different set of actors $\{i, j, l\}$. A change in composition can occur in two ways: 1) an actor dissolves after some time, 2) an actor enters the network after some time.

To account for these types of changes to a network, we adjust the estimation procedure of the AME model such that actor observations only contribute to the likelihood of the model once they enter into the network. This procedure is analogous to that adopted by Huisman & Snijders (2003) for the stochastic actor oriented model (SAOM). They limit the set of actors who can change their outgoing relations (or have incoming relations changed with) to only those that are part of an active set at time t . We implement a process for the AME framework in which composition changes are modeled as exogenous events such that actors are allowed to enter and leave the network at fixed time points. The utility of this approach is that the baseline probability of a tie shifts in accordance with the number of active actors in the network at time t and the time-varying covariates already included in the model.

The a_i and b_j in Equation 1 represent sender and receiver random effects that we incorporate from the SRRM framework:

$$\begin{aligned} \{(a_1, b_1), \dots, (a_n, b_n)\} &\stackrel{\text{iid}}{\sim} N(0, \Sigma_{ab}) \\ \{(\epsilon_{ij}, \epsilon_{ji}) : i \neq j\} &\stackrel{\text{iid}}{\sim} N(0, \Sigma_\epsilon), \text{ where} \\ \Sigma_{ab} &= \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \quad \Sigma_\epsilon = \sigma_\epsilon^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \end{aligned} \tag{2}$$

The interpretation of these parameters is straightforward. The sender and receiver random effects are modeled jointly from a multivariate normal distribution to account for

correlation in how active an actor is in sending and receiving ties. Heterogeneity in the the sender and receiver effects is captured by σ_a^2 and σ_b^2 , respectively, and 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). Beyond these first-order dependencies, second-order dependencies are described by σ_c^2 and a within dyad correlation, or reciprocity, parameter ρ .

While the additive effects from the SRRM can deal with first (differing levels of activity across actors) and second order interdependencies (reciprocity), the multiplicative effects are used to deal with third order dependencies. Specifically, this multiplicative effect allows us to model homophily – the tendency of actors with similar characteristics to form strong relationships than those with differing characteristics – and stochastic equivalence, the possibility that two actors i and j will have similar relationships with every other actor in the network. An AME model accounts for these third order effects using the multiplicative term: $\alpha(\mathbf{u}_i, \mathbf{v}_j) = \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j$. This model posits a latent vector of characteristics \mathbf{u}_i and \mathbf{v}_j for each sender i and receiver j . The similarity or dissimilarity of these vectors will then influence the likelihood of activity, and provides a representation of third order interdependencies (Minhas et al., 2016).

The representation of third order interdependencies is accomplished by a process similar to computing the singular value decomposition (SVD) of the observed network. When taking the SVD we factorize our observed conflict network into the product of three matrices: \mathbf{U} , \mathbf{D} , and \mathbf{V} . This provides us with a low-dimensional representation of our original conflict network in terms of third order dependence patterns arising in the network. Specifically, values in \mathbf{U} provide a representation of how stochastically equivalent actors are as senders in a network, or more simply put how similar actors are in terms of who they are initiating battles with. For instance, $\hat{\mathbf{u}}_i \approx \hat{\mathbf{u}}_j$ would indicate that actor i and j initiate battles with similar third parties. \mathbf{V} provide a similar representation but

from the perspective of how similar actors are as receivers. The values in \mathbf{D} , a diagonal matrix, represent levels of homophily in the network. Parameter estimation in the AME takes place by sampling from the posterior distribution of the full conditionals – further details on the estimation procedure can be found in the Appendix.

Results

We report the results for the sender, receiver, and dyadic covariates included in the AME model in figure 3.¹⁵ First, we find little evidence to support the argument that conflict in neighboring countries drives violence between actors in the Nigerian conflict system. We also do not find that actors become particularly more violent during election years. We do, however, find significant evidence for the argument that actors operating across a larger region of Nigeria are likely to come into more conflict with other actors.

¹⁵Excluded from these results is the dyadic variable for “both are government actors.” This is included and has a negative effect in both models, which simply indicates that government actors are unlikely to fight one another. Trace plots for each of these parameter estimates can be found in the Appendix.

