Why do armed conflicts last so long?
The effect of relational mechanisms on the duration of the Colombian armed conflict

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Abstract

Why do armed conflicts last so long? The answer to this question is of utmost importance not just for humanitarian reasons but also for the development of a country. However, the analysis of armed conflicts using traditional empirical tools is challenging. Statistical methods that assume independence do not capture the system's interdependence. In this paper, I argue that conflicts are better analysed as processes of interaction. I present an approach that relaxes the assumption of independence and captures the complex dependencies of interaction. I study the Colombian conflict through a network analysis framework as these methods can capture the interdependence of dynamic systems. This approach provides better representations of armed conflicts. I use a relational event model to study interaction mechanisms between armed groups and their influence on the direction of the armed conflict. I use the Colombian conflict as it is a ripe example of a chronic conflict. Results suggest that armed groups tend to attack those groups they have previously attacked. This mechanism could be influencing the persistence of the Colombian conflict. Furthermore, I find that recent events have a stronger influence than past events in future attacks. Thus, I conclude that attacking by inertia and the recency of attacks influence the duration of the armed conflict in Colombia. This information has implications on policies for de-escalating conflict and preventing a relapse.

1. Introduction

The consequences of civil conflict are devastating. The pervasiveness of war hinders the economical and social development of countries that endure it. In the end, nobody really wins but the devastation lingers on affecting whole generations. Why then, do civil conflicts last so long? Civil conflicts last longer than interstate conflicts and partly due to this, they are deadlier (Brandt et al. 2008). Longer wars are also less likely to end and affected countries face significant challenges for peacebuilding and a higher risk of relapsing (Jackson, Beswick, and Beswick 2018). Understanding what drives a conflict is a necessary condition for peacebuilding. However, armed conflicts are considerably difficult to understand because they behave as interdependent complex social systems (Wood and Kathman 2015). Every conflict is a unique blend of interacting factors such as the multiple motivations of warring factions, the number of armed groups that engage at any given moment, their strategies, and their geographic mobility. The duration of conflicts is partly determined by these interacting factors. Scholars have found that the duration of a conflict increases if ethnic groups are present, if there is extensive forest cover or if the war started after 1980 but is not affected by inequality or political repression (Collier, Hoeffler, and Söderbom 2001). The exploration of the effect of these variables on the duration of conflict is vast, but there are no clear cut answers to this question.

An approach to reduce the complexity of this analysis is to concentrate on the core phenomena that all conflicts share: attacks. Attacks are belligerent interactions between a pair of warring parties and constitute the basic unit of a conflict (Harbom, Melander, and Wallensteen 2008). Just like political behaviours are determined by the interactions between people and the resulting social processes, attacks drive the onset, duration and intensity of armed conflicts([1]Pilny et al. 2016). I hypothesise that the micro-dynamics of these attacks play an important role in the duration of a civil war. By looking at this basic unit, we can understand the mechanisms that drive the emergence of these interactions, what motivates an actor to attack, and what happens after an attack.

Social network analysis offers a methodological approach for the study of the process of war. A social network is built from a set of two or more units or nodes (i.e. individuals or groups) that interact through ties. In the context of armed conflict, each armed group constitutes a node and the attack itself constitutes a tie. War entails the accumulation of attacks through time. The patterns that arise from this set of interactions provide insight into the dynamic process of war.

In this paper, I argue that war is better represented by tools that can capture the dynamism of the process of war. The analysis of relationships and their interdependence provides a perspective that better resembles the social structures and temporal patterns of armed conflict allowing for a better understanding of conflict (Victor, Montgomery, and Lubell 2017) (Pilny et al. 2016). A better understanding of armed conflict reflects on more accurate predictions about the evolution of conflict (Dorff, Gallop, and Minhas 2020).

The social network approach offers advantages over other statistical tools to capture this dynamism and the interdependence of attacks. Relational data, unlike other types of data, are interdependent. This entails that the occurrence of attacks partly depends on the history of attacks. Methods built on the assumption of variable independence are not fit for this analysis. Instead, network analysis provides tools to capture this interdependence (Dorff, Gallop, and Minhas 2020) (Perliger 2017).

The *relational event model* is among the social network tools fit for the task of analysing dynamic processes. This statistical modelling approach takes into account the sequence of relational events that occur among actors. In this case, the sequence of attacks between armed groups. Fitting data of the Colombian armed conflict, I look at three parameters that drive social interactions: inertia, reciprocity and participation shifts, which I describe in section 3. I argue that understanding which parameters play a role in the formation of

[1]By definition, an armed conflict is the use of armed force to resolve a dispute between at least two parties (UPPSALA n.d.). The paper focuses on Non-International Armed Conflict (NIAC). In this type of conflict, there is a dispute between at least two parties, one of which must be governmental and the other non-governmental armed groups and the hostilities must result in at least 25 battle-related deaths in one year (UPPSALA n.d.).

attacks provides insights into the duration of armed conflict. This information has implications for policies aimed at de-escalating and terminating conflict.

