Network Competition and Civilian Targeting During Civil Conflict

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Abstract

Building on recent developments in the literature, this article addresses a prominent research question in the study of civil conflict: what explains violence against civilians? We use a novel computational model to investigate the strategic incentives for victimization in a network setting; one that incorporates civilians' strategic behavior. We argue that conflicts with high network competition – where conflict between any two actors is more likely – lead to higher rates of civilian victimization, irrespective of the conflict's overall intensity or total number of actors. We test our theory in a cross-national setting using event data to generate measures of both conflict intensity and network density. Empirical analysis supports our model's finding that conflict systems with high levels of network competition are associated with a higher level of violence against the civilian population.

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Introduction

In 2014, over 2,000 civilians were targeted and killed in the Central African Republic compared to less than ten recorded civilian deaths just five years before. At that time, in 1999, nearby countries like Nigeria and the Democratic Republic of Congo witnessed a much higher level of violence against civilians during conflict, confronting an estimated 430 and 2,180 deaths, respectively.[1] What explains this variation in violence against civilians across time and space?

A deepening body of rigorous research tackles this important question and strives to uncover the conditions that drive violence against civilians during conflict. To do so, researchers have considered both internal and external conflict conditions. External conditions, like the role of peacekeepers (Fjelde, Hultman and Nilsson, 2019) or the appearance of international actors who fund rebel groups, shift incentives for violence at the local level and can help explain variation across cases (Salehyan, Siroky and Wood, 2015). Internally, violence against civilians is often characterized as conditional on the competitive nature of the conflict, wherein territory is valued for inherent "resources," such as the sustenance of agricultural lands (Bagozzi, Koren and Mukherjee, 2017), civilian support (Kalyvas, 2006; Arjona, 2017), or profitable commodities such as oil (Lujala, 2010). But because the drivers of competition can manifest through different resource channels, focusing only on one resource motive versus another provides an incomplete theoretical mechanism to explain variation across cases. For this reason, scholars have also turned to explore the dynamics of competition itself to identify meso-level, dynamic mechanisms that capture how both civilian support and access to territory drive violence against civilians over time. This relationship is shown to be particularly acute in regions with multiple warring parties where changing factions and persistent fluctua-

[1] All estimates are calculated using the Armed Conflict Location and Event Dataset.

tions in number of armed groups incentivizes armed groups to commit violence against noncombatants as a way to secure and control resources (Wood and Kathman, 2015). Although changes in the number of armed groups intuitively heighten competition – more actors mean more groups warring over finite resources – increases in just the number of armed groups does not always necessitate competition between groups. The *relational patterns* of competition itself are an important system level mechanism that drives violence against civilians.

In this paper, we follow the call from Balcells and Stanton (2020) for a more "integrated theoretical understanding of multiple actors and interactive social processes driving violence against civilians." To do this, we unite different threads of research on violence against civilians to achieve three goals: (1) we offer a formal, network theoretic approach to explain why interdependent, system-level competition drives violence against civilians during civil war; (2) our approach is informed by studies on the microfoundations of violence against civilians at the subnational level to generate testable, cross-national expectations; and (3) we incorporate civilian choices as part of the multi-actor strategic puzzle.

We argue that competitiveness makes the need for armed groups to victimize for defense more acute in two key ways: first, in a more competitive conflict environment where the amount of fighting between warring groups is high, territorial contestation necessarily increases as belligerents face challenges from "all sides". This increases the value of civilian support, leading armed groups to victimize as a control strategy. Second, if an armed group fights against a wider variety of different challenger groups, then a larger portion of the population's support is suspect, and thus armed groups' incentives for victimization increase against a broader range of the population. The simple presence of many armed groups will not create these incentives, but the risk of each group fighting will increase incentives to victimize.

While we might expect victimization to be a function of overall levels of violence, or the number of armed groups, our model's key finding is that a more competitive conflict network – one in which violence is more evenly committed by many different groups – leads to more civilian victimization *irrespective* of the overall level of violence and the number of groups. This implies that, from a civilian perspective, a setting with multiple moderately violent rival groups presents a situation that is *more dangerous* than an equally violent setting in which there is only one, extremely violent group. This finding is crucial to the growing work on civilian victimization, because it reveals that civilian casualties are not just a function of the total level of violence in a conflict, or the number of violent actors but the strategic interactions between each armed group. Next we describe the conceptual intuition behind our theory followed by our computational model, supporting literature, and the model's results; then we proceed to test our hypotheses using event data. In both simulations from our computational model and the empirical data, we find strong support for the relationship between competitiveness and civilian victimization even after controlling for the overall intensity of conflict.

Theoretical Intuition

In this section, we provide a high-level overview of the intuition driving the choices in our theoretical model.

Armed groups target civilians to help extract resources from the population and to increase their likelihood of prevailing in expected conflicts with other groups (Kalyvas, 2006). Civilians likewise act strategically to minimize their personal likelihood of being killed by armed groups (Arjona, 2017; Kaplan, 2017). Thus, to understand when and where civilian victimization is likely to take place, we need to evaluate this complex, multi-actor strategic environment.

To do this, we estimate the relational, or network competitiveness of the environment. If violence is concentrated around a single actor, where one actor dominates conflict initiation towards many others or receives conflict from many challengers, then civilian victimization will be less likely. If, however, all actors are likely to fight one another – in an all against all competition – civilian victimization will be at its highest. To investigate this, we conceptualize the overall strategic environment as a social network, wherein the nodes in this network are armed groups, and the edges are battles between these groups. We formulate our concept of network competition across each conflict network as follows:[2]

$$\text{Network Competition} = 1 - \sum_{i=1} N(CS_i)^2 \tag{1}$$

N denotes the number of actors and CS_i is the conflict share of actor i, which is a measure of the proportion of battles an armed actor is involved in.[3] Our measure provides us with a representation of how dispersed conflict is in the network. Figure 1 provides a conceptual illustration of a low and high competition scenario.

The left-hand network exhibits low network competition. Here, conflict patterns are dominated by a single sender or receiver in the network. In this network, an armed group's strategic decision to victimize civilians is fairly straightforward – victimization takes place if the coercive effect (causing more non-supporters to reluctantly support the group in charge) outweighs the resources that could be mobilized from non-supporters. In this environment, while there may initially be low levels of victimization, we will quickly approach an equilibrium where most civilians support the groups in control of their territory, and no victimization occurs.

[2]This is a rescaled version of a commonly used measure for market share, the Herfindahl-Hirschman Index.

[3]This type of measurement of competition has been used in a range of works – such as in measuring ethnic and cultural fractionalization (Fearon, 2003) to the competitiveness of party systems (Alfano and Baraldi, 2015).

