The Role of Civilians in Intrastate Conflict Networks: Evidence from Nigeria ☆

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Abstract

Modern-day intrastate conflicts often involve multiple actors operating within an environment in which interactions between any particular pair of actors may be dependent upon the interactions occurring elsewhere in the system. Yet, most work seeking to understand the drivers of intrastate conflict continue to be rooted in either a country-year or government-rebel group dyadic design. This mode of analysis is problematic for explaining the complex systems of conflicts that have developed in countries as varied as Pakistan, Syria, and Nigeria. The endogenous nature of civil conflict has limited scholars' abilities to draw clear inferences about the drivers of conflict evolution. We argue that: (1) actions occurring in the system should not be considered independently of one another; (2) conflict systems can be substantively affected by the entrance of new actors; and (3) civilians play a significant role in influencing the strategic interactions of armed groups. Using ACLED event data on Nigeria, we apply a novel network-based approach to predict the evolution of intrastate conflict dynamics. Our network approach yields insights about the effects of civilian victimization and key actors entering the conflict. Further, our approach significantly outperforms more traditional dyad-group approaches at predicting the incidence of conflict.

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Introduction

Since 1946 more than half of the countries in the international system have experienced a civil war (Gleditsch et al., 2002), and in recent years, though wars between countries have waned, there are a growing number of intrastate conflicts (Pettersson and Wallensteen, 2015). These types of conflicts have proven to be costly, as violence between state and non-state actors within countries as diverse as the Ukraine, Syria, and Nigeria has led to some of the highest yearly fatality counts in the post-Cold War period. The prevalence and costliness of intrastate conflicts have resulted in the development of a rich literature on the causes and consequences of civil war.[1] Through these works, we have developed a better understanding of the links between economic performance and conflict, the link between civil and interstate conflict, and how political institutions themselves can influence the risk of violence.

In producing these findings, the literature has primarily rooted itself in two modes of analysis. First, is the country-year design in which the goal may be to understand why some states devolve into civil conflict and others remain immune. More recent work has shifted to utilizing a government-rebel group dyadic design (Cunningham et al., 2009), through which scholars can consider how attributes of non-state actors and their relationship to the state can be used to understand how conflicts evolve or end. Yet, neither of these empirical perspectives provide much consideration to the interconnected multi-actor dynamics that characterize recent examples of intrastate conflicts. This is a notable absence given that even by 2003 over 30% of active civil wars involved multiple dyads in conflict with one another (Harbom et al., 2008).

For example, in the current Syrian civil war, Bashar al-Assad's government is fight-

[1]For example, see Hegre et al. (2001); Collier et al. (2004); Salehyan (2008); Lacina (2014); Minhas and Radford (2016).

ing against the Islamic State and multiple militarized opposition groups (the Free Syrian Army, Jaysh al-Islam, Ahrar al-Sham and others). Each of these actors is often involved in conflict both with the government and amongst themselves. In other regions, like Mexico, we observe drug trafficking organizations (DTOs) vying both for political influence and territorial control against government actors and other DTOs. Complex systems of conflict dynamics such as those can be found in countries as varied as India, Colombia, and Nigeria. Many researchers recognize that such cases require a consideration of how non-state groups relate to one another and the government (Christia, 2012; Cunningham, 2014). Empirical research on intrastate conflict, however, has done little to recognize that many countries embroiled in violent conflicts are best understood as a single complex system composed of multiple actors in conflict with one another rather than as a set of independent, dyadic conflicts.

Systems of this sort have long been studied in other fields such as sociology, where researchers have argued that to understand an actor's (or group's) behavior it is necessary to understand the system in which the actor is enmeshed (Granovetter, 1973; Wellman, 1982; Wasserman and Faust, 1994). Many of the questions that conflict scholars are interested in require a careful application of these lessons. For example, can the actions of a particular actor lead to greater levels of violence between other actors in the system? How does a government crackdown on one group affect the activities of other challenger groups? Grappling with any of these questions requires developing a methodological approach in which we can account for dependencies between actors. We accomplish this by introducing a network-based approach that allows us to estimate the interdependencies between actors within an intrastate conflict system even as the composition of actors changes over time. In doing so, our paper is the first to apply an empirical-based network oriented methodology to the study of civil conflict evolution. This framework allows us to estimate the dependencies that manifest between actors in a conflict network and consequently better predict how this system evolves over time.

Further reconceptualizing our understanding of civil conflict through a network perspective enables us to better understand the role that civilians play in shaping a conflict. Civilians sustain substantial costs during a war. At the individual level, the civilian often faces the risk of death and physical abuse. At the collective level, civilian populations must navigate the destruction of roads, schools, hospitals, and basic infrastructure. As a growing body of literature contends (Kaplan, 2013; Dorff, 2017), civilians are not merely passive victims of war. Civilians have agency and, in many cases, organize against the violence that surrounds them. However, we argue that their role in a conflict is contingent on whether or not the system is composed of dyadic, independent conflicts or a multi-actor network. Accordingly, we focus on two factors that drive the evolution of conflict. First, by adopting a network approach, we can better understand how the interdependent dynamics between armed groups influences violence and stability between any pair of actors and in the system as a whole. Second, we not only examine how violent groups interact with each other but also with the civilian population, specifically, our study investigates the role of civilian victimization and civilian mobilization in driving the evolution of intrastate conflict.

To study how violence evolves, we turn to the Nigerian case from 2000-2016. During these years, Nigeria has seen the rise of multiple armed non-state actor groups. In the southern delta region, armed actors, such as the Movement for the Emancipation of the Nigerian Delta (MEND), have battled the government for control of oil production. Boko Haram, potentially the most well known of these groups, has caused massive devastation both to human life and infrastructure in the Northern regions of the country. This group often targets Christian civilians via the bombing of schools, churches, and other community centers. Accordingly, Boko Haram has challenged the governments' ability to keep order and protect civilians. We suggest this case is useful for analysis due to its multi-party nature and the role that both civilian victimization and civilian mobilization have potentially played in shaping the conflict's development. By using a network approach, we are able to better understand and predict these dynamics in Nigeria. In particular, this approach yields insights about the effects of civilian victimization–attacks against civilians lead groups to both be more violent, and to become the targets of attacks in subsequent periods–and the impact of key actors entering the conflict–Boko Haram's entrance into the civil war leads to an increase in violence even in unrelated dyads. Further, an approach which looks at both these strategic actions and accounts for the networked nature of the conflict in Nigeria significantly outperforms more traditional dyad-group approaches at predicting the incidence of conflict.

Political Violence, Networks, & Civilian Populations: An Inclusive Approach for Conflict Evolution

Our approach to understanding civil conflict takes, as its starting point, the belief that dynamics in intrastate conflict take place within a system in which each actor observes and reacts to the actions of others. Three primary features characterize complex systems such as these: (1) dependencies between the actions of actors in the system; (2) the impact of armed groups on violence as they enter the conflict network; and (3) the ability of civilians to influence the strategic interactions of armed groups. We expand on each of these propositions below.

Network Patterns in an Intrastate Conflict Context

In the field of interstate conflict studies, network approaches are gaining more attention.[2] Yet, these approaches have seen little usage in the study of civil wars even though the dynamics underlying many modern day intrastate conflicts involve interdependent interactions between multiple groups. The reason for studying dyadic interactions using a network based approach is to acknowledge the possibility that the actions of actors in a system are contingent on one another. By moving away from the assumption that interactions within a system are independent, a significant amount of work has shown that we can better account for the underlying process that generates relational data and make more accurate inferences.[3]

A particular reason for why interactions between actors may not be independent stems from the fact that in social systems we often observe heterogeneity in how central actors are to the activities occurring within the network, meaning that some may initiate and/or be the target of more events. Heterogeneity in the centrality of actors provides us with information on the set of events that led to the network as we observe it and for how the network will continue to evolve (Barabási and Réka, 1999). Namely, the implication of heterogeneity in how active actors are in a network is within-actor homogeneity of ties, meaning that the relationships between the set of dyads $\{i \rightarrow j, i \rightarrow k, i \rightarrow l\}$ will be more similar to each other than they are to other interactions in the system, such as $m \rightarrow n$, because they all involve actor i as the sender of the event (Kenny and La Voie, 1984).