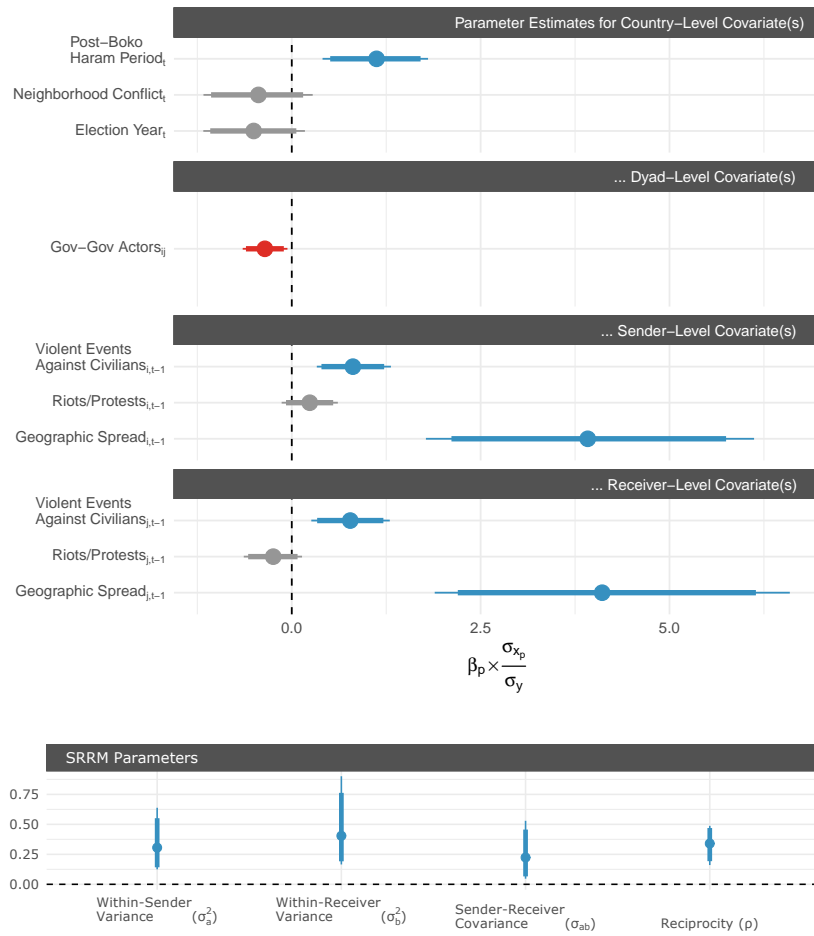


Figure 3: Standardized parameter estimates from AME model. Points represent average value of parameters, thicker line represents the 90% credible interval, and thinner line the 95%.

We see a non-trivial relationship between violence against civilians and participation in a greater number of battles. Targeting civilians is linked both to a higher likelihood of engaging in violence against other military groups, and a higher likelihood of being targeted by other military groups.¹⁶ Moving from the 2.5%ile of violence against civilians to the 97.5%ile (moving from no violence to 17 attacks), while all other variables are

¹⁶This effect holds even if we leave government actors out of the network or add in binary sender and receiver controls for government actors. See the appendix for details.

held at their measure of central tendency,¹⁷ increases the risk of starting a battle by the perpetrator by a factor of about 1.58, and the risk of being targeted for a battle by about 1.55. We cannot causally say that these are the result of violence against civilians, but the fact that the relationship holds even in a mixed-effects model (and one that accounts for network dependencies) is suggestive. Further, anecdotal evidence maintains a similar story. For example, the Óodua People’s Congress (OPC), an organization active in the southwest of Nigeria organized to protect the Yoruba ethnic group, is known to engage in two primary modes of conflict: large-scale ethnic battles that directly result in mass casualties to both rivals and civilians, and smaller-scale episodes wherein the OPC targets the civilian base of rival groups.

In the case of this Nigerian conflict network, there is no evidence of a link between civilian protests and the occurrence of a conflict event. There are a number of possible reasons for this null finding: the protest data we use might contain uncertainty about the targets of the protest, some protests might agitate towards greater military involvement—such as the “Bring Back Our Girls” protests pushing for the government to confront Boko Haram—while other protests might be against violence, or different actors might respond to protest in divergent ways.

Finally, we examine the effect of the Boko Haram insurgency on the level of conflict in the system and find a clear increase in violence in the years that follow Boko Haram’s entry. With all other variables held at their measure of central tendency, a battle between any of the dyads in the system is about 2.82 times as likely in the period after the entrance of Boko Haram as it was before their entrance. Again this is not just the effect of Boko

¹⁷We held whether the dyad was in the Post-Boko Haram period, the presence of neighboring conflicts, whether it was a governmental dyad, and whether it was an election year at their median, all other variables, as well as the random and multiplicative effects at their mean level.

Haram’s propensity to target and be targeted in battles, as those first order effects are accounted for in the AME model. The Boko Haram Insurgency is associated with an increase in conflicts even in the dyads that *do not contain Boko Haram*.