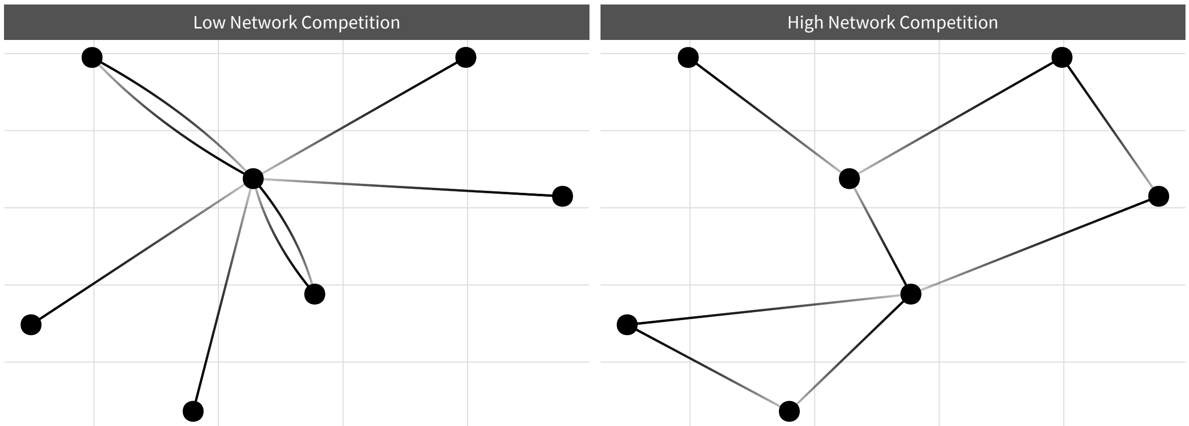

Figure 1: Conceptual networks illustrating low and high network competition scenarios. Network competition is low in the left panel and high on the right, while the number of conflictual events and actors stay constant.

The right-hand network reveals a different picture. This competitive conflict network functions as a Hobbesian war of all against all, where each armed group is ready to attack each other armed group. Almost all actors are at risk of an attack, and they are at risk of an attack from multiple sources leading to even stronger incentives towards victimization. In this case, there is likely a fluid control of territory. Frequent changes in the system increase incentives for violence against civilians; an assumption supported by existing research (Wood and Kathman, 2015). Some of the most intractable and dynamic conflicts–like the modern wars in Somalia– are likely to exhibit this network structure. Our theoretical model, explained below, builds on existing work by formalizing the competitive process in a network environment and including the strategic behavior of civilians as a key predictor of violence against civilians during war.[4]

[4](König et al., 2017) similarly uses a detailed theoretical model to study the interplay between network dynamics and conflict in civil conflict. The main difference is that their study is interested in conflict between armed groups, rather than how conflict between armed groups changes the incentives for one sided violence. In addition, their study focuses on different aspects of the network (actor centrality rather than the overall competitiveness of the network), and their study is an in-depth examination of conflict in the Congo, rather than a cross-national analysis.

Civilian Victimization During War

Current research acknowledges that an armed actor's decision to victimize civilians is conditional on the conflict landscape at large, wherein the decisions of armed groups are informed by the actions of both rival armed challengers and the civilian population. As (Wood, 2010, p. 612) explains, "Unraveling these dynamics is particularly important if scholars wish to fully understand the dense web of interactions that guide insurgent's decisions to use violence." While this literature has begun to uncover the intuition behind how multi-actor conflicts influence victimization, much of the theoretical mechanisms remain underspecified and measurements for complexity rest on accounting solely for the number of armed groups. We draw on the intuition from the literature that the interdependent dynamics of armed groups influence violence against civilians and use it to support each turn in our modeling decisions described below. We demonstrate how unitary choices among actors can generate relational, competitive dynamics across the conflict network.

Model Environment

In this model a country is composed of territories comprised of two types of actors: civilians and armed groups.[5] Armed groups' primary motivation is to gain territory containing resources that can be mobilized (Kalyvas, 2006), where resources in our game are represented by civilian support. Failing this, actors prefer that territory is held by groups with similar preferences. The other key actors in this model are civilians. Civilians are primarily motivated by their personal safety; their secondary motivation is ideological. The inclusion of civilian preferences into our model allows us to innovate and

[5]Armed groups represent both rebel groups and governments. The main difference between the government and rebel actors is that at the start of the game the government controls more territory than non-state actors.

follow research on rebel-civilian relationships that underscores civilian agency in conflict areas (Mampilly, 2012; Kasfir, 2015; Arjona, 2017). Holding all else constant, civilians would prefer that their territory is held by groups with similar political preferences. When political preferences align, even if weakly, all actors experience the benefits of political stability and resource sharing.

Actor Overview

In our model, we characterize armed groups using two variables, a measure of their one dimensional ideal point ($x_i \in [0, 1]$), and a measure of how ideological they are ($\phi_i \in [0, 1]$). Groups that are more ideological benefit (suffer) from having other groups with similar (dissimilar) preferences controlling territory, and thus have less (more) motivation to fight them.[6] Civilians are also characterized by their ideal point (η_i), but whereas the ideal points of armed groups are public, armed groups cannot directly observe the preferences of the civilian population.

In this game, armed groups draw resources from relationships with civilians. This "instrumentalist" perspective follows from research conceptualizing victimization as a strategic choice shaped by armed groups' desire to control resources and territory while capturing civilian support and undermining support for opponent groups (Wood, 2014). Yet, notably, our model also incorporates civilian decision-making, which is different than typical "instrumentalist" conceptualizations of civilians.[7] To extract resources, armed groups try to mobilize support from the civilian population and gain more resources as support increases. Furthermore, when the territory that civilians inhabit is

[6] We treat the government actor as moderately ideological, because in most cases a government will not allow a strong challenger to hold territory simply because they have politically congenial views, but they would still prefer to attack more ideologically distant groups.

[7] A modification of the game would be to allow for groups to have natural resources or foreign support which depends on territorial control but not civilian support (Ross, 2004; Salehyan, Gleditsch and Cunningham, 2011).

under attack from another armed actor, civilians can choose to support the attacking group in order to increase that group's likelihood of victory.

Each actor makes two potential choices: armed groups can choose to attack territories to try to conquer them and gain more resources; and they can victimize civilians in territory they control. Civilians choose whether to support an armed group in or attacking their territory. In addition, civilians can choose to flee from one territory to another in search of a more congenial (or less indiscriminately violent) armed group.

When an armed actor attacks another territory, a battle occurs, and each participant has a probability of winning based on their share of spatially weighted resources – it is easier to mobilize support from proximate regions than distant ones. To calculate resources, we need to understand the extent to which civilians support the armed groups. Each supporter of the group gives the total possible resources (normalized to 1). Conversely, because a non-supporter of the group requires coercion to yielding resources, the armed group only captures ψ resources (where $0 < \psi < 1$). Finally, if a civilian supporter is in one of the territories where the conflict is taking place, and they support one of the opposing armed groups, that civilian will actually reduce the resources available to the group which controls the territory by k (where $0 < k < 1$). This civilian-armed group nexus follows previous scholarship on the incentives for civilian abuse which argues that both governments and non-state actors target the population in order to gain support or shift support away from their opponent (Valentino, 2014; Azam and Hoeffler, 2002; Kalyvas, 2006; Wood, 2010).

If the attacking group wins, they take control of the territory, and in any case, resources are lost and civilians casualties occur in all territories that are the source or target of an attack.[8] When a group is deciding which territory to attack, they compare

[8] Losses in the attacking territory represent civilians who were mobilized and died in the fighting.

all their neighboring territories, and choose to attack the one that gives the biggest difference in utility between fighting in a battle, and the status quo if they were to refrain from attacking.