This paper seeks to contribute to the political networks literature. The findings have important implications in political studies because the dynamic behaviour of armed conflict influences the emergence of political states (Padgett 2017). Studying this behaviour provides clues about the processes that give rise, maintain or change political states (Padgett 2017). It also contributes to theorising about networks and the study of their evolution (Victor, Montgomery, and Lubell 2017). Understanding the mechanisms that influence tie formation in armed conflict can improve predictions on the duration and intensity of war Moore (1995).

The paper is organised as follows. In Section 2, I introduce the *relational event model* and describe how it can be used to study the mechanisms of war continuation. In Section 3, I demonstrate how the relational event model can be applied to analyse the Colombian armed conflict. In this section, I present the data, the case study and discuss the data imputation process. In Section 4, I discuss the results of the applied relational event model. Finally, in Section 5, I draw the main conclusions of my findings. Additionally, Appendix I provides the Goodness of fit measures.

2. Conflict through the lens of a Relational Event Model

The core aim of a Relational Event Model (REM) is to gain insights into the 'processes underlying social dynamics' by studying the history of events (Butts 2008; Bonabeau 2002; Robins 2015). REM provides statistics on the micro-dynamics of social action by fitting longitudinal data of events that occur between actors and which hold temporal information (Pilny et al. 2016). The temporal aggregate of relational events forms the structure of ties that are studied in classical network analysis (Butts 2008).

Each interaction between actors can be defined as a relational event - a "discrete event generated by a social actor and directed toward one or more targets" (Butts 2008) (P.159). Actors can be individuals or collectives, and in some cases, the receiving end of the action may even be an inanimate object. As time passes, the aggregation of the sequence of relational events forms an event history. This event history forms a dynamic network structure in which each action influences other actions in the system (Wood and Kathman 2015). For example, in the context of armed conflict, a relational event is an attack that occurs between two armed groups. The aggregate of relational events constitutes the ordered history of attacks of the armed conflict. Attacks are not independent events because they do not happen at random. This means that the conditional probability of an attack depends on the outcome of the history of attacks.

The REM is based on the underlying assumption that past events shape the context of present events and change the propensities for the occurrence of future events (Robins 2015). For instance, REM can be used to study the tendency for an actor to be the sender or the receiver of an action; how covariates can alter the probability of an action; and how past events impact future events (Butts 2008). Thus, REM can evaluate the extent to which several mechanisms can drive an actor's decision of attacking and provide alternative explanations to the duration of an armed conflict. These mechanisms are discussed below.

Inertia

The first mechanism is *inertia* which is the assumption that the relevant factor driving an actor's decision of attacking is its past behaviour (Moore 1995). Inertia refers to the continuation of attacks regardless of the outcomes of such attacks. This approach to the understanding of conflict persistence relies on the belief that violence is a means to maintain power (Fleck 2021). I hypothesise that armed groups will tend to attack those armed groups they have attacked the most in the past (H1). In other words, the bulk of past attacks is a predictor for future attacks within the conflict network. In addition to this, I also want to evaluate the effect of the recency of the attacks. I hypothesis that armed groups will tend to attack with higher frequency those groups they have recently attacked (H2).

Reciprocity

The second mechanism is **reciprocity** which refers to the "supposition that the behaviour of one actor is conditioned by the behaviour of other actors in a given social system" (Moore 1995)(P. 133). In a war context, reciprocity is a violent response towards an aggressor expecting future gain Fehr and Gachter (2000). In his study, Moore (1995) found that "African nationalists and Rhodesian state reciprocated one another's behaviour during armed conflict" (Moore 1995)(P. 163). Knowing that a decrease in violence by one group would be reciprocated by another has important implications for the de-escalation of conflict. Taking this into account, I hypothesise that armed groups will tend to attack those armed groups that attacked them the most in the past (H3). I also seek to evaluate the effect of the recency of the attacks. In this case, I hypothesise that armed groups will tend to reciprocate attacks from those armed groups that recently targeted them (H4).

2.1 Relational Event Model metrics for the evaluation of Inertia and Reciprocity

REM can capture the dynamic process of the event history of an armed conflict. By estimating statistics on certain parameters, I can gain insight into the inertia and reciprocity mechanisms that give continuation to the conflict. The parameters I evaluate in this research are explained below.

- *Social Persistence* 'is the tendency of past contacts to become future contacts' (Butts 2008). This parameter measures the influence of the aggregation of past events on future interactions. The influencing factor here is the bulk of events. With this definition in mind, Inertia refers to the tendency of armed groups to direct future attacks towards those armed groups who have been targets of most of their past attacks. Reciprocity, on the other hand, refers to the tendency of armed groups to direct future attacks towards those armed groups who have attacked them the most in the past. For example, as illustrated in Table 1, group A directs an attack to group B. If the formation of attacks is driven by inertia, then the tendency in the future is for group A to direct an attack to group B. On the contrary, if the predominant mechanism is reciprocity, then in the future, group B will attack group A.