We plot variance parameters from the SRRM in the bottom of figure 3. By looking at the sender and receiver heterogeneity estimates (σ_a^2, σ_b^2) , we see significant first order effects—different actors not only have different baseline levels of conflict, but the variance changes too. We also see a moderate value for σ_{ab} indicating that actors which initiate more conflictual links also receive more conflictual links in return. Relatedly, the positive value for ρ indicates that actors whom receive a conflict from a particular sender reciprocate that conflictual behavior. The fact that each of these variance parameters is positive and significantly greater than zero indicates that the assumption of observational independence relied on by standard generalized linear models (GLM) are violated in this dyadic conflict dataset.

Boko Haram’s Entrance

In figure 4 we show that there is both more intense and more widespread conflict with the beginning of Boko Haram’s uprising. In this visualization, we shade dyadic relationships that experience more conflict after the beginning of Boko Haram’s insurgency in blue, those that saw less in red, and those that stay the same in green. Interestingly, much of this conflict does not actually involve Boko Haram. Their conflict is predominantly against the Nigerian Police and Military forces, and yet after their entrance we also see increases in conflict between other groups, and in regions of the country where Boko Haram is not present.

The uptick in conflict after 2009 is most consistent with a logic of multiple rebel groups strategically interacting with the government. Other rebel groups are able to witness Boko Haram’s success against the government, and this increases their beliefs that they

can challenge the government successfully (or, as Fjelde & Nilsson (2012) argue, fight each other due to governmental weakness). At the same time, if the government is unsuccessful against Boko Haram, they are incentivized to prove their continued effectiveness against other groups who try to deter future challenges. After Boko Haram's entry in 2009 we see increased attacks between rebel groups, and increased attacks by those groups against the government, but we also see increased attacks by the government—consistent with this logic.

The effect of Boko Haram's entrance underscores the need for a networked approach to intrastate conflict. A standard approach to intrastate conflict, which focuses on the government-rebel dyads, or in particularly ambitious cases, also looks at rebel-rebel dyads, would capture Boko Haram's direct effect on conflict, but it would miss this indirect effect.

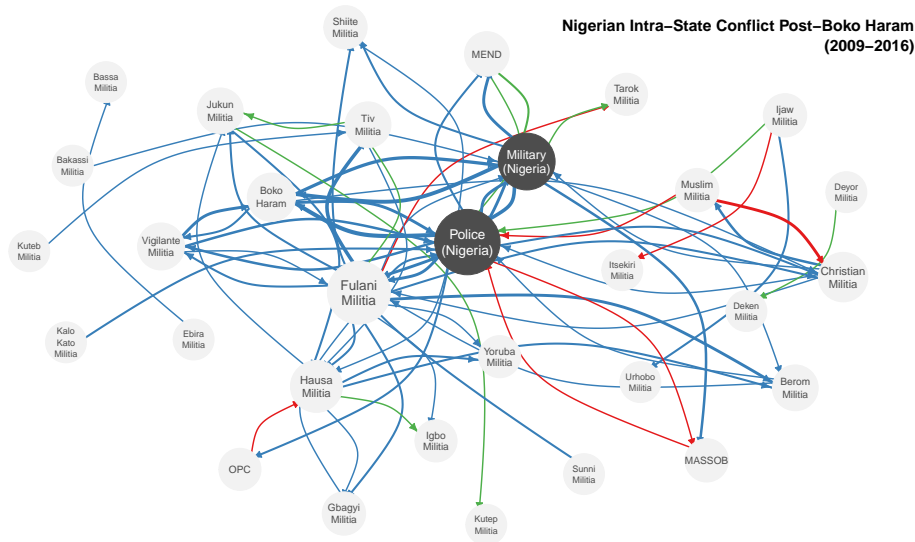


Figure 4: Conflict network 2009–2016. Pairs with more conflict have larger links. Government groups are in black, all other groups are in grey. Blue links indicate more interactions in the 2009–2016 period than in the 2000–2008 period, red indicates less, green no change.

Network Dependencies

We use a network model to understand the Nigeria conflict system not just because it can give more precise parameter estimates, but also because it aids in understanding

the interdependencies among the actors in the network. Such an approach allows us to infer actor relationships that are typically unobservable. We depict the sender (\hat{a}_i) and receiver (\hat{b}_j) random effects in figure 5.