A straightforward example for why we may see this type of dependence emerge in intrastate conflict networks may involve government actors, who likely have interests in asserting their control across the country. Specifically, in a scenario where rebel groups

[2]For example, see Kinne (2012); Metternich et al. (2015); Minhas et al. (2016b).
[3]For example, see Snijders (1996); Hoff and Ward (2004); Dorff and Ward (2013); Erikson et al. (2014).

$\{j, k, l\}$ are operating in different parts of a country, we would expect a government actor i to be a more likely initiate of conflict with those rebel groups than an actor with non-competing interests. This logic can obviously extend to non-government groups as well. For example, a rebel group may be acting upon ambitions of establishing control over broad swaths of the country, and, as a result, it may become a more central initiator of conflicts in the network. For similar reasons we may observe heterogeneity in how likely actors are to receive conflict events, and, relatedly, we are likely to find that actors initiating more conflicts are likely to also face more conflicts, in general. Each of these effects relates to reasons why there may be dependence between the observations involving a particular actor. An additional form of network dependence includes reciprocity, which is the notion that the interaction between $i \leftarrow j$ and $j \leftarrow i$ are dependent upon one another. The concept of reciprocity has deep roots in the study of relations between states (Richardson, 1960; Keohane, 1989), and it is no less relevant when considering how actors in an intrastate conflict context may act towards one another.

Apart from these nodal and dyadic patterns that commonly arise in social systems, networks often exhibit patterns of dependence involving multiple actors. These types of patterns can broadly be summarized in terms of the concepts of stochastic equivalence and homophily (Wasserman and Faust, 1994). Stochastic equivalence may manifest in a network in which actors cluster into groups, and the group determines an actor's patterns of relations with other groups. More concretely, a pair of actors ij are stochastically equivalent if the probability of i relating to, and being related to, by every other actor is the same as the probability for j (Anderson et al., 1992). Consider a case in which actors nest in groups based on, for example, a shared but unobserved ideology: $\mathbf{a} = \{i, j\}$ and $\mathbf{b} = \{k, l\}$. Here we may likely find that the relations of i towards k and l is similar to how j behaves towards those actors, and this similar to above induces a dependence in the relations of actors within the system. Specifically, the behavior of actors within the conflict system may be a function of a latent community to which they belong. Homophily is an additional type of dependence pattern involving multiple actors, and is typically used to explain the emergence of triads, cases in which actors $\{i, j, k\}$ are each connected and form a triangle, within social systems (Shalizi and Thomas, 2011). In the intrastate setting, conflict triads may emerge when multiple actors are competing for control over the same territory or resource.

The principal idea underlying each of the dependence patterns discussed above is that the actions, or inactions, of any actor, are taking place within an interdependent system. Given this, the entrance or even exit of an actor may have a notable impact on the type of conflict patterns we observe across the network. We will demonstrate the importance of considering these effects in the context of the Nigeria conflict network.

Key Player

An often undiscussed concept in networks and conflicts relates to the ripple effects that the entrance of a key player can have on a system. The entry of a particularly active or violent group could lead to an increase in conflict through a number of mechanisms. As Kathman and 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 entrance of certain groups increases the level of conflict. One possible mechanism through which violence might increase is through a process of rebel group outbidding, where in order for different groups to get support and resources from the population, they need to prove their conviction and capabilities through increasingly violent acts (Crenshaw, 1981; Bloom, 2004; Nemeth, 2014). The entrance of additional groups might also make ending conflict harder, as Cunningham et al. (2009) notes, because the entrance of an additional (dominant) group makes de-escalating conflict more difficult as it increases the number of veto players in peace negotiations.

We also argue that the entrance of key players affects violence because of their strategic relationship with the government. The arrival of a new challenger group that successfully challenges the government may shift perceptions of the government as weak or vulnerable, leading other groups to more willingly challenge the government, as shown in Walter (2006). This particular dynamic also gives the government incentives to react with violence, rather than negotiation, to deter the development of future challengers. Fjelde and Nilsson (2012, p. 613) find "states with weak coercive power create opportunities for nonstate actors to engage in armed struggle against each other."

A perfect example of this effect relates to the role of Boko Haram in the Nigerian conflict network. Boko Haram gained such success that in mid-2014 they were able to effectively control swathes of territory in and around their home state of Borneo. The rise of Boko Haram and the challenges it posed to Nigeria's security apparatus provides incentives for other groups to increase their level of violence, even in dyads that do not involve Boko Haram.

Civilians in Armed Conflict

More often than not, analyses of armed conflict, civil war, and widespread criminal violence shine a spotlight on those actors that seek to wield power through collective violence against a given population or government. However, this narrative has begun to change. With uprisings across the last five years–the Tunisian revolution, the Egyptian revolution, the Syrian Civil War, and the 2014 protests in Venezuela–attention has shifted to recognize the potential power of the population to influence environments of extreme violence and repression.

Compared to the number of studies focusing on economic (Collier and Hoeffler, 2004), political (Humphreys and Weinstein, 2008), and identity-based (Cederman et al.,

2010) drivers of conflict, existing research has largely neglected the role of civilians in influencing the behavior of armed actors. A large body of research explores the origins of collective action and mobilization (Gurr, 1970; Opp, 1988; Tarrow, 1994; Tucker, 2007), and recent scholarship has assessed the effectiveness of "maximalist campaigns" to show that countries are more likely to be democratic following nonviolent campaigns (Chenoweth and Stephan, 2011). However, as articulated by Celestino and Gleditsch (2013), even the macro-level relationship between nonviolent campaigns and state-level outcomes such as democracy or regime transitions remains unclear. Importantly, Celestino and Gleditsch find that nonviolent campaigns destabilize regimes, but the trajectory of peace and democracy following nonviolent campaigns is conditional on the precise actions employed by campaign organizers.

Building on the research agenda motivated by macro-level studies, we investigate the link between civilian mobilization and violence between armed actors at the local level. At present, there is little empirical evidence that civilian action, such as protest armed vigilantism, should or should not "work" in contexts of high violence at the subnational level. Several possible logics link civilian mobilization and violence between armed groups.

First, there might be no relationship between civilian protests and violence. Protests might have other benefits and thus persist for reasons outside of the stated goals driving protest organizers. For example, non-violent activism via protests might stimulate community between survivors of violence and foster a sense of purpose and belonging in the midst of crisis. Additionally, protests against insecurity might target at both types of armed actors (i.e., the state and the non-state challenger), these actors could respond to protests through other means other than violence. For instance, non-state armed groups could make public appeals to civilians, saying that they are there for civilians' protection. Similarly, governments might respond with media campaigns, speeches, or through a general effort to try to divert political attention from violent events. A second mechanism driving a null relationship between protests and violent events is participant risk. Following a protest, participants could be targeted because of their activism, possibly resulting in fewer protests over time but with no clear consequences for violence between armed groups.

Second, participants might achieve their stated aims and decrease violent conflict in their region. If protests successfully demand that the government invest greater resources in the prevention of violence, then we would expect fewer incidents of violence following protests. If protests also demand that non-state actors stop warfare with the state, this manifests as a public disapproval of attempts by the non-state group to coerce or control the civilian population. With enough discontent, protests disrupt the ability of non-state actors to operate in their region.

Third, protests could lead to an increase in violence. As violence between armed actors (state and non-state) increases, non-state actors often victimize civilians to highlight the government's inability to protect the population. Even if protestors demand a non-violent solution to warfare, a plausible logic connecting protests and violence is that protests raise the cost of government inaction so that armed government actors are more likely to fight hard in the next round of contestation. This logic would suggest an antagonistic government actor, one who is politically motivated to demonstrate competency through violent policy.