Table 1: Representation of Inertia and Reciprocity

Parameter	Past	Future
Inertia		
Reciprocity		

- *Recency* is the tendency of recent contacts to become future contacts. This parameter measures the influence of recent events on future interactions, regardless of other past interactions or who the actor is. Recency differs from social persistence in that the emphasis relies on the temporal aspect of the attacks and not the number of events. Two recency parameters can relate to inertia and reciprocity. I refer to these as 'recency of attacking' and 'recency of being attacked.' 'Recency of being attacked' refers to the tendency of armed actors to attack those groups who have attacked them most recently. This parameter is related to reciprocity. The recency of attacking refers to the tendency of armed groups to attack those they have recently targeted. This parameter is related to inertia. For example, as illustrated in Table 1, if the mechanism at play is 'recency of being attacked,' group A was recently attacked by group B, then in the future, group A will tend to reciprocate attacks. When on the contrary, the mechanism is 'recency of attacking,' if group A recently attacked group B, it will tend to continue attacking group B in the future.

- *Participation Shifts* refer to the 'moment-by-moment shuffling' of roles of the actors participating in an armed conflict (Gibson 2003). In the context of conflict, these roles can be partitioned into an attacker, a target, and an unidentified recipient (i.e., civilian). So, a participation shift happens when an actor plays the role of a target in one event and shifts to the attacker in the next event. The idea of this parameter is to estimate the effect of all the 'possible shifts in dyadic interaction' (Butts 2008) (P. 171). Gibson grouped 13 participation shifts into four categories: turn receiving, turn claiming, turn usurping and turn continuing. In this research, I selected those I deem relevant which are depicted in Table 2 and explained below. In the turn receiving category, I measure a participation shift that captures the reciprocity effect: Group A is an attacker and in the next turn, it changes to a target role. That is, the roles of the attacker and target shuffle in the subsequent attack. I also measure three turn usurping shifts. The role attacker and target of the subsequent event change. In the first shift, a fourth group attacks A or B or Y. These participation shifts could indicate alliances by reciprocity: group A attacks B and X defends B by attacking A. Or alliances by inertia: group A attacks B and then group X attacks B. Or a complete shift, indicating multiple instances of war: group A attacks B, then two different actors engage in an attack. Finally, the turn continuing shift depicts the dominance of one group. Group A attacks B and then continues to attack another group. This p-shift is akin to inertia but the target is not the same.

Table 2: Representation of Participation Shifts

Group	Shift	Interpretation
Turn receiving	A → B, B → A	A attacks B, then B attacks A
Turn usurping	A → B, X → A	A attacks B, then X attacks A
	A → B, X → B	A attacks B, then X attacks B
	A → B, X → Y	A attacks B, then X attacks Y
Turn continuing	A → B, A → Y	A attacks B, then A attacks Y

3. Application of the Relational Event Model to the Colombia armed conflict

In this research, I fitted data of attacks between armed groups in the Colombian conflict to a relational event model. In section 2, I explain the Relational Event Model and its application to the context of conflict. Here is a summary of the main ideas followed by the description of the conflict network studied. The unit of analysis of this research is the attacks between armed groups. Attacks between armed groups are interactions of war and they can create patterns of belligerence (Gross and Jansa 2017). A belligerent action is an act carried out under the lawful waging of war. These actions respond to a defined military objective and make use of lawful means and weapons in combat (Reparación y Reconciliación (Colombia) 2013). With this in mind and following the relational event model framework, in this research, every attack held between two armed groups is a relational event. A relational event 'occurs between actors at a specific time-point,' and can succeed across time in a sequence (Robins 2015) (P.46). The sequence of attacks forms the event history and can be depicted with a network.

This research is a whole-network study that relies on longitudinal data. The network is unipartite and directed. In this conflict network, the nodes are the armed groups and the edges are the attacks. The basic unit of analysis is the dyad formed by the attacking armed group and the targeted armed group. This level of analysis suits this research hypothesis that "dyadic relations predict other dyadic relations" (Gross and Jansa 2017).

Attacks are inherently directional and in this case, the edges are dichotomous, meaning that they take on two values (0 = absent, 1 = present). The relational event model uses this directionality to estimate statistics for each parameter. The data I use in this analysis is relational and the directionality was recorded for most of the observations. However, there are some observations in which the directionality is not discernible. For those cases, I input the relations with data imputation. I explain the data imputation process further below.

3.1 The Colombian Armed Conflict

Colombia has endured a longstanding chronic conflict that surged in the rural and political landscape of the 1920s (Estrada 2015; Giraldo 2015). The conflict unravelled over the whole territory and has been mainly fought on the periphery of the relatively stable major cities where the presence of the state is practically non-existent. This authority void enabled other groups to dominate. Among these groups, there are rebel groups, warlords, and paramilitary defence forces. These dominant forces replaced the legal structures of power and paralleled the state's functions through indiscriminate violence, especially against civilians (Reparación y Reconciliación (Colombia) 2013). Several peace attempts and military interventions have tried and failed to end the conflict. The most recent example is the peace deal ratified in 2016 with one of the rebel groups. Despite the efforts, none of these strategies has been successful so far.