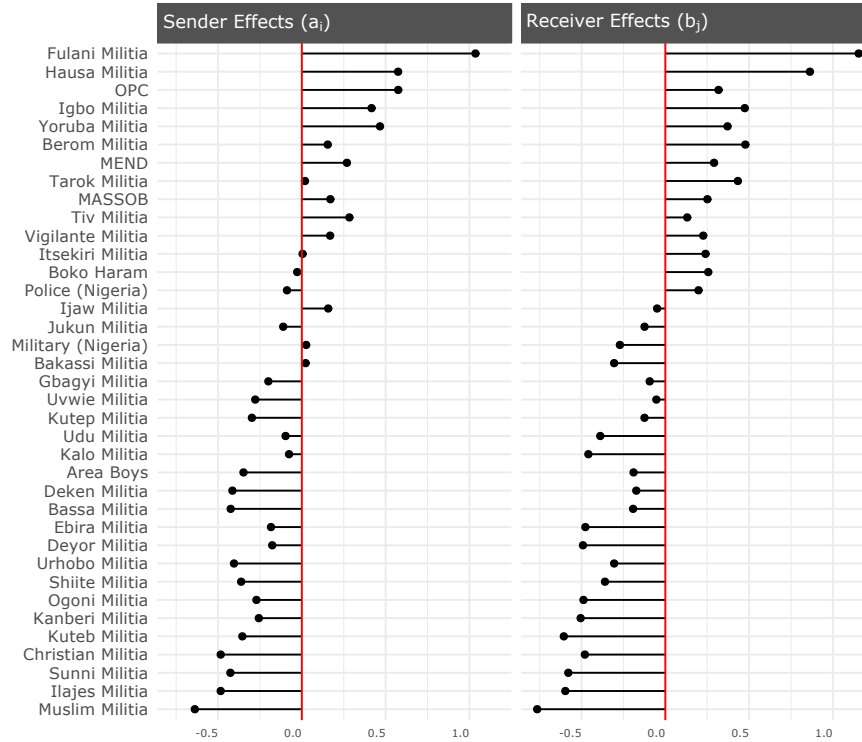


Figure 5: Sender and receiver random effect estimates.

This figure shows which actors are more (and less) violent than would be predicted by just accounting for the exogenous covariates we reviewed in the previous section. We can see, for example, that Boko Haram actually has a random sender effect that is approximately zero, implying that once we account for their high tendency to target civilians and the secular increase in violence that followed their entry into the conflict the model is able to accurately predict the group's tendency towards initiating conflict. On the other hand, actors like the Fulani and Hausa militias have notably positive sender and receiver effects (and the Christian and Muslim Militias have notably negative effects). This gives us cause to believe that our model has done a somewhat worse job capturing the

Figure 6 shows the directions of actors’ latent factors for both sending, left panel, and receiving violence, right panel. The directions of \hat{u}_i ’s (for sending conflict) and \hat{v}_i ’s (for receiving conflict) are noted in blue and red, respectively. The size of the label assigned to the points is a function of the magnitude of the vectors. The purpose of this figure is to discern groups of actors that are more similar to each other in terms of whom they send conflict to (left panel) or receive conflict from (right). Actor similarity here results from third order dependence patterns – specifically, homophily and stochastic equivalence – that remain after accounting for the other parameters estimated by the model.

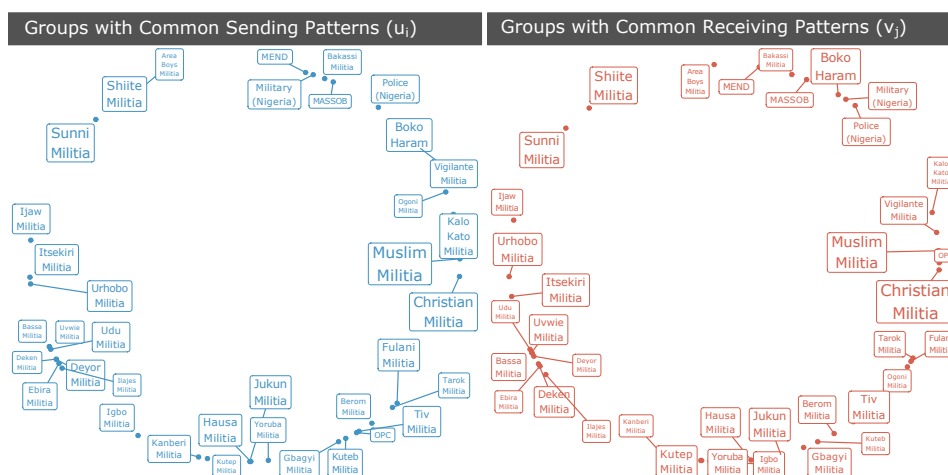


Figure 6: Visualization of multiplicative effects.