Decision to Victimize

Armed groups can choose to victimize civilians in territories they control. These groups' ability to be selective in victimization relies on their access to trustworthy information, as in Kalyvas (2006). The probability of successful victimization (targeting a non-supporter) is a non-linear function of support in a territory. On the one hand, access to information increases with support (Lyall, Shiraito and Imai, 2015). On the other hand, in the absence of information, the armed group will victimize at random and the more supporters they have, the more likely they are to target a supporter.[9] In this model selective violence is effective at coercing civilians into giving support, whereas indiscriminate violence (targeting ones' own supporters) is counterproductive. When an actor targets a supporter, the range of ideologies that will provide support to the actor shrinks (since the safety provided by supporting the actor is illusory) and when they target a non-supporter, the range of ideologies grow.[10]

Civilian Support

When civilians choose whether or not to support an armed group, they do so with knowledge of the risk of violence. In particular, if the territory is not the site of a battle, civilians' decision on who to support is based on their expectation of who other civilians will support. If they believe other civilians will support the incumbent power in a region,

[9] An exception here is when they have either universal support, or no support. In the first case, the decision rule prohibits them from victimizing. In the second case, there is no risk of unintentionally targeting a supporter since there are no supporters to target.

[10] Fjelde and Hultman (2014) show that that the number of civilians targeted by armed groups (government and non-state alike) is higher in areas populated by the enemy's ethnic constituency.

it becomes more effective to "go along" with the rule of this actor in order to avoid the risk of violence. If a territory is the site of a battle, the calculations for civilians change. Now civilians seek to trade off between ideological distance and the chance a group will triumph. In particular, civilians choose to support the group that has the greatest product of ideological proximity and expected probability of victory. Civilians also can choose to flee a territory to an adjacent one, though this is not a decision that is taken lightly. When civilians decide whether to remain in a territory they are not simply looking for the best armed actor controlling a territory, they are also often paying serious material costs in order to relocate. Thus, we model the decision to flee as beginning with a quite high threshold that decreases as a war rages on.

Sequential Order of Events

We depict the main stages of the game in Figures 2 and 3. In these graphics, territories are represented by rectangles, rectangle size is determined by its civilian population. Territories of the same color are held by the same armed group. The beginning stages of the game are shown in row 1, Figure 2. In row 2 (left panel), we illustrate an armed groups' choice to attack in a given territory (if any). Civilians are arranged in the territory based on their ideological preferences (row 2, right panel); this graphic also shows civilians' decision to support an armed actor. The outcomes for both armed actor and civilian decisions are in the final row. In Figure 3 we depict how a third actor represented in this conflict environment would choose to victimize civilians. This actor's calculus depends on both whether an attack is likely, as well as the possible consequences of victimization. Below, we discuss the intuition behind the decision rules for each group in the graphic. For the explicit mathematical criterion for each choice, see section A.1 in the appendix.

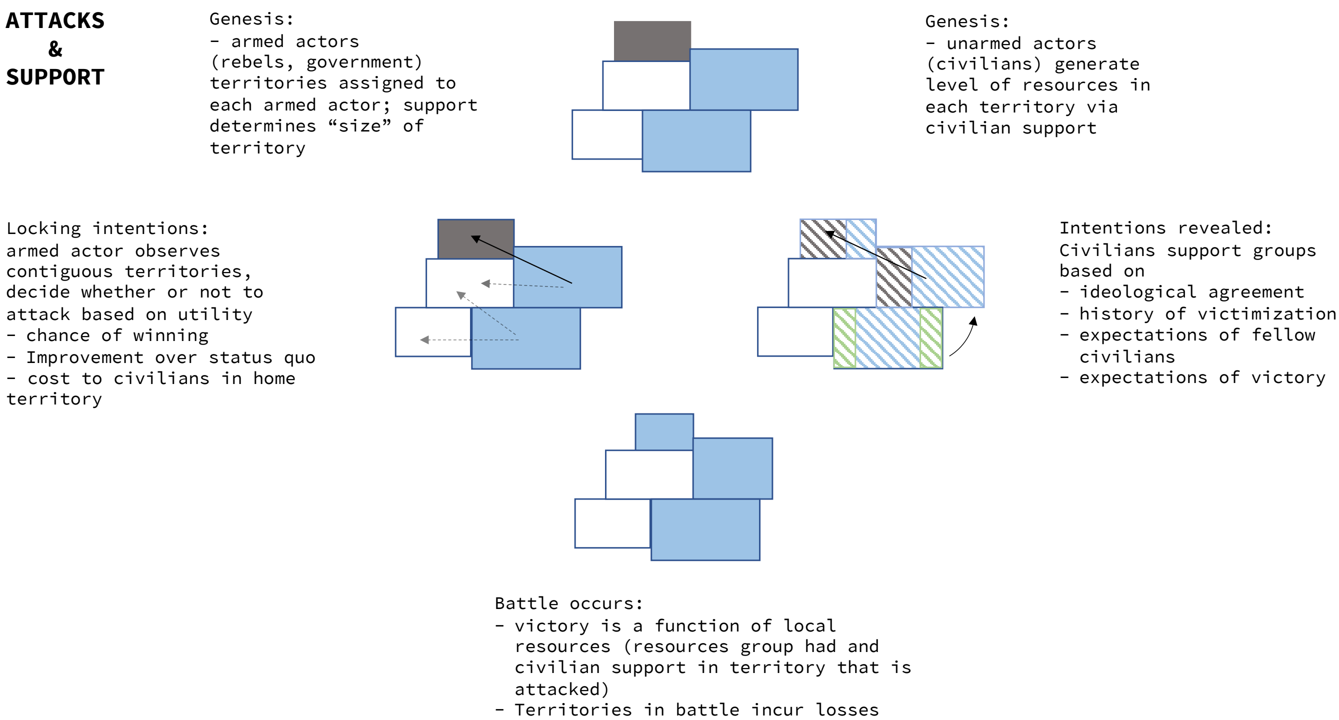

Figure 2: Graphic illustrating the choice of an armed actor to attack, and the choice of civilians to support the actor or not. Rectangles represent territory, with territory size based on the size of the civilian population. For the solid colors, color represents the group controlling the territory. The arrows illustrate the potential territories this group can attack. A solid arrow indicates the actual choice. The diagonal lines represent the civilian population in each territory, ordered by ideology. In the two territories that are part of the battle, civilians choose between two combatants; in the other territory, the civilians choose between supporting the blue group or supporting no one. Based on the resources from civilian support, the battle concludes with blue group's victory.