3.2 Data

The **Belligerence Actions data set** contains 36740 reports of events of war from 1958 to 2021. The data set was collected by the Observatory of Memory and Conflict - OMC. The OMC is a Colombian institution responsible for documenting the actions of the war and its victims (OMC 2021). The OMC reviews and contrasts the information contained in databases from institutional and social sources including archives, documentary collections, physical and digital press, active searches of public information on the Internet, information systems of public entities that have agreements with the Observatory and fieldwork (OMC n.d.). As of July 2016, the OMC had identified and collected information from 382 sources and 1,118 documents (OMC n.d.). In some cases, the information was collected directly from the victims' testimonies.

The observations in this data set include information on the actors that participated in the attack, the date of the event, and the location. Each observation specifies the name of the armed groups and identifies the group that initiated the attack. I assigned a unique identifier to each actor and used the information on who initiated the attack to create the nodes and edges lists. For the instances where the attacker and the receiver were both rebel armed groups, the sender and receiver were not differentiated in the data collection process. In these instances, I randomly allocated the sender and receiver roles using a Bernoulli distribution with 10 permutations. I expand on the issue of missing data in the section on Data Reliability and Validity.

In addition to this, the OMC also recorded the date of the events. Knowing the order of the events allows fitting temporally ordinal relational event models. In this analysis, I fit 31664 observations to the ordinal time relational event model on `R`. I use the `relevent` package developed by (Butts 2008) for the estimation of the relational event models and their statistics.

Observations and variables

I perform the analysis on a clean data set of 31664 records from 1958 to 2021 (see Table 3). I retained the variables that hold information on:

- **date of the event**: day, month, year
- **location of the event**: region, department (equivalent to states in the US), and municipality (equivalent to counties in the US)
- **groups involved in the attack**: sender and receiver of the attack

Data Aggregation

The Colombian conflict has been long and widespread varying greatly between different regions and throughout time (Ávila 2019). Likewise, the topography and diversity of the country are important sources of heterogeneity that can affect the readability of the analysis. Based on the assumption that different armed groups were organised throughout the territory in subgroups, and to minimise the variability between regions, I aggregated the data into biogeographic regions to reduce the effect of factors such as distance between events. I chose biogeographic regions. Biogeographic regions, or **ecoregions**, are geographical areas that share a particular collection of ecological communities and species (Olson et al. 2001). Colombia is divided into five ecoregions: Amazon, Andes, Caribbean, Orinoco, and Pacific. I subsetted the complete event list creating a list for each ecoregion and then I fitted these subsets to ordinal relational event models. The summary of the distribution of the data is presented in Table 3.

Table 3: Data overview for the ecoregions

Map	Ecoregion	Events	Percentage	Nodes	Edges
	Country	32584	100.00	56	436
	Amazon	3492	10.71	31	100
	Andes	13669	41.95	50	301
	Caribbean	3591	11.02	39	200
	Orinoco	6338	19.45	39	152
	Pacific	5494	16.86	36	217

3.3 Data Reliability and Validity

Despite the rigorous process of the OMC to provide accurate data, the data set has issues that could lead to measurement errors. The most salient of these problems is data missing at random of the type 'false negative edges' resulting from 'item non-response' Huisman (2014). The direction of the edges of attacks between the guerrilla groups and the paramilitary groups is missing. This accounts for 30% of the data, which is considered to be a low to intermediate missingness proportion (Huisman 2014).

Overlooking the interaction between paramilitary and guerrilla groups would have a negative impact on the interpretation of parameters of the relational event model (Dorff, Gallop, and Minhas 2020). Failing to address this issue could also lead to limited statistical power, bias and hindered capacity to explain the context of conflict pertaining to the interaction between non-state armed groups (Huisman 2014), (Robins, Pattison, and Woolcock 2004).

Robins suggests a pragmatic approach to address this problem. This approach requires restricting the attention to the 'subset of individuals for whom network information is complete' (Robins, Pattison, and Woolcock 2004). In this case, all the edges between guerrillas and paramilitary groups are missing. Given that the ties are missing at random and that the portion missing lies close to the low to medium missingness threshold, I address this missing data issue using a random imputation strategy (Gross and Jansa 2017), (Robins, Pattison, and Woolcock 2004). Data imputation consists of replacing 'missing values by plausible estimates' so that no information is lost providing the researcher with completed data for the analysis (Huisman 2014). No prior information is available to assume the probabilities of the attacks. Therefore, I impute the missing directionality of the edges assuming a Bernoulli distribution. More specifically, a Uniform distribution, so each edge direction has an equal probability of realising (P=0.5) (Wasserman and Faust 1994). I estimate the mean out of 10 binomial permutations with equal probability for the roles of sender and receiver of an attack. Then, I assign the value of the mean (0 = receiver, 1 = sender) to one of the armed groups in each observation. It is worth noting that the underlying distribution of edge directionality is unlikely to be a Bernoulli distribution (Steinley and Wasserman 2006).

Further research could improve this simulation by going back to the original data source of each observation. The probability of an armed group's role could be recalibrated from the sources of the data. By consulting a subset of these sources of the attacks between guerrilla and paramilitary groups, and estimating the frequency of the role for each armed group.