By using an AME approach, we are able to better identify previously unobservable patterns of conflict in Nigeria. For example the cluster involving Boko Haram, MASSOB, and MEND is an example of stochastic equivalence: in particular these parties, though spatially heterogeneous, are each predominantly engaged in fighting with the Nigerian military and police for control of territory (the Niger Delta for MEND, the state of Biafra for MASSOB, and the North West for Boko Haram).

We also find certain groups of actors who are not just more likely to fight common third parties, but they are also more likely to fight *each other*: for prominent examples of this we can see the proximity between the Sunni and Shiite militias, or the Christian and Muslim militias. Additionally, groups in the bottom of figure 6 such as the Fulani, Tiv, Berom, and Kuteb militias each tend to predominantly operate in the Middle Belt of Nigeria, and form geographically concentrated conflict clusters in which each group initiates or receives conflict with one another – this is an example of a set of homophilous relations.

Out-of-Sample Performance Analysis

By accounting for exogenous and network dependent patterns that give rise to conflict systems we are able to better account for the data generating process underlying relational data structures. To show that this is the case, we examine whether our approach achieves better predictive performance in an *out-of-sample context* than traditional dyadic models. Given that our model is more complex than a GLM, we would expect it to do better *in-sample*, but inclusion of more parameters will only improve performance *out-of-sample* if these parameters are helping us to better capture the underlying data generating process. To evaluate our model, we use a cross-validation procedure where we randomly divide our data into k groups, estimate model parameters without observations from a group, and then predict those excluded observations from the estimated parameters (Minhas et al., 2016).

We set a number of benchmarks for comparison. First we compare the AME model to a GLM model using the same covariates to show the effect of accounting for network dependencies on predicting conflict. We supplement this with an alternative GLM that includes not just these covariates, but also a lagged dependent variable and a lagged reciprocity term. The lagged dependent variable is the equivalent of saying that conflict

and peace are relatively likely to persist between dyads, while the inclusion of a lagged reciprocity term in a GLM framework is a simple way to account for retaliatory strikes.

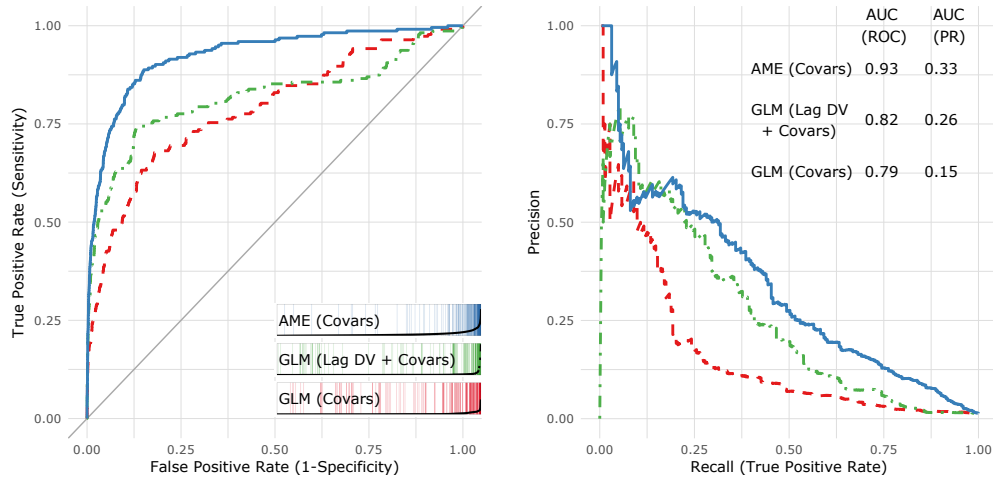


Figure 7: Assessments of out-of-sample predictive performance using ROC curves, separation plots, and PR curves. AUC statistics are provided as well for both curves. In each curve, the AME model is in blue, the GLM with lagged DV and covariates is in green, the GLM with only covariates is in red.

We utilize three performance criteria to compare the models: Receiver Operator Characteristic (ROC) curves, Precision Recall (PR) curves, and separation plots. ROC curves look at the trade-off between true positive rates and false positive rates at different thresholds of classification. ROC curves can be problematic for analyzing conflict because conflict is relatively rare at the dyadic level. If peace is common, even a poor model will have a very low False Positive Rate. PR curves, on the other hand, examine the trade-offs between the percentage of conflicts a model predicts, and the percentage of predicted conflicts which occur. Lastly, we use separation plots to provide an intuitive visualization of the accuracy of our predictions. All of the models' performance out-of-sample by these metrics are displayed in figure 7. The AME model with covariates is the best performing model out-of-sample in all cases. This model outperforms each of the GLM variants by a

notable margin.¹⁸

Discussion

Intrastate Conflict as a Dynamic Network

Intrastate conflicts are often more complex than Manichaeian struggles between a government and a unified opposition. More and more, they involve a number of actors operating in an environment where interactions can be interdependent. The improved predictive performance of our network approach is a result of the fact that there is significant network based structure underlying the Nigerian conflict system. Apart from pointing to the utility of taking network patterns into account, our study also highlights how we can use the AME model to uncover the types of first, second, and third order dependence patterns that emerge.