In addition to civilian mobilization, civilian victimization also influences conflict dynamics. While there is a robust debate over what causes civilian victimization,[4] discussion of the consequences of civilian victimization, particularly as they relate to battlefield outcomes has been more limited (Hultman, 2007; Raleigh, 2012). Hultman (2007)

[4]For example, see Valentino et al. (2004); Downes (2006); Kalyvas (2006); Idean Salehyan and Wood (2015); Prorok and Appel (2014); Humphreys and Weinstein (2006).

finds that rebel group violence against civilians is a military strategy aimed at pressuring governments to concede to rebel challengers.Berman and Matanock (2015) argues 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 more likely. Condra and Shapiro (2012) find support for this relationship in Iraq. Areas where US-led coalition forces kill civilians are associated with a higher likelihood of future insurgent attacks, and areas where insurgent forces kill civilians are associated with a lower risk of future insurgent attacks (against the US-led coalition). Lyall (2009), however, finds a contrary effect and demonstrates that indiscriminate violence against civilians in Chechnya is associated with a lower risk of rebel attacks, possibly because these attacks deprive insurgents of resources.

These accounts of civil conflict primarily focus on a rebel-government dyad.[5] In this dyad, conflict is zero-sum: conditions that enable the government to attack rebels make the rebels less able to attack the government, and vice versa. As we have discussed at length, many conflicts are non-dyadic, they have a multitude of violent groups. The dynamics of civilian victimization change significantly when we move from a purely dyadic setting to a multi-actor network (Raleigh, 2012).[6] When an armed group kills civilians in a multi-actor environment, the results are no longer zero-sum. Consider the plight of civilians victimized by a violent rebel group. According to previous research on dyadic conflicts, civilians know who to turn to obtain protection and revenge–the group that did not victimize them. Yet, in a networked conflict, the choice to respond to victim-

[5]An exception is a 2015 study by Kathman and Wood. They find that due to competition over resources the entry of additional rebel groups leads to an increase in civilian victimization, and that direct conflict between rebel groups increases civilian victimization.

[6]For an analogous discussion of how moving from dyadic to three player interactions destabilizes interstate conflict, see Gallop (2017).

ization by informing on the perpetrators (or siding with their opponents) is less clear. In this setting, civilians observe that the very existence of multiple challenger groups weakens the government. Thus in a multiparty conflict, the government is less likely to be viewed as capable of effective civilian protection as fighting between rebel groups increase (Fjelde and Nilsson, 2012). In addition, if rebel group A predates civilians, civilians may not be able to safely identify or contact the victimizers' rival rebel group *nor* trust a weakened or uninterested government for protection.

Whereas in dyadic conflicts we might expect civilian victimization to mitigate a group's ability to commit violent actions, in a multi-actor setting we do not expect civilian victimization to be associated with an armed group carrying out fewer attacks. In fact we expect the opposite to be the case because the incentives for groups to target civilians increase. In a multi-actor environment the countervailing effects of targeting civilians are weakened as civilians become less likely to report predation. Groups might target civilians in order to consolidate resources or signal military strength (Kathman and Wood, 2015; Hultman, 2007). In either case targeting civilians helps a group carry out attacks in the future. At the same time, we also expect groups that target civilians to be the victims of future attacks. First, because of retaliation or due to direct responses by challenger groups to aggressive behavior, and second because, while the networked nature of conflict reduces civilians incentives to provide aid to rivals, it does not eliminate them.

In this paper, we test these competing logics using the case of Nigeria. In particular, we are interested in how conflict evolves following certain strategic actions: civil mobilization against military actors and civilian victimization by those actors. We investigate whether riots and protests targeting a group make them more (or less) likely to both attack other groups and be attacked by groups in the future. Similarly, we look at whether groups which target civilians are involved in more attacks, and are attacked more in the future.

The contribution of this study is two-fold. We explain and demonstrate the importance of considering conflict processes through a network framework. In doing so, we suggest that networks of conflict constitute a meaningful outcome of interest and depart from the vast majority of the literature which focuses on dyadic outcomes to measure conflict intensity or duration. Second, we contribute to a growing scholarship concerned with the influence of civilian victimization and mobilization on trajectories of violence and stability. Our study focuses on the complex and on-going civil conflict in Nigeria which we turn to next.

The Conflict[s] in Nigeria

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).[7]

President Obasanjo faces many more violent episodes during his first term. As Christian-Muslim disputes continue in the Northern regions, a tribal war foments 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. In April of 2003, Obasanjo is reelected, though the election's legitimacy is

[7] See `http://articles.latimes.com/2001/oct/16/news/mn-57819`.

widely questioned. Obasanjo's second term is marked by continuing violence in the north, driven by Christian-Muslim clashes and deepening violence in the Niger Delta where cities like Port Harcourt are besieged by militants vying for control of oil production centers.

In 2002, Mohammed Yusuf emerged as the radical leader of the religious extremist group, the Boko Haram.[8] Yusuf spreads an anti-state, anti-elite ideology couched in Sunni Muslim teachings. His message is popular among the poor in many towns across the northeast. Conflict in the northern region of Nigeria continues along religious lines, and by 2008 Boko Haram has grown increasingly well organized, effectively 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, and culminates in the death of scores of police officers, more than 700 members of Boko Haram, and the capture of Mohammed Yusuf.[9]

In 2010, Vice President Goodluck Jonathan succeeds to the presidency after the death of his predecessor. Around this time, Boko Haram's leader is killed by Nigerian police in a raid. This leads to an intensification of tactics by Boko Haram, which includes greater violence against civilians. Demonstratively, in December of 2010, Boko Haram bombs kill an estimated 80 people in the central city of Jos. This event sparks a response from opposing Christians leading to roughly 200 more deaths.[10]

Attacks on civilians continue and in April of 2014 Boko Haram chooses a target

[8]There is evidence that the early leadership of the movement formed at this time, though in many reports the fully armed, organized, radical group forms closer to the year 2008. See Walker (2016) for details.

[9]See `http://edition.cnn.com/2014/06/09/world/boko-haram-fast-facts/`.

[10]See `http://www.aljazeera.com/news/africa/2013/09/201397155225146644.html`.

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 protests and vigilantism ensue following the children's kidnapping. This devastating attack even sparks the now internationally known "#bringbackourgirls" social media hashtag (Maiangwa and Agbiboa, 2014). Violence against civilians 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. In the same month, the Boko Haram detonate an improvised explosive devise (IED) in a market in Ngurosoye village, killing at least 16 people.

Battles between Boko Haram, local militant groups, and security forces continue today. While Boko Haram is the dominant armed non-state actor, there are also major ethnic militias such as the Urhobo Ethnic Militia and the MEND.[11] Yet, Boko Haram's entrance into the conflict network in 2009 has had unique consequences.

[11]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 region.