Another issue lies in the aggregation of the edges. The study period is ample and by aggregating the data, I assume that nodes and edges are persistent through time. As explained at the beginning of this chapter, the nature of conflict is dynamic and so is the participation of nodes and the persistence of edges. Part of this issue is addressed by the flexibility of relational event models to capture event history (Gross and Jansa 2017). Nonetheless, I consider this to be a topic subject to future research.

4. Discussion

In this research, I fitted relational data on the Colombian conflict to a relational event model. I used the metrics in the relational event model to evaluate the effect of inertia and retaliation on the duration of the conflict. I built the model including the parameters *preferential attachment*, *social persistence*, *recency*, *fixed effects* and *participation shifts*. Out of these parameters, recency, social persistence and participation shifts show a significant effect in the conflict process with slight variations in each region. Table 4 reports the estimates for the statistically significant parameters.

Social Persistence

The inertia coefficients are positive and highly significant for every region except the Pacific region.[2] These coefficients, although somewhat small, support the first hypothesis (H1). This hypothesis proposed that the bulk of past attacks is a predictor of future attacks within the network. The positive and significant coefficients on this term indicate that past attacks positively predict future attacks. This means that the more an armed group has attacked another group in the past, the more likely they are to do so in the future.

On the contrary, and consistent with the results for inertia, the reciprocity term shows a negative significant effect in the Amazon, Andes and Pacific regions. The Caribbean and Orinoco coefficients are non-significant and very small. The negative coefficients indicate that in these regions, armed groups are less likely to attack those who attacked them in the past. Therefore, these results do not support the hypothesis proposed that armed groups tend to reciprocate attacks directed at them over time (H3).

These results suggest that given all the effects modelled, actors tend to preferentially attack those actors who comprised most of their interaction history. In other words, armed groups tend to attack those they have previously attacked rather than those who attacked them in the past.

Recency

I also seek to evaluate the effect of recency on inertia and retaliation. To that end, I formulated two additional hypotheses and I used two terms of the relational event model to test them. The first hypothesis explores the effect of recency on inertia. It proposes that armed groups will tend to attack those groups they have recently attacked (H2). To test this hypothesis, I used the term 'Recency of Attacking.' The coefficients for this term show a positive effect and highly significant values. These coefficients are higher than in any other term and support the hypothesis (H2). This indicates that armed groups tend to attack those groups they have recently attacked. Recency seems to be playing a role in the continuation of the conflict.

The second hypothesis explores the effect of recency of reciprocity. It proposes that armed groups will tend to reciprocate attacks from groups that have recently targeted them (H4). To test this hypothesis, I used the term 'Recency of being attacked.' The coefficients for this term also show positive and significant effects supporting the hypothesis (H4) but are lower than those of the 'Recency of Attacking' term. This indicates that the effect of recency on inertia is stronger than the effect on the reciprocity of attacks.

[2] It is noteworthy to mention that in the Pacific region, inertia has a positive effect although non-significant. This could be signalling a tendency similar to the other regions.

Participation Shifts

The coefficients for the turn receiving p-shift (AB-BA) that captures reciprocity are negative and significant for all the regions. These results do not support the reciprocity hypothesis (H4) that proposed that armed groups will tend to reciprocate attacks from those armed groups that recently targeted them. The negative values of this P-shift show the tendency by armed groups to avoid reciprocating to their attackers. This finding is consistent with the literature. According to the literature, in scenarios of dominance threats, it is expected for actors to avoid this turn-receiving behaviour (Butts 2008).

The coefficients of the turn-usurping effects measured are negative and significant for every region. These negative values indicate the groups' tendency to avoid these shifts. For instance, the negative values indicate avoidance of the turn-usurping p-shift (AB-XY) that could indicate 'simultaneous wars' or attacks. This shows there is a low probability that a third group X attacks a fourth group Y after an attack between groups A and B.

The turn-usurping p-shifts AB-XA or AB-XB also show negative and significant coefficients. These p-shifts can be interpreted as alliances between groups. For example, a military group A attacks a guerrilla group B and then a paramilitary group X attacks a guerrilla group B). The coefficients of these p-shifts do not seem to support the common narrative about alliances between groups like the one between military and paramilitary groups. A caveat here is that part of this result might be coming from the data imputation process that was necessary given the missing information on the directionality of the attack.

Lastly, the coefficients for the turn-continuing p-shift (AB-AY) are positive and significant in every region except in the Amazon. This coefficient captures the effect of inertia. It signals that an armed group A will tend to hold onto its role as the attacker in future events. The positive values of inertia support the hypothesis that proposes that armed groups will tend to preferentially attack those groups they have recently attacked (H2).