The implication of first order dependence patterns is that there are latent actor attributes not accounted for by our model specification that could be used to explain why some actors are more conflictual than others. Interestingly, one of the more striking findings is that the Fulani militia is particularly more active in engaging in battles than the exogenous sender, receiver, and dyadic variables in our model would predict. This highlights the opportunity for further research into understanding what latent attributes may drive such inflated conflictual behavior. Our findings with regards to second order dependencies demonstrate the strong role of reciprocity in this network. This reflects a common intuition from the interstate conflict literature and our study of Nigeria highlights that this type of pattern also persists in intrastate conflicts. Last, our visualization of the

¹⁸We also test model forecasting ability temporally by dividing the data into a training and test set, where the test set corresponds to the last period in the dataset that we have available. Results for this analysis are shown in the appendix and here again we find that our network based approach has better out-of-sample predictive performance than the more traditional logistic alternatives.

multiplicative effects captures third order dependencies and shows strong evidence that actors in this system form various communities of conflict. Each of these dependencies points to the fact that there is an underlying structure to the set of dyadic interactions that we observe in this network even after accounting for the effects of exogenous covariates. Since these patterns play a role in the data-generating process of intrastate conflict, our approach out-performs more traditional frameworks that ignore such dependencies.

Implications for Future Research

By utilizing information about dependencies between actors to accurately consider how conflicts develop over time, we are also able to more accurately test exogenous actor and dyadic level explanations for conflict. First, because we are able to estimate a network model in which actor composition changes over time, we can assess the impact that particular actors such as Boko Haram have on the system. We find that the entrance of this single actor profoundly changed interactions across the system. Boko Haram's entrance does not simply increase conflict *directly*, it also is associated with a marked rise in violence in the dyads that *do not include Boko Haram*. This raises an important question for future research which is whether or not we can formally study why some actors have stronger effects on shaping interactions across a network than others.

Our present study is necessarily limited in that we retroactively observe the influence of Boko Haram on the conflict network. However, our results dovetail with current findings about Boko Haram's rise and expansion and provides insights for defining key actors in other conflict settings. First, we have shown that Boko Haram is particularly violent and targets both the government and civilians. Weeraratne (2017) argues that a key determinant of Boko Haram's rise is their rapid increase in the use of violence against societal actors, government armed groups, religious communities, and civilians. Osumah (2013) details how the targeting strategies of Boko Haram has weakened the government's

security apparatus and heightened tensions across the country. Second, there is evidence to suggest that Boko Haram was particularly well-organized and well-resourced even in the first few years of its operation (Osumah, 2013). Group-level attribute data would provide a way to test whether groups that are highly organized, well-resourced, and target a wide range of actor types are likely to have a broad affect on sub-national level violence, similar to the Boko Haram's influence in Nigeria.

Additionally, our results highlight the role that civilian victimization can play in further perpetuating violence within a network context. Even after controlling for network related dependencies within this system, we find that actors who target civilians are more likely to receive and send conflict themselves. Relatedly, we find little evidence that civilian led protest against a particular actor changes that actor's likelihood in initiating conflict. To some extent, these findings showcase the limitations of civilian populations to change the behavior of actors in environments of extreme violence. Future research should compare and contrast these findings beyond the Nigerian case to better illuminate the networked nature of civilian mobilization in conflict environments. The findings with regards to the role of civilian victimization and civilian riots/protests might not generalize beyond the Nigerian case. Nigeria may be unique for several reasons, its 150 million people are divided almost equally between Muslims and Christians. Further, Nigerians split into even finer divisions based on tribe, of which there are over 200 in the country.

Conclusion

Our study has embraced the complexity of multi-actor conflicts, rather than discounted it. We have shown that network dynamics help explain the occurrence of violence between groups over time, even as actors enter and exit the conflict. We have demonstrated how key, violent actors can increase violence within a network system. Additionally, our approach achieves a longstanding goal of conflict studies: to accurately predict violence

over time. Our approach offers important insights into how conflict studies can utilize methodological innovations to expand theoretical inquiry.