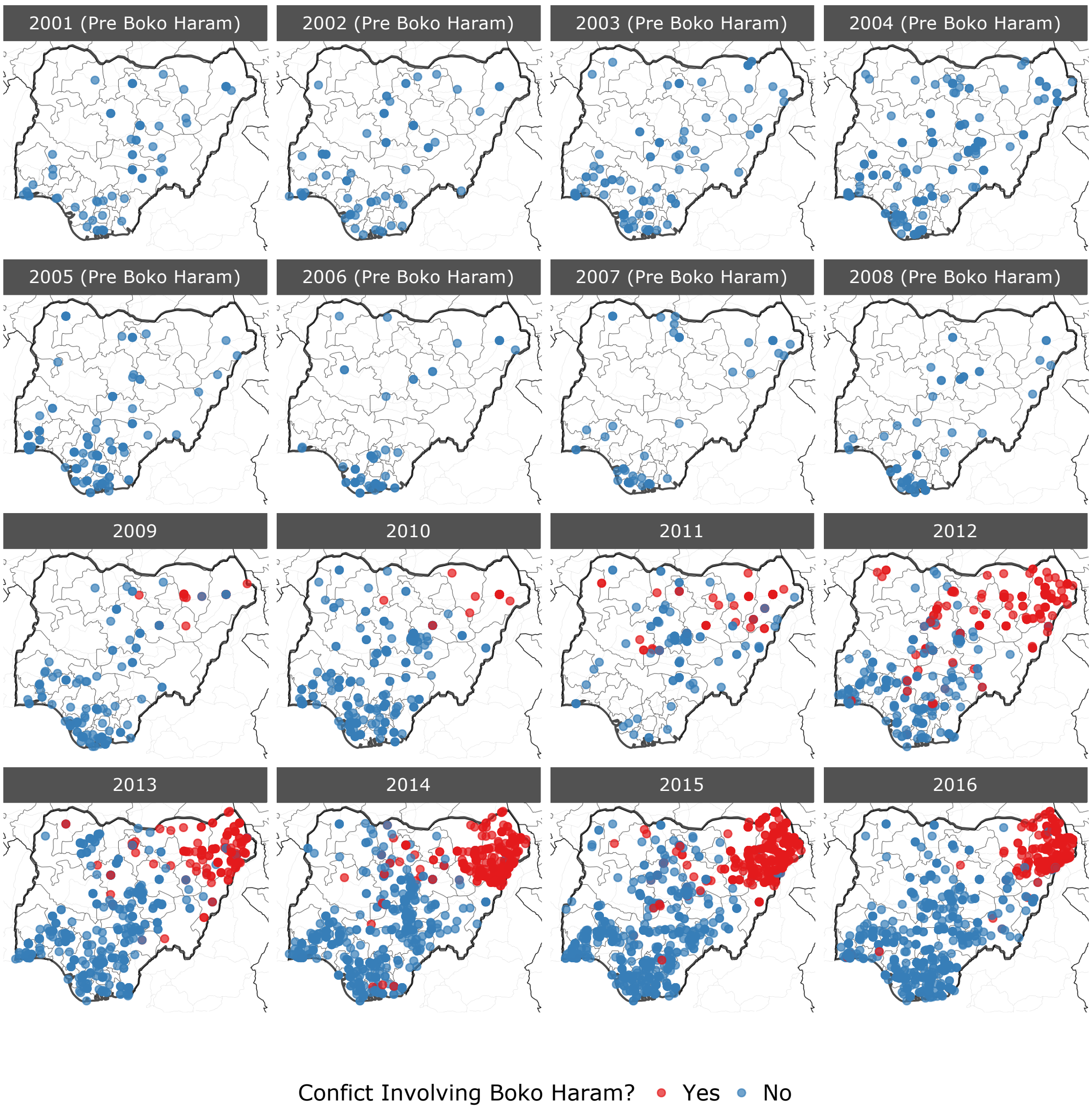

Figure 1: Spatial distribution of conflict in Nigeria from 2001 to 2016. Points colored in blue represent conflict events between sets of actors not including Boko Haram, and points in red events that do involve Boko Haram as either the initiator or target of conflict.

Figure 1 shows the spatial distribution of violence in Nigeria from 2001 to 2016, points in red represent conflictual 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. What becomes clear when examining how the distribution of conflict in Nigeria changes over time is that Boko Haram's entrance into the system corresponds with an increase in both the level and spread of conflict. Interestingly, this proliferation of conflict is not attributable to just armed conflict events involving Boko Haram, we see that the likelihood of conflictual events between actors on the other side of the country substantially increase.

ACLED Data

To study intra-state conflict patterns in Nigeria we utilize the Armed Conflict Location and Event Data Project (ACLED) 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). 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, ethnic groups, and civilians.[12]. Additionally, we utilized secondary resources to confirm the existence and approximate location of each actor in the data.[13] 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).

[12]For detailed definitions of these actors, see the on-line ACLED Africa data codebook maintained at `www.acleddata.com`.

[13]Notes and resources about each are included in the Appendix.

To understand the role that civilians play in shaping conflict within the Nigerian system we create two nodal level covariates. First, we create a count of the number of protests/riots led by civilians against a given actor at time $t-1$. Second, we create a count of the number of violent actions that an actor committed against civilians at time $t-1$. We include these nodal covariates to explain both the probability of an actor sending and receiving a conflictual tie.

Additionally, when modeling the likelihood of conflict between a particular pair of actors we also control for spatial effects. First, we add in 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.[14] We include a "Geographic Spread" variable as both a sender and receiver covariate. Second, a notable literature has developed explicating the mechanisms through which civil conflict can diffuse between countries.[15] To account for this effect, we use the ACLED dataset to count the number of conflict events occurring within Nigeria's contiguous neighbors.

Last, we add three other covariates to the model. First, we create a control for whether both actors are a part of the government. There are only two actors within the 37 that we study in the Nigerian system that would fall under this classification, namely, 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.[16] Second, we include a binary variable that is one if the following year is an election year and zero otherwise. This is to account for the fact that

[14]For example, to model $y_{ij,t}$, we calculate this by taking all the events involving group i in the 3 years prior to t and estimating the variance.

[15]For example, see Starr and Most (1983); Salehyan (2009); Salehyan and Gleditsch (2007); Metternich et al. (2015); Braithwaite (2010); Beardsley (2011).

[16]An alternative approach would be to include sender and receiver level government indicator variables, our results are similar when using that approach.

elections in Nigeria are rarely just waged peacefully in the ballot box, but are typically also followed or preceded by bouts of conflict. More 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 is one once the Boko Haram insurgency has begun (in 2009) and zero beforehand.[17]

Modelling Approach

To estimate conflict in this system in a way that accounts for interdependencies between actors, we rely on a network based approach that combines the social relations regression model (SRRM) – for details on this model see Li and Loken (2002); Hoff and Ward (2004); Dorff and Minhas (2016) – and the latent factor model developed by Hoff (2009). Together the SRRM provides a set of additive effects that we can use to capture first and second order dependencies, and the latent factor model provides a set of multiplicative effects that we use to model third order dependencies. We refer to this estimator as the additive and multiplicative effects (AME) model:

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

[17]We choose this date both because 2009 is considered the beginning of the Boko Haram insurgency in most media reports, despite their founding in 2002, and because 2009 features the first battle including Boko Haram in the ACLED Dataset.

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 ($\boldsymbol{\beta}_d^T \mathbf{X}_{ij,t}$), sender ($\boldsymbol{\beta}_s^T \mathbf{X}_{i,t}$), and receiver covariates ($\boldsymbol{\beta}_r^T \mathbf{X}_{j,t}$). Then we decompose the error using the SRRM and latent factor model. a_i and b_j represent sender and receiver random effects that we incorporate from the SRRM framework:

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

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_ϵ^2 and a within dyad correlation, or reciprocity, parameter ρ.

While the additive effects from the SRRM can deal with first (differing popularity and activity of 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 are more likely 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: $\alpha(\mathbf{u}_i, \mathbf{v}_j)$. 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 therefore account for these third order interdependencies (Minhas et al., 2016a).[18]

Results

Parameter Estimates

We report the results for the sender, receiver, and dyadic covariates included in the AME model in figure 2.[19] First, in terms of our control variables, we find little evidence to support the argument that conflict in neighboring countries is driving violence between actors in the Nigerian conflict system. We also do not find actors becoming particularly more violent during election years. We do, however, find significant evidence for the argument that actors operating in a wider region of Nigeria are likely to come into more conflict with other actors.[20]

Moving to the variable of particular theoretical interest to us, 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

[18] Parameter estimation in the AME takes place by sampling from the posterior distribution of the full conditionals. Details on the estimation procedure can be found in the Appendix.

[19] Excluded 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 figure A1 of the Appendix.

[20] This effect holds even if we leave government actors out of the network or add in binary sender and receiver controls for government actors.

military groups, which is in line with what we hypothesized. We cannot causally say that these are the results 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 which directly result in mass casualties to both rivals and civilians, and smaller-scale episodes wherein the OPC targets the civilian base of rival groups. Both violent actions lead to direct engagement of opposition forces.

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 the null finding here: the protest data we use might have some uncertainty about the targets of the protest, some protests might agitate towards greater military involvement–"Bring Back Our Girls" protests pushing for the government to confront Boko Haram for example–while other protests might be against violence, or different actors might respond to protest in differing ways.[21]

[21] We see no consistent effect of protest, whether we focus only on anti-government protest, only on protests against non-government groups, or when we look at all protests.