Table 4: Parameter Estimates

	Amazon					Andes					Caribbean					Orinoco					Pacific				
Parameter	$\hat{\theta}$	se	z	Pr(|z|)		$\hat{\theta}$	se	z	Pr(|z|)		$\hat{\theta}$	se	z	Pr(|z|)		$\hat{\theta}$	se	z	Pr(|z|)		$\hat{\theta}$	se	z	Pr(|z|)	
Inertia	1.63	0.21	7.71	0	***	1.42	0.08	17.54	< 2.2e-16	***	0.66	0.15	4.38	0	***	1.31	0.14	9.53	< 2.2e-16	***	0.16	0.12	1.30	0.19	
Reciprocity	-0.66	0.19	-3.39	0	***	-0.60	0.09	-6.84	0.00	***	0.09	0.16	0.55	0.58		0.13	0.12	1.06	0.29		-0.60	0.12	-5.02	0	***
Recency of attacking	2.23	0.11	20.88	< 2.2e-16	***	2.12	0.04	52.46	< 2.2e-16	***	2.08	0.07	28.65	< 2.2e-16	***	2.20	0.08	28.88	< 2.2e-16	***	2.18	0.06	34.99	< 2.2e-16	***
Recency of being attacked	1.96	0.11	18.36	< 2.2e-16	***	1.65	0.04	42.57	< 2.2e-16	***	1.62	0.07	22.94	< 2.2e-16	***	1.94	0.07	27.93	< 2.2e-16	***	1.80	0.06	29.97	< 2.2e-16	***
Turn-taking (AB-BA)	-0.18	0.05	-3.75	0	***	-0.32	0.03	-9.61	< 2.2e-16	***	-0.28	0.07	-3.87	0	***	-0.23	0.04	-5.50	0	***	-0.24	0.04	-5.4	0	***
Turn-usurping (AB-XA)	-0.95	0.08	-11.55	< 2.2e-16	***	-0.68	0.04	-18.14	< 2.2e-16	***	-0.80	0.07	-11.15	< 2.2e-16	***	-0.70	0.06	-11.66	< 2.2e-16	***	-0.87	0.05	-16.26	< 2.2e-16	***
Turn-usurping (AB-XB)	-0.69	0.08	-8.49	< 2.2e-16	***	-0.37	0.04	-10.23	< 2.2e-16	***	-0.51	0.07	-7.51	0	***	-0.46	0.06	-8.10	0	***	-0.69	0.05	-13.38	< 2.2e-16	***
Turn-usurping (AB-XY)	-1.23	0.11	-11.49	< 2.2e-16	***	-0.86	0.03	-26.23	< 2.2e-16	***	-1.28	0.06	-22.02	< 2.2e-16	***	-1.11	0.06	-18.06	< 2.2e-16	***	-1.24	0.05	-23.87	< 2.2e-16	***
Turn-continuing (AB-AY)	0.12	0.08	1.48	0.14		0.37	0.03	11.10	< 2.2e-16	***	0.27	0.06	4.33	0	***	0.30	0.06	5.10	0	***	0.21	0.05	4.15	0	***

5. Concluding Remarks

In this study, I aim to identify patterns of interaction that drive the persistence of armed conflict. I used longitudinal event data on the Colombian armed conflict to fit a relational event model. The relational event model is capable of capturing the interdependence of interactions posing an advantage over other statistical tools.

I examine hypotheses that propose that the interactions between armed groups are affected by the effects of inertia and reciprocity. The inertia hypothesis states that armed groups will tend to attack those armed groups they have attacked the most in the past. The reciprocity hypothesis states that armed groups will tend to attack those armed groups that attacked them the most in the past.

The results support the inertia hypothesis. In other words, the results suggest that the armed groups participating in the Colombian conflict tend to attack those groups they have attacked in the past. These groups attack driven by inertia and not to reciprocate attacks.

I also evaluate the effect of the temporality of the attacks. I formulate two additional hypotheses to test the effect of recency of attacking or being attacked. One of the hypotheses states that armed groups will tend to preferentially attack those groups they have recently attacked. The other hypothesis states that armed groups will tend to reciprocate attacks from those armed groups that recently targeted them.

The implications on this are particularly relevant for thinking about conflict as a process that evolves and that can be shaped strategically. For instance, in light of these findings, we could gain insight into the conflict in Colombia, and how it seems to be driven by a predominant offensive strategy rather than a defensive one. This is important as it could hold the key to the de-escalation of violence.

Another conclusion refers to the temporal aspect of the influence exerted by this mechanism. The evidence shows that recent events have more influence on an actor's future attacks than past events. The results support the hypothesis of the effect of recency inertia. In other words, armed groups tend to attack those groups they have recently attacked, rather than reciprocate those that recently attacked them. The inertia and reciprocity hypotheses are supported by the participation shifts effects. The results show the tendency of attacking armed groups to attack in the future as opposed to changing roles from an attacker to a target.

This could be indicative of the decline in the importance of the narrative about the origin of armed groups. What seems to matter is the current situation. Therefore, the de-escalation of conflict needs to address the current state of affairs rather than the history of the conflict.

The missingness of data poses a significant challenge for this research. In particular, missing data hinder interpretations of the relationship between rebel groups and paramilitary groups. Setting boundaries for the networks is also challenging. The dynamics of armed groups is a source of bias. Having groups entering, splitting and exiting the conflict is difficult to track.