These contributions are not without their limitations. While our study affirms the utility of ACLED data efforts, more actor-level characteristics are needed to fully engage the rich literature on civil war dynamics. Such data would enable even more precise investigation of covariates of interest for determining changes in rebel group behavior over time. Second, though our study has revealed meaningful findings with respect to key covariates such as civilian victimization, more research is needed to explore the generalizability of such results. We hope this study motivates future work that more fully considers the conflictual behavior of armed actors in complex settings.

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- Acemoglu, Daron & James A Robinson (2001) A theory of political transitions. *American Economic Review* 91: 938–963.
- Akcinaroglu, Seden (2012) Rebel interdependencies and civil war outcomes. *Journal of Conflict Resolution* 56(5): 879–903.
- Alesma, Adriaan (2015) The farc’s biggest fear: Colombia’s paramilitary groups. *Colombia Reports*: 10 July (<https://colombiareports.com/the-farcs-biggest-fear-colombias-paramilitary-groups/>).
- Bapat, Navin A & Kanisha D Bond (2012) Alliances between militant groups. *British Journal of Political Science* 42(4): 793–824.
- Beardsley, Kyle (2011) Peacekeeping and the contagion of armed conflict. *The Journal of Politics* 73(04): 1051–1064.
- Beauchamp, Zack (2014) The kurdish war: How isis and syria are reigniting an old conflict in turkey. *Vox*: 15 October (<https://www.vox.com/2014/10/15/6977599/pkk-turkey-isis-kobane-syria>).
- Berman, Eli & Aila M Matanock (2015) The empiricists’ insurgency. *Annual Review of Political Science* 18: 443–464.
- Bodea, Cristina & Ibrahim Elbadawi (2007) Riots, coups and civil war: Revisiting the greed and grievance debate.
- Braithwaite, Alex (2010) Resisting infection: How state capacity conditions conflict contagion. *Journal of Peace Research* 47(3): 311–319.
- Bueno de Mesquita, Bruce; Alastair Smith; Randolph M Siverson & James D Morrow (2005) *The Logic of Political Survival*. Cambridge, Mass: MIT Press.

- Buhaug, Halvard; Scott Gates & Päivi Lujala (2009) Geography, rebel capacity, and the duration of civil conflict. *Journal of Conflict Resolution* 53(4): 544–569.
- Chenoweth, Erica & Maria J Stephan (2011) *Why civil resistance works: The strategic logic of nonviolent conflict*. Columbia University Press.
- Collier, Paul & Anke Hoeffler (2004) Greed and grievance in civil war. *Oxford Economic Papers* 56: 563–595.
- Condra, L.N. & J.N. Shapiro (2010) Who takes the blame? The strategic effects of collateral damage. *American Journal of Political Science*.
- Condra, Luke N & Jacob N Shapiro (2012) Who takes the blame? The strategic effects of collateral damage. *American Journal of Political Science* 56(1): 167–187.
- Cunningham, David E (2006) Veto players and civil war duration. *American Journal of Political Science* 50(4): 875–892.
- de Soysa, Indra (2000) The resource curse: Are civil wars driven by rapacity or paucity? In: FIND PLEASE (ed.) *Greed and Grievance: Economic Agendas in Civil Wars*. Boulder, Colorado, USA: Lynne Rienner chapter FINDIT, , FINDIT.
- Dorff, Cassy & Shahryar Minhas (2017) When do states say uncle? network dependence and sanction compliance. *International Interactions* 43(4): 563–588.
- Downes, A.B. (2006) Desperate times, desperate measures: The causes of civilian victimization in war. *International Security* 30(4): 152–195.
- Fjelde, Hanne & Desirée Nilsson (2012) Rebels against rebels: Explaining violence between rebel groups. *The Journal of Conflict Resolution* 56(4): 604–628.

-
- Gleditsch, Kristian S (2007) Transnational dimensions of civil war. *Journal of Peace Research* 44(3): 293–309.
- Goemans, Hein E (2000) Fighting for Survival: The Fate of Leaders and the Duration of War. *Journal of Conflict Resolution* 44(5): 555–579.
- Gurr, Ted R (1970) *Why Men Rebel*. Princeton, NJ: Princeton University Press.
- Harbom, Lotta; Erik Melander & Peter Wallensteen (2008) Dyadic dimensions of armed conflict, 1946—2007. *Journal of Peace Research* 45(5): 697–710.
- Huisman, Mark & Tom A Snijders (2003) Statistical analysis of longitudinal network data with changing composition. *Sociological methods & research* 32(2): 253–287.
- Hultman, Lisa (2007) Battle losses and rebel violence: Raising the costs for fighting. *Terrorism and Political Violence* 19(2): 205–222.
- Humphreys, Macartan & Jeremy M Weinstein (2006) Handling and manhandling civilians in civil war. *American Political Science Review* 100(3): 429–447.
- Kalyvas, Stathis (2006) *The Logic of Violence in Civil War*. New York: Cambridge University Press.
- Kathman, Jacob D & Reed M Wood (2015) Competing for the crown: Inter-rebel competition and civilian targeting in civil war. *Political Research Quarterly* 68(1): 167–179.
- La Rosa, Lucy & David Shirk. The new generation: Mexico’s emerging organized crime threat. Technical report Justice in Mexico.
- Lujala, Päivi; Nils P Gleditsch & Elisabeth Gilmore (2005) A diamond curse? Civil war and a lootable resource. *Journal of Conflict Resolution* 49: 538–562.