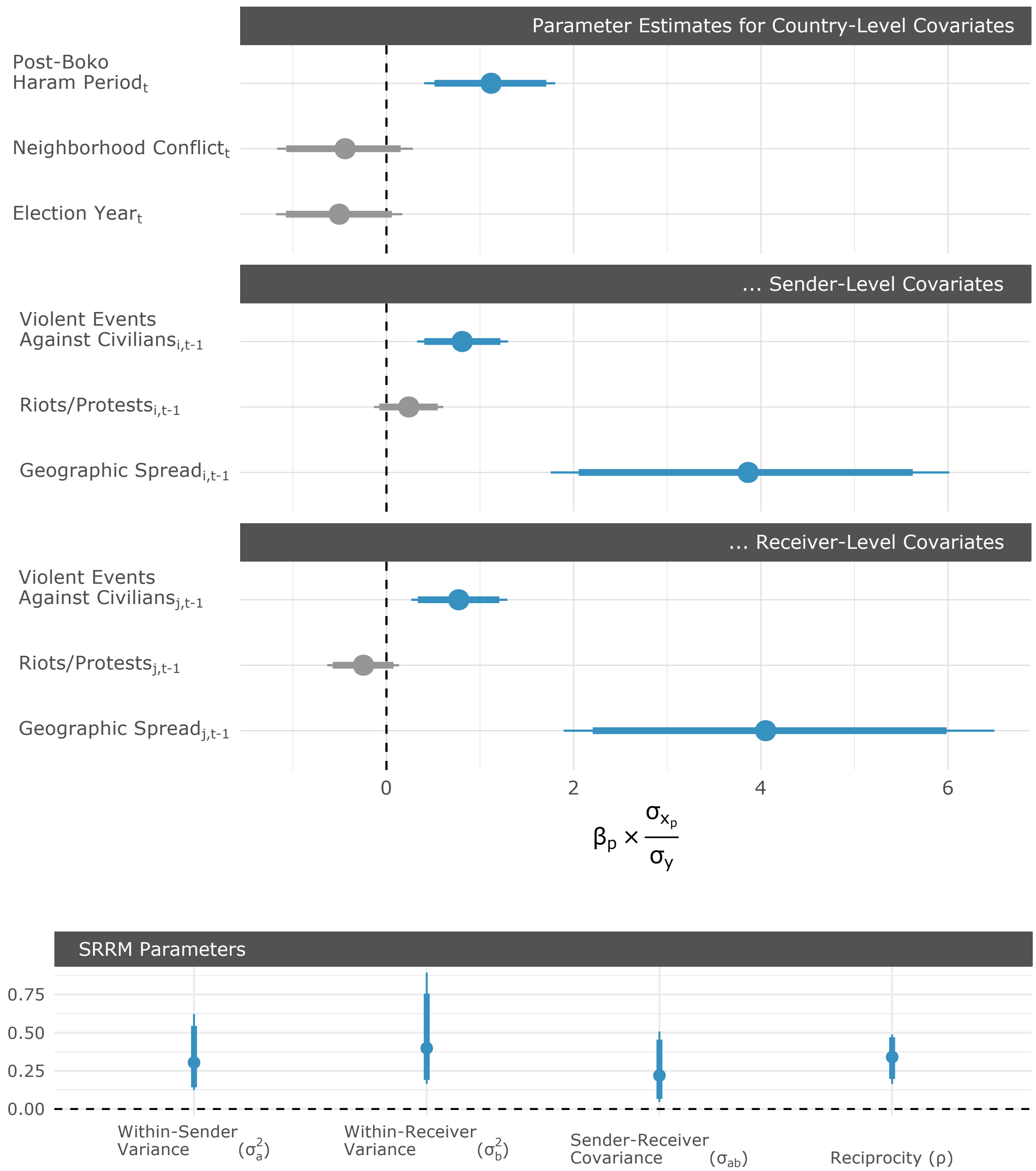

Figure 2: Standardized parameter estimates from AME model. Points represent average value of parameters, thicker line represents the 90% credible interval, and thinner line the 95%.

Finally, we examine at the effect of the beginning 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. Again this is not just the effect of Boko 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 2. By looking at the sender and receiver heterogeneity estimates ($\sigma_{a^2}, \sigma_{b^2}$), 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 whom 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 3, 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.

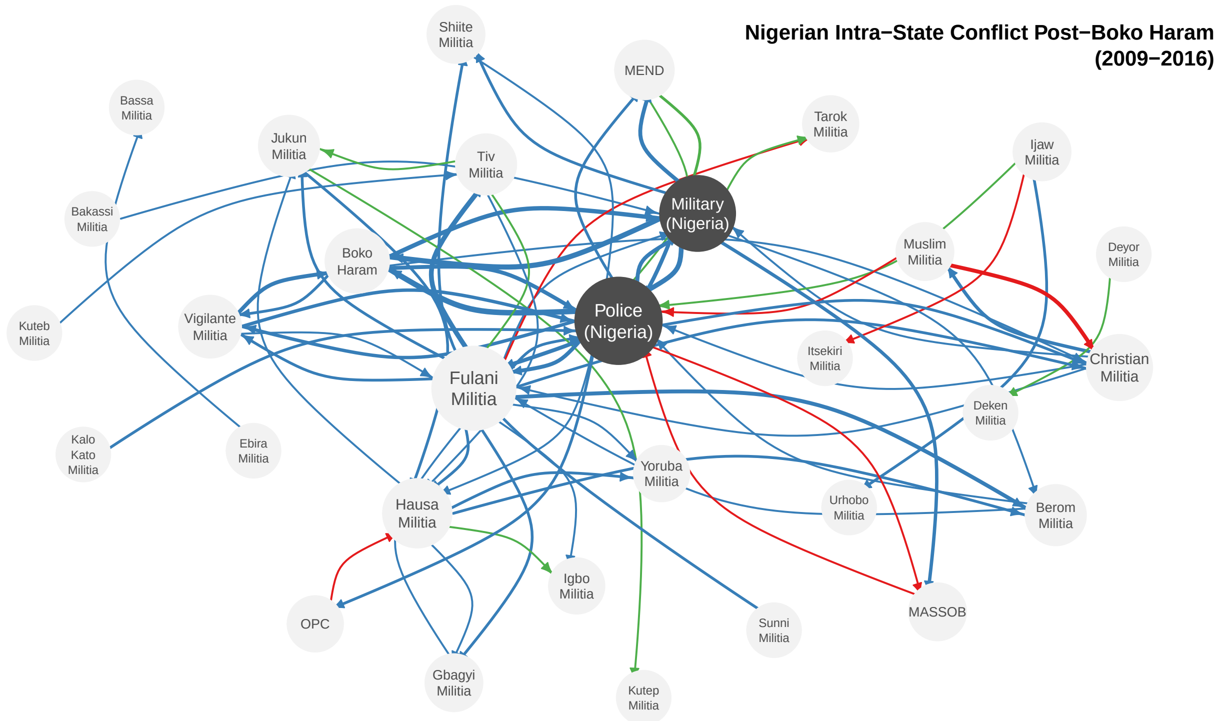

Figure 3: Conflict network 2009-2016. Pairs with more conflict have larger links. Government groups are in black, all other groups are in grey. Blue links indicate more interactions in the 2009-2016 period than in the 2000-2008 period, red indicates less, green no change.

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 and Nilsson (2012) argue fight eachother due to governmental weakness). At the same time, if the government is unsuccessful against Boko Haram, they are incentivized to prove their contintued effectiveness against other groups to 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.

What we can say is that the effect of Boko Haram demonstrates the need for a networked approach to interstate conflict. A standard approach to interstate conflict, which focuses on the government-rebel dyads, or in particularly ambitious cases, also looks at rebel-rebel dyads, would catch Boko Haram's direct effect on conflict, but it would miss this indirect effect. We see the entrance of a group to a network increasing the levels of activities even in uninvolved dyads.