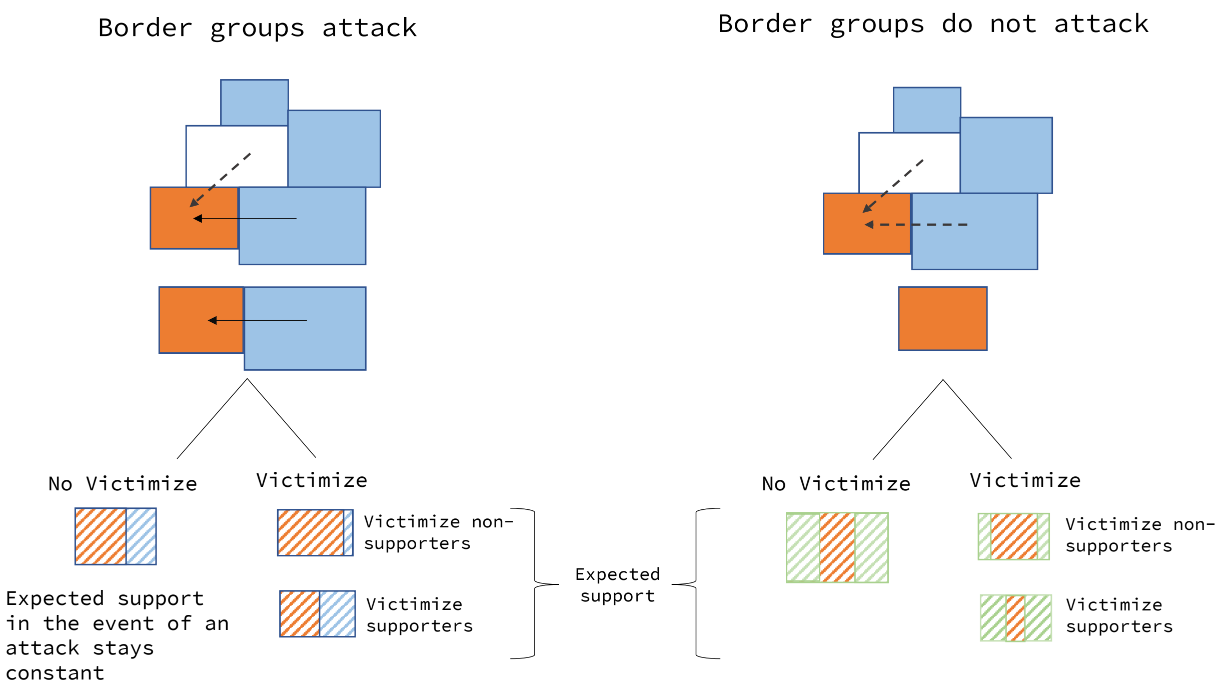

Figure 3: Graphic illustrating the choice of an armed actor to victimize civilians. The orange group first determines whether any of their neighbors are likely to attack. If they are likely to attack, the orange group decides whether to victimize to maximize their support and chance of winning in a battle, if they choose not to victimize, they do so to maximize the resources they gain from the territory. Victimizing can either "succeed" (by targeting a non-supporter) or "fail" (by indiscriminately targeting a supporter) based on both levels of support in the territory and random chance. If it achieves it's aims, the ideological range of support for the incumbent group increases, if it fails, the range contracts.

(0) Genesis of Country and Actors

We begin by generating all of the relevant actors and territories. We first generate a number of territories that is at least as large as the number of armed actors in the game. The territories are connected via a random adjacency matrix that we define such that no territory is totally isolated. We then generate some number of armed actors, each with a random ideal point (x_i) and level of ideology (ϕ_i). Each armed actor is assigned a territory, and the remaining territories are given to the last group, the government.[11] We then generate the number of civilians in each territory, each with a random ideal point (η_i). With this foundation, we are ready to begin the game.

(1) Armed groups choose which territories to invade

When an armed actor attacks another territory, each group involved in the territory has a probability of winning based on their share of spatially weighted resources.[12] Armed groups estimate their likelihood of victory using either their prior beliefs about the distribution of civilian preferences, or the past actions taken by civilians in a territory towards a particular armed group. Specifically, the potential attacker assesses how much utility they will gain from attacking a territory compared to how satisfied they will be if they do nothing. The difference between these two factors is the payoff for attacking a given territory. Groups choose to attack in a territory where there will be the biggest payoff from attacking compared to the status quo (or if none of these are positive, they attack nowhere). This decision is illustrated in Figure 2. When more distinct groups choose to attack each other, our measure of network competitiveness will be higher.

(2) Civilians choose whether to support armed groups

[11]We also define the government with moderate ideal point $x_i = 0$, and somewhat ideological (ϕ_i is drawn from a distribution with a lower maximum than other actors.)

[12]These are discussed in the appendix in equation A5 and A4.

Civilians' decisions are conditioned not just on the characteristics of armed actors, but on the behavior of other civilians.[13] When civilians choose who to support, they assume that other civilians will make support decisions probabilistically based on their proximity to armed groups. (See equation A8). Civilians that are ideologically close to the armed group are assumed to be highly likely to support them and civilians that are very far from the armed group will be much less likely to support them. If a group has a history of killing supporters, all civilians are perceived as less likely to support the group.

If the territory is the site of a battle, civilians will make an estimation about each group's likelihood of victory given expected levels of support, and choose to support the group that has the best combination of 1) ideological congruence, 2) history of treating their supporters well, and 3) likelihood of winning the battle. If the territory is not the site of a battle, support will be based on ideological similarity and expected civilian support (since groups with larger amounts of civilian support are better able to gather information and punish non-supporters).[14]

(3) Battles take place and winners are determined

If a territory is the site of a battle, one group will win probabilistically based on their share of locally weighted resources, (c) civilians in each involved territory will die, and the winning group will take control of the territory.

(4) Armed groups choose which territories to victimize.

When deciding to victimize, the armed group that controls a territory will first try to ascertain whether that territory is at risk of an attack. If it is, the incumbent group

[13]This is admittedly difficult to observe, but the assumption holds in the broader literature on collective action. Larson et al. (2019) show how protest participation is driven by network relations; Steele (2017) describes how civilians' decision to leave their community is interdependent across individuals in the community.

[14]Discussed in detail in equations A9 and A10.

will victimize if it helps them to win a potential future battle, if not they will only victimize when it increases the amount of resources they can extract from the territory. In general, when network competitiveness is low, groups will be more tolerant of non-supporters in order to maximize how many resources they can mobilize, which will lead to a lower level of victimization.

When an armed group chooses to victimize, they know that there is some chance that they will successfully victimize a non-supporter, and some chance that they will instead victimize a supporter, based both on their access to solid intelligence (a function of the number of supporters) and in the absence of intelligence random chance. When a civilian is victimized, it has both a direct and indirect effect. The direct effect is that a civilian – who may be a supporter of the armed group, a non-supporter who can be coerced, or a potential supporter of a rival attacking group – is killed, then this support can no longer be realized. The indirect effect is that when a group targets a supporter, the range of the ideological space that supports that group contracts, and when they target a non-supporter, it expands. Thus, armed groups take both effects into account when they choose whether or not to victimize, but when the territory is at risk of attack, the incentives to victimize are higher, because the direct effect, or targeting potential supporters of an invading group, may be positive, whereas when there is no risk of attack, the direct effect is always a cost, and so victimization is only chosen if the indirect effect outweighs this cost. The tradeoffs for the armed group in each of these cases is illustrated in Figure 3.

(5) Civilians Choose to Flee

After victimization, civilians choose whether or not to flee from a territory into an adjacent territory. We have a threshold for fleeing that decreases as the conflict endures.[15]

(6) Game Iterates

Stages 1-6 will continue until one of three end conditions are met: a) the government controls all the territories, b) the government controls no territories, c) the game reaches the predetermined turn limit and ends in a stalemate.

Network Competition in the Game

In our game, network competition is not simply an exogeneous parameter, it is the product of strategic choices by the different actors in the game, which profoundly impacts the other choices, in particular, the choice to use or refrain from using One Sided Violence. At the same time, One Sided Violence also can impact the future strategic decisions made and thus endogeneously influence the level of network competition.

The level of network competition in a given period of the game is defined by groups choices about which territories to attack. If many groups attack and are the targets of attack, network competition will be high. If only a few groups attack, or all the attacks are against a common target (for example the government), competition will be low. The level of network competition then influences the overall level of civilian support for incumbent groups – civilians face a different calculus depending on whether their territory is a battlefield, and will often be less supportive of incumbents in periods of high network competition (because they are more likely able to support an ideologically congenial invading group). When network competition is low, we will also see less territories changing hands, since conflict will be limited to a few pairs of groups, and most territorial change will occur in a small number of border regions. Importantly, network competition undergirds three key conditions that influence victimization: the

[15] Second, in each territory, there will be new civilians added to the game based on the global growth rate parameter G (rounded down to the nearest integer).

likelihood of territorial attack, the frequency of territorial change, and levels of civilian support for armed groups. Through these channels, network competition acutely influences the decisions of armed groups to engage in one-sided violence against civilians. Importantly, network competition exacerbates three key conditions that influence victimization: the likelihood of territorial attack, the frequency of territorial change, and levels of civilian support for armed groups. Through these channels, network competition acutely influences the decisions of armed groups to engage in one-sided violence against civilians.