- Lyall, Jason (2009) Does Indiscriminate Violence Incite Insurgent Attacks?: Evidence from Chechnya. *Journal of Conflict Resolution* 53(3): 331–362.
- Metternich, Nils; Shahryar Minhas & Michael Ward (2017) Firewall? Or wall on fire? A unified framework of conflict contagion and the role of ethnic exclusion. *Journal of Conflict Resolution* 61(6): 1151–1173.
- Minhas, Shahryar; Peter D Hoff & Michael D Ward (2016) Let’s say amen for latent factor models. Working paper available at <https://arxiv.org/abs/1611.00460>.
URL: <https://arxiv.org/abs/1611.00460>
- Osumah, Oarhe (2013) Boko haram insurgency in northern nigeria and the vicious cycle of internal insecurity. *Small Wars & Insurgencies* 24(3): 536–560.
- Prorok, Alyssa K & Benjamin J Appel (2014) Compliance with international humanitarian law: Democratic third parties and civilian targeting in interstate war. *Journal of Conflict Resolution* 58(4): 713–740.
- Raleigh, Clionadh (2012) Violence against civilians: A disaggregated analysis. *International Interactions* 38(4): 462–481.
- Raleigh, Clionadh; Andrew Linke; Håvard Hegre & Joakim Karlsen (2010) Introducing ACLED: An armed conflict location and event dataset special data feature. *Journal of Peace Research* 47(5): 651–660.
- Regan, P.M. & D. Norton (2005) Greed, grievance, and mobilization in civil wars. *Journal of Conflict Resolution* 49(3): 319–336.
- Regan, Patrick M (2002a) *Civil wars and foreign powers: Outside intervention in intrastate conflict*. Ann Arbor: University of Michigan Press.

- Regan, Patrick M (2002b) Third party interventions and the duration of intrastate conflicts. *Journal of Conflict Resolution* 46(1): 55–73.
- Ross, Michael (2004) How do natural resources influence civil war? Evidence from thirteen cases. *International Organization* 58(1): 35–67.
- Salehyan, Idean & Kristian S Gleditsch (2007) Refugees and the spread of civil war. *International Organization* 60(2): 335–366.
- Schmitt, Eric (2018) Battle to stamp out isis in syria gains new momentum, but threats remain. *New York Times*: 30 May (<https://www.nytimes.com/2018/05/30/world/middleeast/isis-syria-battle-kurds-united-states.html>).
- Tarrow, Sidney (1994) *Power in Movement: Social Movements, Collective Action and Politics*. Cambridge and New York: Cambridge University Press.
- Tucker, Joshua A (2007) Enough! Electoral fraud, collective action problems, and post-Communist colored revolutions. *Perspectives on Politics* 5(3): 535–551.
- Valentino, Benjamin; Paul Huth & Dylan Balch-Lindsay (2004) ‘draining the sea’: Mass killing and guerrilla warfare. *International Organization* 58(2): 375–407.
- Walker, Andrew (2016) *‘Eat the Heart of the Infidel’: The harrowing of Nigeria and the rise of Boko Haram*. London: Hurst and Company.
- Walter, Barbara F (2006) Information, uncertainty, and the decision to secede. *International Organization* 60(1): 105–135.
- Weeraratne, Suranjan (2017) Theorizing the expansion of the boko haram insurgency in nigeria. *Terrorism and Political Violence* 29(4): 610–634.

Weinstein, Jeremy M (2007) *Inside rebellion: The politics of insurgent violence*. Cambridge: Cambridge University Press.

Wucherpfennig, Julian; Nils Metternich; L.-E Cederman & Kristian S Gleditsch (2012) Ethnicity, the state, and the duration of civil war. *World Politics* 64(1): 79–115.

Zeigler, Sean M (2016) Competitive alliances and civil war recurrence. *International Studies Quarterly* 60(1): 24–37.

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