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. We depict the sender ($\hat{a}_i$) and receiver ($\hat{b}_j$) random effects in figure 4. 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 behavior of these groups as some unobserved factors is driving their tendency to send and receive conflict.

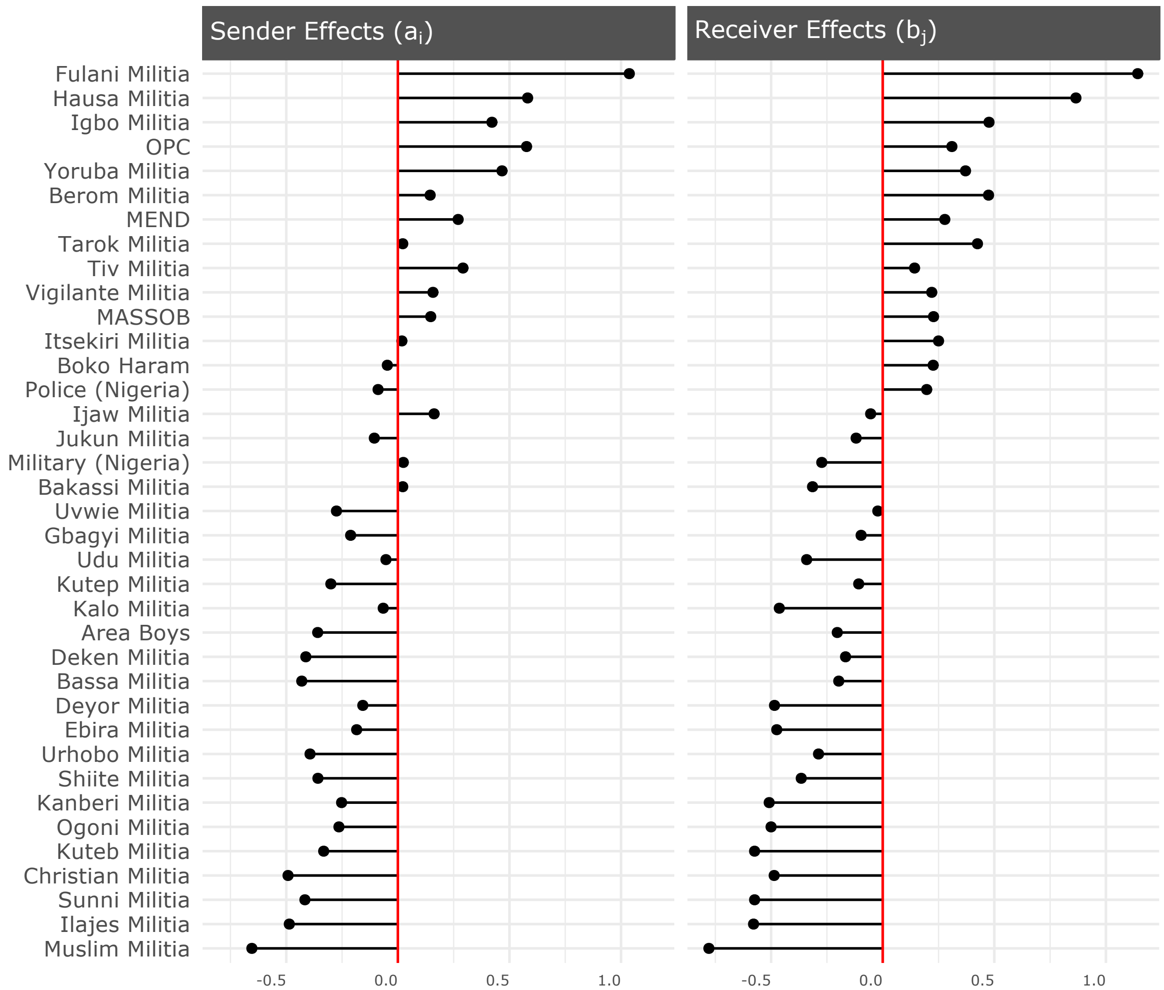

Figure 4: Sender and receiver random effect estimates.

Figure 5 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.[22] 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 (outer ring) or receive conflict from (inner ring). Actor

[22] Figure A2 in the appendix summarizes how well we capture first, second, and third order dependencies using our model.

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.

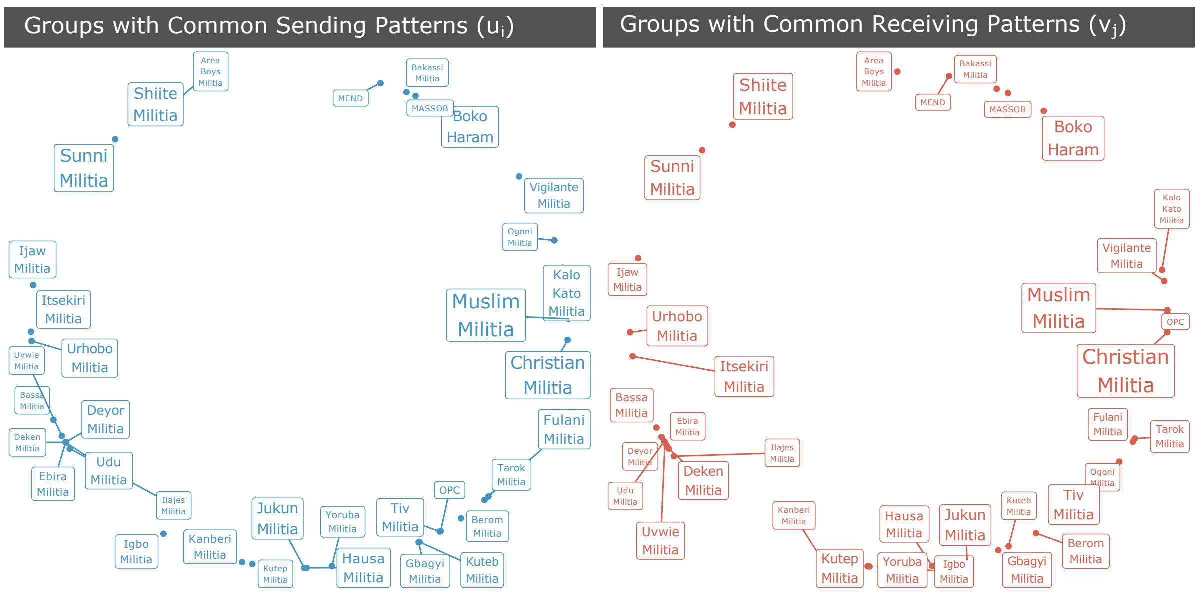

Figure 5: Visualization of multiplicative effects.

By using an AME approach, we are able to better identify 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 each predominantly are 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 5 such as the Fulani, Tiv, Berom, and Kuteb militias each tend to predominantly operate in the Middle Belt of Nigeria, and form spatially 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. To evaluate our model, we randomly divide the $\binom{n}{2} \times T$ data values into $k = 30$ sets, letting $s_{ij,t}$ be the set to which pair ij, t is assigned. Then for each $s \in \{1, \ldots, k\}$, we:

1. estimate model parameters with $\{y_{ij,t} : s_{ij,t} \neq s\}$, the data not in set s,
2. and predict $\{\hat{y}_{ij,t} : s_{ij,t} = s\}$ from these estimated parameters.

The result of this procedure is a set of sociomatrices $\hat{Y}$, in which each entry $\hat{y}_{ij,t}$ is a predicted value obtained from using a subset of the data that does not include $y_{ij,t}$.

We set a number of benchmarks for comparison. First we compare the AME model to a GLM trained 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 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.

We utilize three performance criterions 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. An issue with an ROC Curve when looking at conflict, is that it is relatively rare at the dyadic level: in most years only 3% of possible dyads are in conflict with one another. If peace is common, even a poor model will have a very low False Positive Rate.