Simulation Results from Computational Model

To determine the macro-level effects of the micro-actions described above, we run a simulation analysis with 10,000 separate conflict scenarios. In each scenario, we chose parameters determining the conflict environment at random, each of these parameters are listed in Table 1. From the simulations, we record three main conflict statistics – the number of armed groups in the network, the overall level of violence in the network, and our measure of network competition. We also capture the frequency of civilian victimization in each run of the game.

To estimate the effect that our three statistics have in relation to civilian victimization, we employ a negative binomial regression with fixed effects on the conflict scenarios and another in which we use random effects. We depict the results of this analysis in Figure 4, the left plot shows the result with fixed effects and the right with random effects.

Name	Description	Simulated Distribution
N	Number of actors	Poisson(10)
S	Number of territories	max(Poisson(13), N+1)
γ	Connectivity of territories	Uniform(0.2, 0.75)
S	Average number of civilians per territory	Poisson(45)
v	Reward (penalty) for (in)discriminate victimization	Uniform(0.05, 0.3)
k	Resources lost for enemy supporters during battle	Uniform(0.25, 0.75)
δ	Spatial discounting of resources	Uniform(0.1, 0.75)
c	Cost (in deaths) of a battle	1 + Poisson(1)
G	Global growth rate for civilians	0.1
ϵ	Error rate for victimization given correct information	Uniform(0, 0.1)
T	Maximum number of turns	1 + Poisson(10)

Table 1: Summary of the parameters in our computational model.

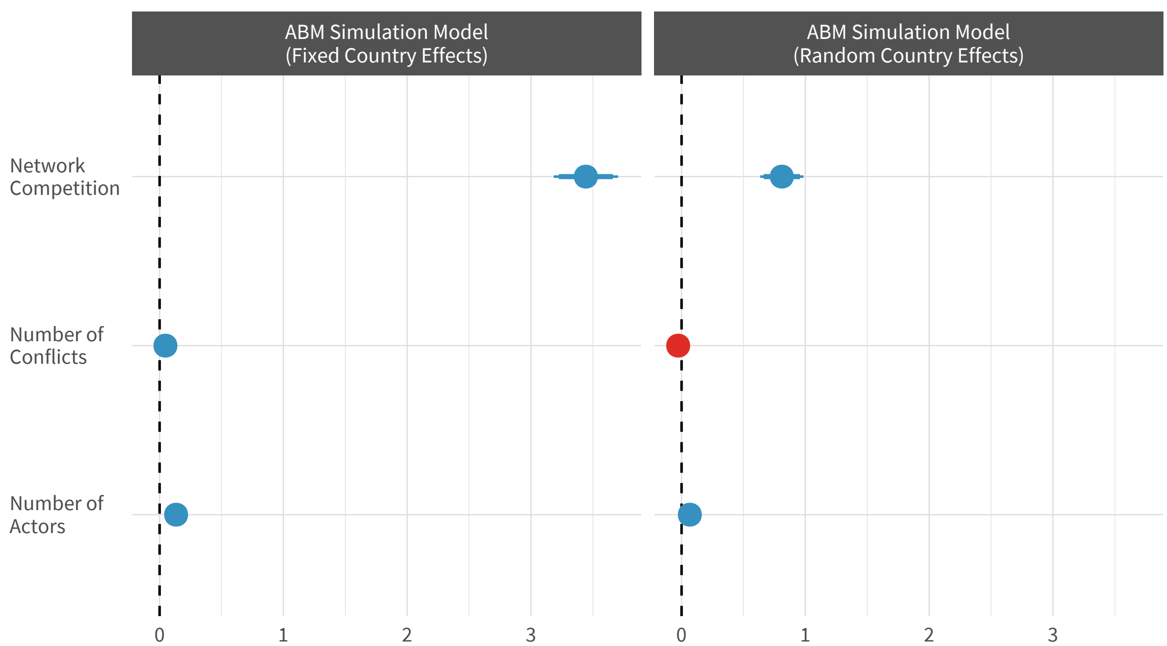

Figure 4: Analysis of determinants of victimization in computational model. The left panel visualizes coefficient estimates when using fixed effects on conflict scenarios and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

Here we can see that more competitive conflict networks have a higher expected frequency of civilian victimization.[16] This finding generates our main hypothesis for empirical investigation: *Even when controlling for the overall level of violence, a more competitive conflict network leads to higher levels of civilian victimization.*

Empirical analysis

To investigate the implications of our computational model empirically, we use the Armed Conflict Location and Event Dataset (ACLED) dataset developed by Raleigh et al. (2010). ACLED collects the "dates, actors, locations, fatalities, and types of all reported political violence and protest events around the world." Our first step is to calculate the level of network competition for countries experiencing intrastate conflict according to the *battles* data provided by ACLED. Battles are defined by ACLED as "a violent interaction between two politically organized armed groups at a particular time and location."[17] We assume that relevant actors to our study are those actors that have been involved in a battle event either as a primary or associated actor. Our final cross-national sample ranges from 1997 to 2020 and includes 42 countries.[18]

For each country in our sample we construct a conflict adjacency matrix in which a value of one is recorded if there was a battle between an armed group in the row and column of the matrix. Given that untangling who initiated a particular battle can be difficult, the conflict adjacency matrices we construct are symmetric. Our conflict matrices also include any actor–whether listed as the primary actor or associated actor

[16] It is worth noting here that in the ABM, victimization both refers to the overall number of civilians strategically targeted by armed groups and the number of victimization incidents. In the empirical results to follow, we focus on the number of civilians targeted.

[17] As defined by the 2019 ACLED code book found at `https://www.acleddata.com/wp-content/uploads/dlm_uploads/2019/04/General-User-Guide_FINAL.pdf`

[18] To account for potential COVID-19 impacts on our results, in Figure A15 of the Appendix, we run our analysis with a sample that ranges from just 1997 to 2019. Our results in that more limited sample remain consistent with what we present in the manuscript.

in ACLED– involved in a given battle. The set of actors in these adjacency matrices include both rebel groups and government forces. We aggregate military and police forces from the same country into one government actor.[19] Additionally, we exclude international actors such as peacekeepers, militaries from other countries, the United Nations, and election observers from our analysis. Finally, we also clean the data for any "unidentified" actors. These steps help ensure that our actors capture armed groups involved in conflicts against one another at the intrastate level of analysis. In some cases, these actor cleaning steps lead to empty adjacency matrices with no actors.[20]

For inclusion in our sample, we impose a restriction that a country must have at least three years of non-empty conflict adjacency matrices.[21]. Our resulting data clearly show that intrastate conflicts are often much more complex than a war between the government and a few mobilized challengers. From 2011 onwards the majority of conflicts involve five actors or more. The data also reveal that highly complex conflicts, where a country has 10 or more active armed groups in a given year, are on the rise.

[19] All of our data pre-processing steps are found in our replication files.