Future research using relational event models with the exact time of the events can feed the analysis with information on the boundaries of the conflict. For instance, the rate at which an armed group retaliates attacks could help frame the duration of an active dyad. It could also help understand the effect of reciprocity on the rate of an attack and learn if the rate of inertia is affected by reciprocity. Another important area of exploration relates to how these mechanisms drift depending on the modality of conflict. That is if the reciprocity rate changes depending on the modality of conflict used in the attack (i.e. aerial attack, frontal confrontation, etc.)

Appendix I: Goodness of Fit

As mentioned in the Methodology section, I built this model using a forward selection approach. This means that I built the model entering each parameter at a time. The purpose of this approach is to evaluate the accuracy of the model and the significance of the variables. Table 5 shows the metrics of model assessment comparing the initial reduced model and the full model for all the regions. In every case, the full model showed smaller values of AIC and BIC as well as reduced deviance values. These differences indicate that the full models show a significant improvement to the reduced model. Thus, adding parameters to the model improves the goodness of fit values.

In addition to the AIC and BIC values, the classification measures indicate the proportion of attacks that the model predicted correctly. Table 5 reports the proportion of events that were incorrectly predicted (misclassification rate), and I include in the description the fraction of events for which sender and receiver are exactly predicted and the fraction of events for which either sender or receiver was predicted. The Amazon full model has the highest accuracy predicting the event that actually happened 36% of the time; either sender or receiver about 52% of the time; and out of these, the model predicts the sender 45% and the receiver 42% of the time. This is followed by the Orinoco, with an exact prediction of 29.94% of the events, either sender or receiver 57.72% of the time; and out of these, the model predicts the sender 39.44% and the receiver 38.22% of the events. In third place, the Pacific model predicts the event that actually happened exactly right 24.42% of the time; either sender or receiver right 47.76% of the time; and of these, predicts the sender 39.03% and the receiver 33.05% of the events. For the Andes, the model predicted 22.92% of the attacks; either sender or receiver 47.66% of the time; and of these, the model predicts the sender 40.43% and the receiver 30.15% of the events. Lastly, the Caribbean case has the lowest accuracy, predicting 17.85% of the events exactly right; either sender or receiver about 46.7% of the time; and of these, predicts the sender 38.37% and the receiver 26.17% of the events.

References

Ávila, Ariel. 2019. *Detrás de La Guerra En Colombia.* Editorial Planeta.

Bonabeau, Eric. 2002. "Agent-Based Modeling: Methods and Techniques for Simulating Human Systems."

Table 5: Goodness of fit metrics. Comparison between the reduced and the full models.

	Amazon		Andes		Caribbean		Orinoco		Pacific	
Metric	Reduced	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced	Full
Residual deviance	40134.82	15735.31	199651.4	91401.09	50036.47	27240.84	69211.69	30081.56	84677.71	40450.27
AIC	40136.82	15765.31	199653.4	91431.09	50038.47	27270.84	69213.69	30111.56	84679.71	40480.27
BIC	40142.98	15857.68	199661	91543.93	50044.66	27363.63	69220.3	30210.73	84686.46	40581.59
Misclassification rate	76%	63.9%	89.19%	77.07%	91.42%	82.14%	81.54%	70.05%	85.92%	75.57%

Proceedings of the National Academy of Sciences 99 (suppl 3): 7280–87. https://doi.org/10.1073/pnas.082080899.

Brandt, Patrick T., T. David Mason, Mehmet Gurses, Nicolai Petrovsky, and Dagmar Radin. 2008. "WHEN AND HOW THE FIGHTING STOPS: EXPLAINING THE DURATION AND OUTCOME OF CIVIL WARS." *Defence and Peace Economics* 19 (6): 415–34. https://doi.org/10.1080/10242690701823267.

Butts, Carter T. 2008. "A Relational Event Framework for Social Action." *Sociological Methodology* 38 (1): 155–200. https://doi.org/10.1111/j.1467-9531.2008.00203.x.

Collier, Paul, Anke Hoeffler, and Måns Söderbom. 2001. "On the Duration of Civil War," 34.

Dorff, Cassy, Max Gallop, and Shahryar Minhas. 2020. "Networks of Violence: Predicting Conflict in Nigeria." *The Journal of Politics* 82 (2): 476–93. https://doi.org/10.1086/706459.

Estrada, Jairo. 2015. "Acumulación Capitalista, Dominación de Clase y Rebelión Armada." In *Contribución Al Entendimiento Del Conflicto Armado En Colombia.* Comisión Histórica del Conflicto y sus Víctimas.

Fehr, Ernst, and Simon Gachter. 2000. "Fairness and Retaliation: The Economics of Reciprocity," 106.

Fleck, Dieter, ed. 2021. *The Handbook of International Humanitarian Law.* Fourth edition. Oxford Handbooks. Oxford, United Kingdom: Oxford University Press.

Gibson, D. R. 2003. "Participation Shifts: Order and Differentiation in Group Conversation." *Social Forces* 81 (4): 1335–80. https://doi.org/10.1353/sof.2003.0055.

Giraldo, Jorge. 2015. "Política y Guerra Sin Compasión." In *Contribución Al Entendimiento Del Conflicto Armado En Colombia.* Comisión Histórica del Conflicto y sus Víctimas.