To better assess which models predict the presence of conflict, not just its absence, we look at PR Curves. These examine the trade-offs between the percentage of conflicts a model predicts, and the percentage of predicted conflicts which occur. Lastly, we examine separation plots (Greenhill et al., 2011). These provide an intuitive visualization of the accuracy of our predictions by juxtaposing a line showing the predicted probability of conflict with whether conflict actually occurs for all cases (where the cases are sorted by the predicted probability and then colored to indicate the outcome). Here a perfect model would have all cases where conflict actually exists on the right with a predicted probability of 1, and would predict 0 in all other cases.

All of the models' performance out of sample by these metrics are displayed in figure 6. 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.

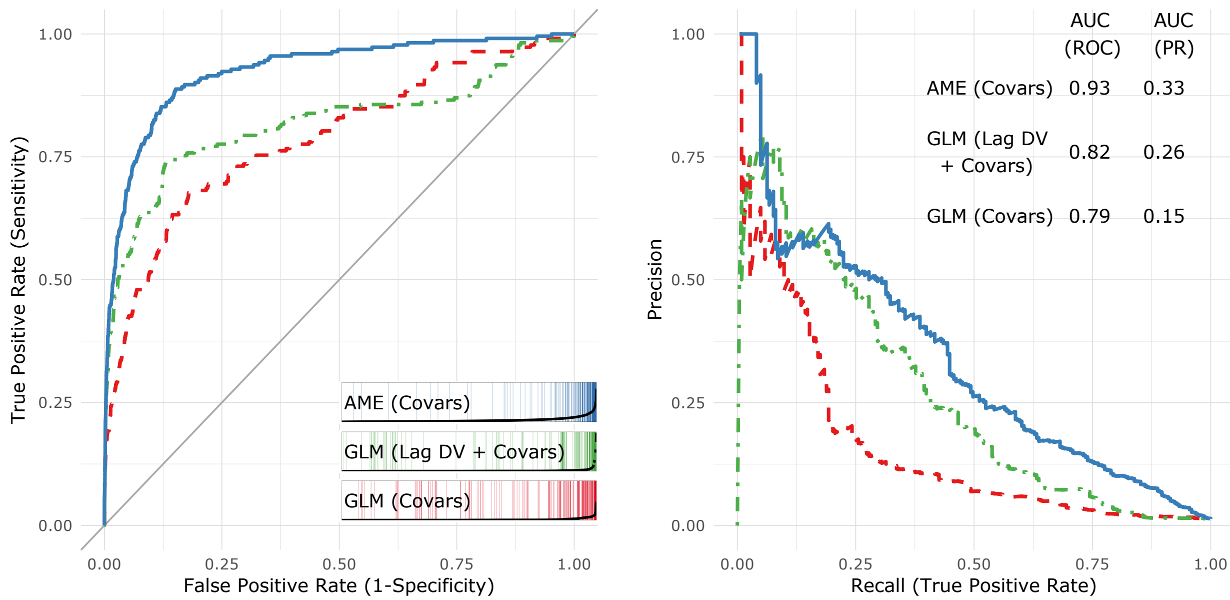

Figure 6: Assessments of out-of-sample predictive performance using ROC curves, separation plots, and PR curves. AUC statistics are provided as well for both curves. In each curve, the AME model is in blue, the GLM with lagged DV and covariates is in green, the GLM with only covariates is in red.

Typically, conflict scholars are also interested in generating forecasts from their models, and to assess the performance of their model instead of taking a cross-validation approach they often attempt to forecast the last period of data. We perform such an exercise as well by dividing up our sample 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 Figure 7 and here again we find that our network based approach has better out of sample predictive performance than the canonical alternatives.

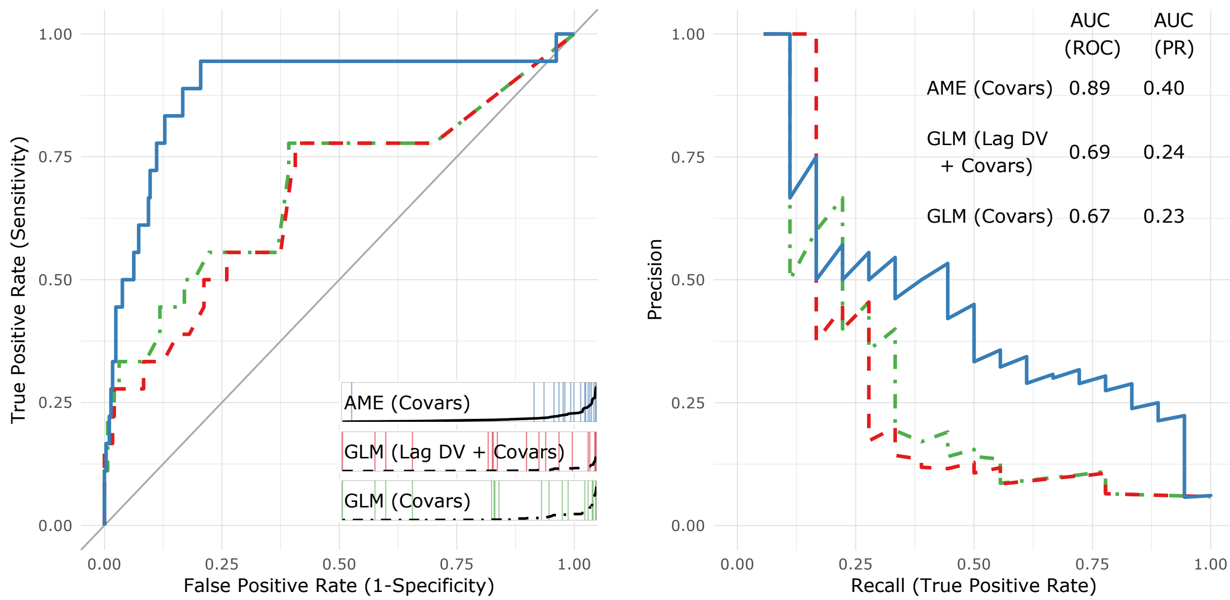

Figure 7: Assessments of out-of-sample predictive performance when forecasting out the last period using ROC curves, separation plots, and PR curves. AUC statistics are provided as well for both curves. In each curve, the AME model is in blue, the GLM with lagged DV and covariates is in green, the GLM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

Conclusion

conclusion structure

- contributions
  - what did we learn from nigiera using our network based approach interdependent system, effect of a single actor
  - civilian - conflict literature: civilian vicitmization
  - discuss limitations of our analysis with regards to nigiera ... ie protests may not have worked here because of x
- conclude with generalzations about how this type of approach is relevant outside of nigeria

- when doing so dont say that AMEN is the only thing to use, there are other ways to incoprorate network based approaches such as ERGMs, community detection models, etc
  - what is it about certain actors that make them so disruptive to conflict networks?

Intrastate conflicts often involve multiple actors operating within an environment in which interactions between any particular pair of actors may be dependent upon the interactions occurring elsewhere in the system. In the case of Nigeria, we find significant evidence of first, second, and third order dependence patterns. The implication of first order dependence patterns is that there are certain actors in the network who are more likely to send and receive conflictual ties to other actors. We also find evidence that those actors initiating more conflict are more likely to be the target of conflict – and vice versa. Our findings with regards to second order dependencies highlights the strong role of reciprocity in this network. Last, in our visualization of the multiplicative effects we find evidence that groups of actors in this system form stochastically equivalent communities. Each of these dependencies points to the fact that there is underlying structure to the set of dyadic interactions that we directly observe in this network. By accounting for these dependencies using a network based approach we are able to better predict the conflictual patterns that emerge within Nigeria between 2000–2016 than regression based techniques that make a priori assumptions of dyadic independence.

Our results also highlight the role that civilian victimization can play in further perpetuating violence. 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. In the Nigerian case, this points to the notion that the observation of violence against civilians can at times do little in mitigating conflict. At the same time, the fact that actors targeting civilian groups are more likely to become targets themselves is certainly important to point out. 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 highlight the limitations of civilian populations in being able to change the behavior of actors in environments of extreme violence.