[20] This occurs as some ACLED battle events with a country year may only involve interactions between a government and an unidentified militia group. As a result of our actor inclusion rules, no actors but the government in this case would be recorded.

[21] In Figure A14 of the Appendix, we vary this restriction in two ways. First, we lower our restriction by letting any country enter our sample if they had at least one non-empty conflict adjacency matrix, and, a second, in which we tighten the restriction by requiring countries have at least five years of non-empty adjacency matrices. In both cases our results remain consistent with what we present in the manuscript.

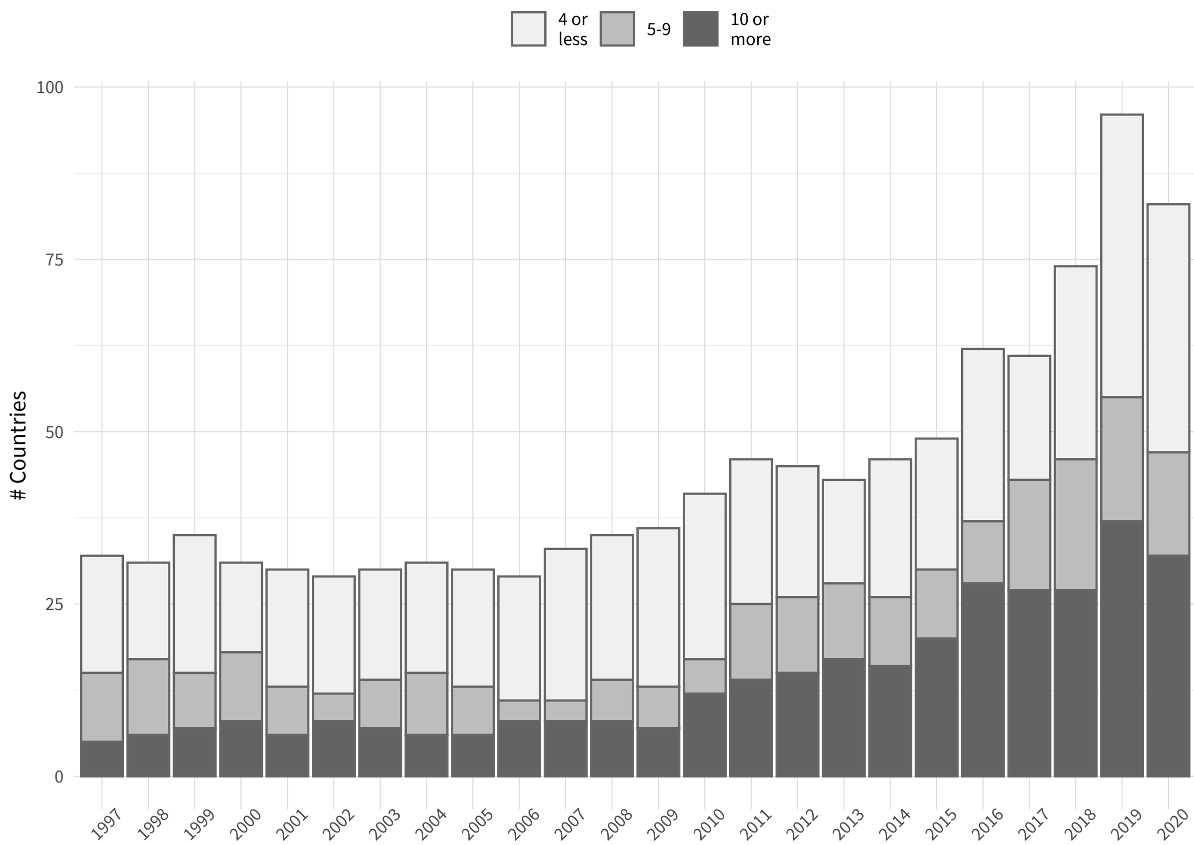

Figure 5: Number of active armed groups in countries from the ACLED dataset between 1997 to 2020. Dark grey represents armed conflicts with 4 or less active armed groups, light grey represents armed conflicts with 5-9 active armed groups, and white represents armed conflicts with 10 or more armed groups.

Once we have generated our set of adjacency matrices for every country-year we then calculate the number of actors and the level of network competition in the networks. We control for the overall level of violence by counting the number of battle events a country faces in a given year. Apart from the ACLED based data, we incorporate a number of other controls that have been argued to affect the level of civilian victimization at the country-year. For brevity, these are listed in Table 2.[22] Importantly,

[22]Descriptive statistics for each of the variables we present below are included in Tables A2, A3, and A4 of the Appendix.

we can directly measure some controls through the ACLED data, such as the number of actors in a given conflict. Other measures, such as Polity scores, population, excluded population, and the presence of Peacekeepers are measured at the country-level and are thus easily adapted to our study. These measures are included as control variables to account for conditions that are known to influence the level and type of conflict in a given country. The inclusion of excluded population variable into the model, for example, is important because the number of excluded groups is shown to affect conflict mobilization and thus would have a downstream effect on the number and strength of armed groups as well as civilian victimization (Fjelde and Hultman, 2014; Uzonyi and Demir, 2020). Similarly, regime type can influence the likelihood that conflict actors victimize civilians (Harff, 2003; Eck and Hultman, 2007).

Notably, however, there is no annually updated available data on the attributes of armed actors that spans across both space and time at the actor-level. To overcome this, we rely on Cunningham, Gleditsch and Salehyan (2013)'s "Non-state actors in civil wars" (NSA) data. The NSA data extends the UCDP/PRIO Armed Conflict Dataset (Themnér and Wallensteen, 2013) and covers all internal armed conflicts from 1945-2011.[23] The NSA data contains information about rebel-government dyads and only includes actor dyads that generate 25-battle related deaths in a calendar year. We aggregate the NSA data to the country level for two reasons. First, our analysis is at the country-level and we require cross-national data for our empirical models. Second, the NSA data is based on different event data then our study and necessarily includes a number of restrictions on which actors are included in the data. This means that the actors in the NSA data do

[23]Because Cunningham, Gleditsch and Salehyan (2013) base their data collection off of the UCDP data base, their criteria for case inclusion is different than ours. Namely, in order for a conflict to be coded as an internal armed conflict in the UCDP/PRIO Armed Conflict Dataset, "it must meet five general criteria—the conflict must (1) involve the government of the state, (2) take place primarily within the state, (3) involve organized opposition forces, (4) be fought over either control of the government or territory and (5) generate 25 battle deaths in a calendar year."

not neatly match every actor in the ACLED data. Nevertheless, we assume that these measures can still provide important information about general conflict dynamics at the country level. Specifically, we aggregate NSA measures to create country-level covariates that proxy the balance of power between armed non-state actors and governments in a given conflict. Our full aggregation strategy can be found in the replication files. To summarize, we first create binary indicators from each row of data for each category of interest in the NSA data. With these indicators we can then summarize if, on average, rebel groups in a given country were much weaker or much stronger than the government and if they, on average, tended to have foreign support.

Variable	Source	Last Year of Data	Base	Base + Controls (1997-2018)	Base + Controls (1997-2012)
Network Competition Number of Actors Number of Conflicts	Raleigh et al. (2010)	2020	X	X	X
Polity	Marshall et al. (2009)	2018		X	X
Log(Population) Log(GDP per Capita)	World Bank Group (2016)	2019		X	X
Excluded Population	Vogt et al. (2015)	2017		X	X
Presence of Peacekeepers	Kathman (2013)	2012			X
Rebel(s) Stronger than Govt. Rebel(s) Supported by Foreign Govt. Govt. Supported by Foreign Govt.	Cunningham et al. (2013)	2014			X

Table 2: Summary of data used in our empirical analysis.