Gross, Justin H., and Joshua M. Jansa. 2017. "Relational Concepts, Measurement, and Data Collection." *The Oxford Handbook of Political Networks.* https://doi.org/10.1093/oxfordhb/9780190228217.013.7.

Harbom, Lotta, Erik Melander, and Peter Wallensteen. 2008. "Dyadic Dimensions of Armed Conflict, 1946—2007." *Journal of Peace Research* 45 (5): 697–710. https://doi.org/10.1177/0022343308094331.

Huisman, Mark. 2014. "Imputation of Missing Network Data: Some Simple Procedures." In *Encyclopedia* *of Social Network Analysis and Mining*, edited by Reda Alhajj and Jon Rokne, 707–15. New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-6170-8_394.

Jackson, Paul, Danielle Beswick, and Danielle Beswick. 2018. *Conflict, Security and Development: An Introduction.* Third edition. Abingdon, Oxon ; New York, NY: Routledge.

Kuperman, Ranan D. 2001. "Rules of Military Retaliation and Their Practice by the State of Israel." *International Interactions* 27 (3): 297–326. https://doi.org/10.1080/03050620108434987.

Moore, Will H. 1995. "Action-Reaction or Rational Expectations?: Reciprocity and the Domestic-International Conflict Nexus During the 'Rhodesia Problem'." *Journal of Conflict Resolution* 39 (1): 129–67. https://doi.org/10.1177/0022002795039001006.

Olson, David M., Eric Dinerstein, Eric D. Wikramanayake, Neil D. Burgess, George V. N. Powell, Emma C. Underwood, Jennifer A. D'amico, et al. 2001. "Terrestrial Ecoregions of the World: A New Map of Life on Earth: A New Global Map of Terrestrial Ecoregions Provides an Innovative Tool for Conserving Biodiversity." *BioScience* 51 (11): 933–38. https://doi.org/10.1641/0006-3568(2001)051%5B0933:TEOTWA%5D2.0.CO;2.

OMC. 2021. "Acciones Bélicas." *Observatorio de Memoria y Conflicto.* http://micrositios.centrodememoriahistorica.gov.co/observatorio/portal-de-datos/el-conflicto-en-cifras/acciones-belicas/.

———. n.d. "Metodología." *Observatorio de Memoria y Conflicto.* Accessed May 11, 2021. http://micrositios.centrodememoriahistorica.gov.co/observatorio/sievcac/metodologia/.

Padgett, John F. 2017. *The Emergence of Organizations and States.* Edited by Jennifer Nicoll Victor, Alexander H. Montgomery, and Mark Lubell. Vol. 1. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190228217.013.2.

Perliger, Arie. 2017. "Terrorism Networks." *The Oxford Handbook of Political Networks.* https://doi.org/10.1093/oxfordhb/9780190228217.013.28.

Pilny, Andrew, Aaron Schecter, Marshall Scott Poole, and Noshir Contractor. 2016. "An Illustration of the Relational Event Model to Analyze Group Interaction Processes." *Group Dynamics: Theory, Research, and Practice* 20 (3): 181–95. https://doi.org/10.1037/gdn0000042.

Reparación y Reconciliación (Colombia), Comisión Nacional de, ed. 2013. *¡Basta Ya! Colombia, Memorias de Guerra y Dignidad: Informe General.* Segunda edición corregida. Bogotá: Centro Nacional de Memoria Histórica.

Robins, Garry. 2015. *Doing Social Network Research: Network-Based Research Design for Social Scientists.* Los Angeles: Sage Publications Ltd.

Robins, Garry, Philippa Pattison, and Jodie Woolcock. 2004. "Missing Data in Networks: Exponential

Random Graph (p) Models for Networks with Non-Respondents." *Social Networks* 26 (3): 257–83. https://doi.org/10.1016/j.socnet.2004.05.001.

Steinley, Douglas, and Stanley Wasserman. 2006. "Approximate Distributions of Several Common Graph Statistics: Hypothesis Testing Applied to a Terrorist Network." In *Proceedings of the American Statistical Association, Statistical Applications in Defense and National Security*. Rand Corporation.

UPPSALA. n.d. "Definitions - Department of Peace and Conflict Research - Uppsala University, Sweden." Accessed January 24, 2022. https://www.pcr.uu.se/research/ucdp/definitions/#state-based.

Victor, Jennifer Nicoll, Alexander H. Montgomery, and Mark Lubell. 2017. "Introduction: The Emergence of the Study of Network in Politics." *The Oxford Handbook of Political Networks*. https://doi.org/10.1093/oxfordhb/9780190228217.013.1.

Wasserman, Stanley, and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Structural Analysis in the Social Sciences 8. Cambridge ; New York: Cambridge University Press.

Wood, Reed M., and Jacob D. Kathman. 2015. "Competing for the Crown: Inter-Rebel Competition and Civilian Targeting in Civil War." *Political Research Quarterly* 68 (1): 167–79. https://doi.org/10.1177/1065912914563546.