However, the findings with regards to the role of civilian victimization and civilian riots/protests should not necessarily be generalized 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. Nonetheless, what we have shown is that to account for intrastate conflict dynamics in environments as complex as these, scholars need to move beyond a priori assumptions of dyadic independence. Doing so enables us to account for endogenous structures that develop within systems. By taking these structures into account, we are able to not only more precisely estimate the effects of exogenous parameters, but, in addition, we can better capture the data generating process underlying the relational system of interest.

A.1. Appendix

A.1.1. Trace plots for parameter estimates

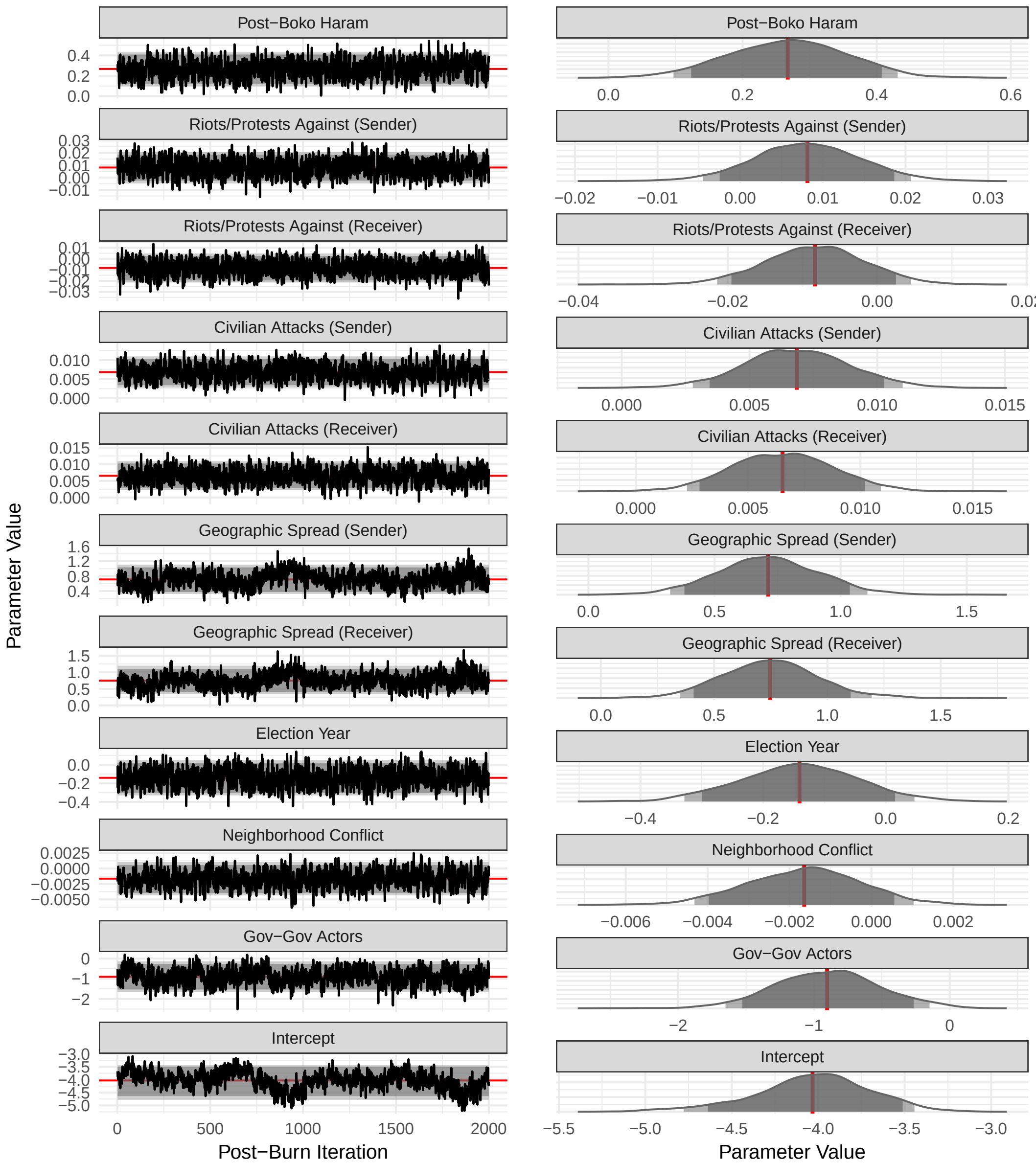

Figure A1: Trace plots for exogenous parameters.

A.1.2. Network Goodness of Fit Assessment

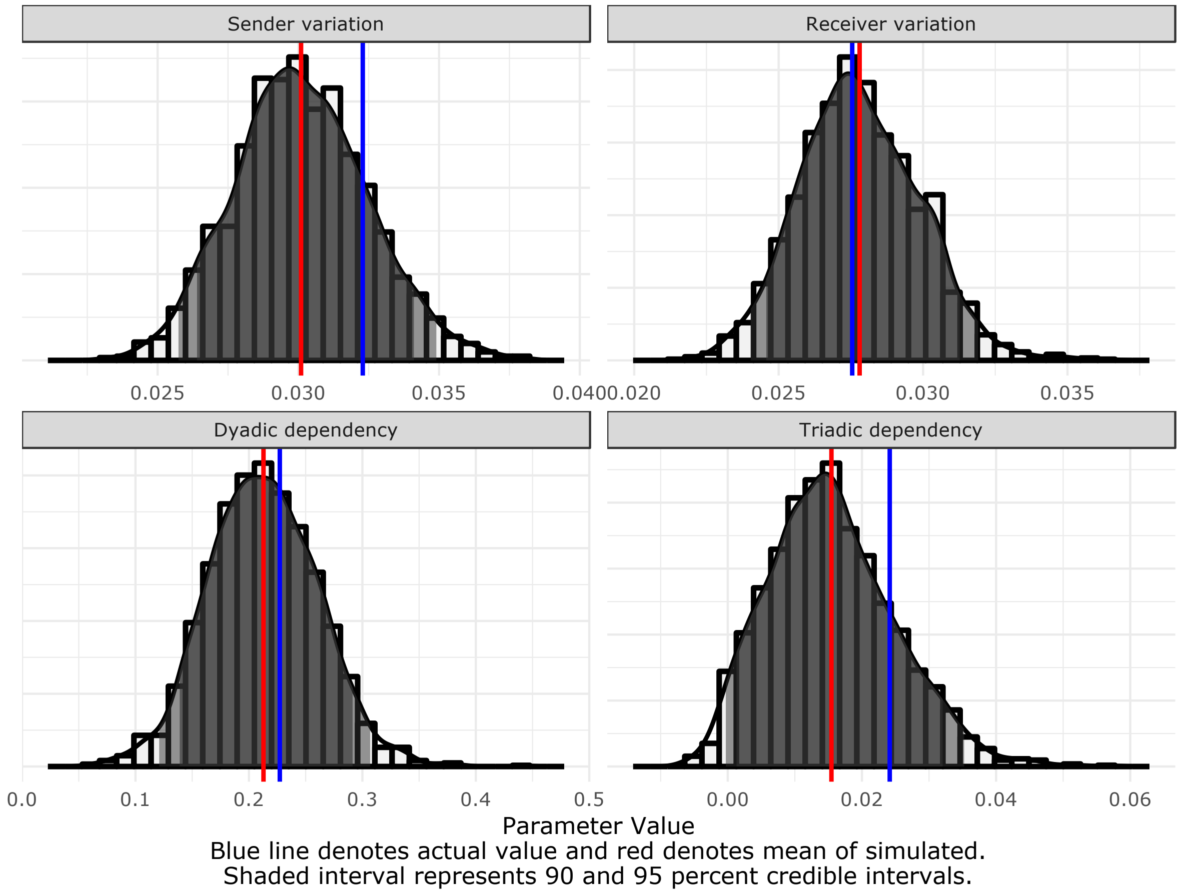

Figure A2: Network goodness of fit summary.

A.1.3. Rebel Group Information

stuff

A.1.4. Additive and Multiplicative Effects Gibbs Sampler

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