While the ACLED data is available from 1997 to 2020, the availability of other data sources varies notably. We list the last year of available data for each of the other variables in Table 2. To maximize the possible size of our sample, we run several models. First, we run a "Base" model that just includes the variables we derive from ACLED, which gives us a sample of 42 countries from 1997 to 2020.[24] The next model we run in-

[24]We list the countries used to estimate each of the models in Table A1 of the Appendix.

cludes polity, population, GDP per capita, and a measure of excluded population from the Ethnic Power Relations dataset (Cederman, Wimmer and Min, 2010). The sample for this model includes 38 countries and ranges from 1997 to 2018. In the last model, we create a binary variable to indicate whether any peacekeepers are active in a given country year based on data from Kathman (2013). We also include controls from the Non-State Actor database for rebel strength relative to the government and whether rebel(s) or governments receive support from foreign countries (Cunningham, Gleditsch and Salehyan, 2013).[25] The sample for this final model ranges from 1997 to 2015 and includes 19 countries.

Our dependent variable is a count of the number of civilians killed during a country-year. We retrieve this information from the "Violence against civilians" event type in the ACLED dataset. According to the ACLED codebook, this variable represents "violent events where an organized armed group deliberately inflicts violence upon unarmed non-combatants. By definition, civilians are unarmed and cannot engage in political violence. The perpetrators of such acts include state forces and their affiliates, rebels, militias, and external/other forces." To model this, we utilize a negative binomial framework. We report the results for our "Base" models of civilian victimization in Figure 6 below. The left panel shows results using fixed effects on countries and the right random effects.

[25]Variables from the Non-State Actor database are coded through 2011. If we were to truncate our sample for the second set of controls to 2011, we would lose almost half of our sample. To avoid this we follow (Kathman and Benson, 2019) in replicating the 2011 values forward to 2014. Remaining with just the limited number of observations from the coded data leads to results for our network competition measure that are in still line with our expectations but less precisely measured.

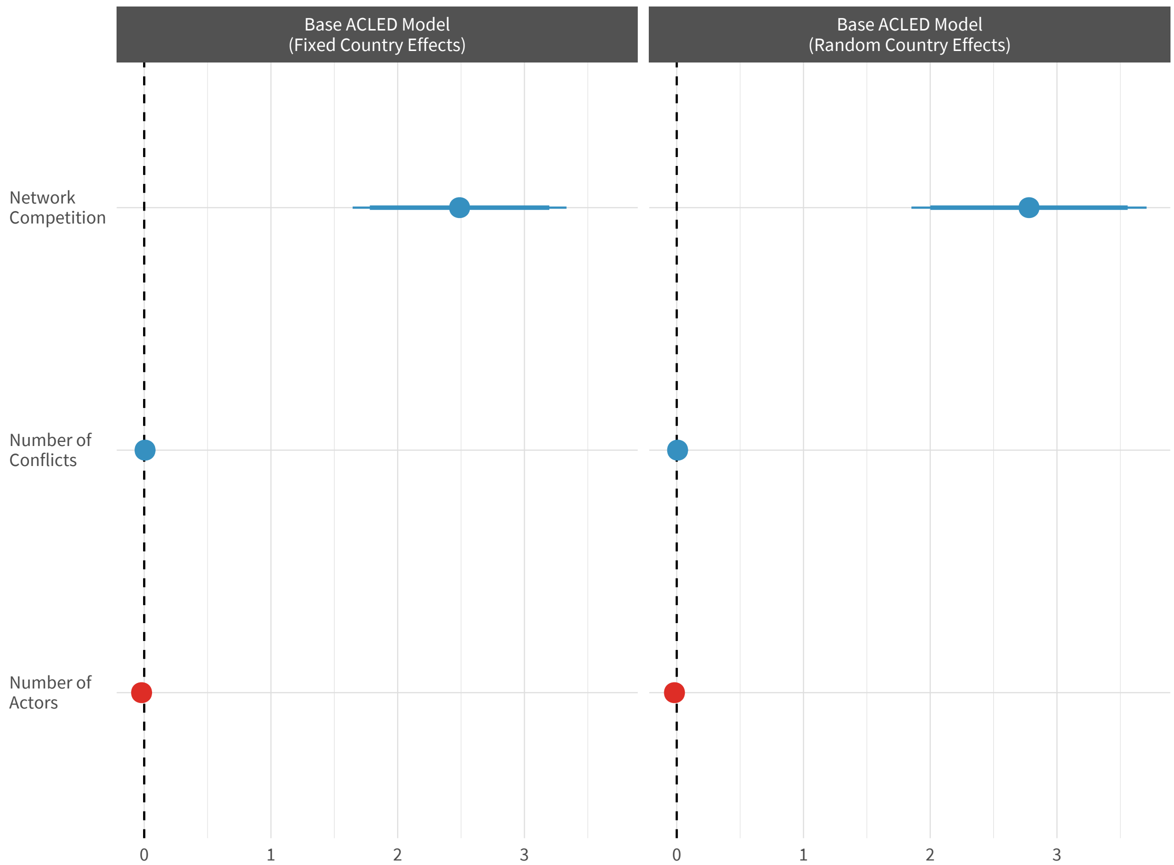

Figure 6: Regression results for the Base model specification includes 42 countries from 1997 to 2020. The left panel visualizes coefficient estimates with country-level fixed effects and the right visualizes the results with random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

In both cases, we find strong support for the effect of network competition on civilian victimization even after controlling the overall level of conflict intensity and the number of actors in the network. Next we test the robustness of this finding by incorporating other factors that have been argued to affect civilian victimization. These models are estimated via random effects as some of the covariates have little variation within countries over time.[26] Additionally, many of the control variables that we include have

[26]Results with fixed effects are presented in Figure A1 of the Appendix and our consistent with regard

a notable amount of missing data. As detailed in Honaker and King (2010), simply employing listwise deletion can lead to inferential issues.[27] We utilize a Bayesian multiple imputation scheme to estimate a posterior of imputed datasets, run our models on ten randomly sampled datasets from the posterior, and then show the combined parameter estimates using Rubin's rules in Figure 7 below.[28] The results from this analysis show that the effect of network competition continues to have a substantive impact on civilian victimization even after accounting for the control variables listed in Table 2.

to the effect of network competition.

[27]In our case, results on the unimputed data lead to the same finding with regards to the relationship between network competition and victimization. These results are shown in Figures A2 and A3 of the Appendix.

[28]Specifically, we employ a semiparametric copula estimation scheme that has been shown to have equivalent or better performance to alternatives such as `mice` and `Amelia` by Hollenbach et al. (2018).

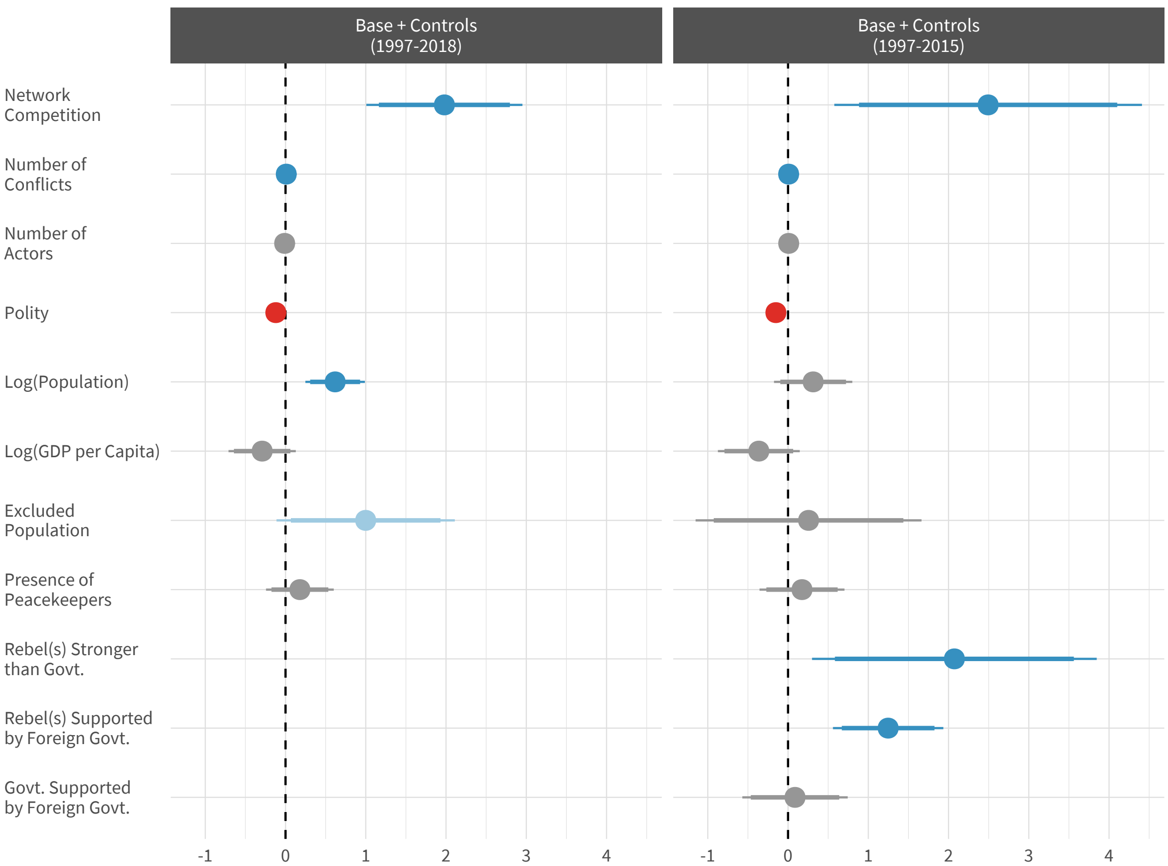

Figure 7: Regression results from multiply imputed datasets when pairing Base specification with controls using random effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

We visualize predicted levels of victimization for the effect of network competition using a simulation based approach (King, Tomz and Wittenberg, 2000). The results of this analysis are shown in Figure 8, each column in this figure corresponds with a model from Figure 7. Irrespective of the controls included, we can see that there is considerable variation in predicted levels of victimization as network competition increases.

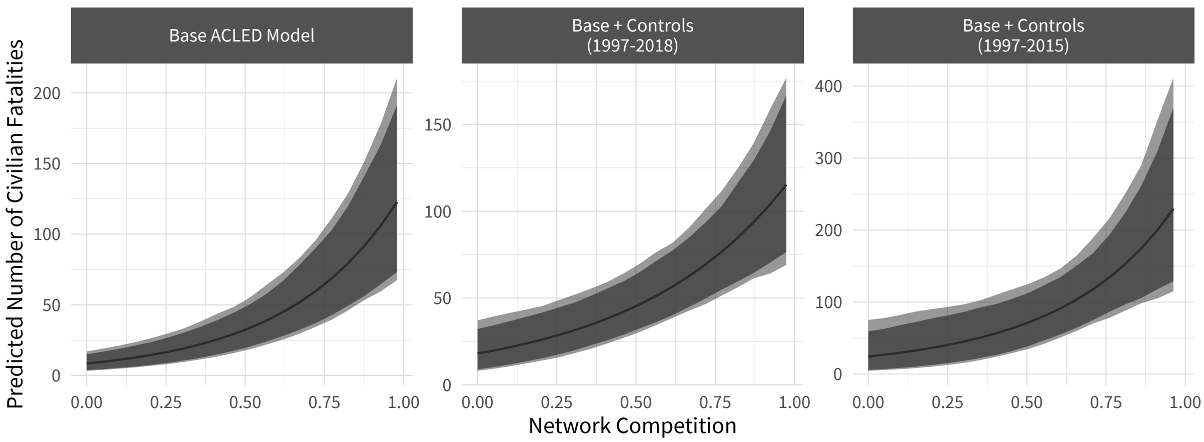

Figure 8: Simulated substantive effect of our measure of network competition across each model.

Robustness Checks

We also ran a number of checks to test the robustness of our findings. We discuss these checks briefly here and invite readers to learn more in the Online Appendix. Given the difficulties in accurately measuring fatality counts from conflict (Dawkins, 2021), we also reestimate our model using a count of one-sided violent events in a country-year as the dependent variable. With this alternative dependent variable we still find that our network competition measure has a positive and significant effect on the number of civilian victimization events in a given year using either a random or fixed effects framework. Another prominent concern is that information from various event datasets can vary widely across countries (Eck, 2012). Recognizing this we run our analysis using information from UCDP as well. Ideally, we would like to integrate information from both data sources (Donnay et al., 2018), but such a task would require building a dictionary that can bridge actor level information between UCDP and ACLED. Nonetheless, when using information from UCDP our network competition measure remain positive and significant.[29]

We also test the robustness of our network competition finding to the inclusion of a number of other controls. First, to account for potential persistence in victimization over time, we include a lagged dependent variable and our findings remain substantively unchanged. We also examine how controlling for the geographic proximity of actors in an armed conflict affects our estimates of network competition.[30] Notable concern here is that high levels of victimization could be a result of actors in an armed conflict being geographically concentrated rather than being a function of network competition. When controlling for the geographic spread of armed groups we find that our measure of network competition still aligns with our theoretical expectations. Another potential complicating factor for estimating the effect of network competition on victimization is that low levels of victimization might occur not because network competition is low but because a high proportion of the armed groups in the network are allied. To deal with this, we estimate a latent measure of amity between groups using the conflict data – in doing this we are building on a number of works seeking to solve a similar problem (Cheng and Minhas, 2021; Gallop and Minhas, 2021; Dorff, Gallop and Minhas, 2021).[31] When including a measure representing how many groups are allied

[29] For the manuscript, we choose to focus on results using UCDP, however, because UCDP data records information only on groups that commit a specific threshold of violence during a battle, whereas ACLED data contains information about all groups relevant to all battles, regardless of the number of deaths incurred. Due to our focus on measuring network competition based on how groups are interacting with one another we focus on results with ACLED.

[30] See Online Appendix for details on the calculation of this measure.

[31] See Online Appendix for details on the calculation of this measure.

in a country-year, we still find the substantive implications of our network competition measure to be unchanged.

Additionally, COVID-19 may impact not only our results but even the reporting of conflict data in a number of ways. To insure that our results are not being affected by this type of exogenous dynamic, we reran our analysis with only data between 1997 and 2019. With this smaller sample, our results for network competition still remain unchanged. Last, for the results presented in the manuscript, the underlying sample had a requirement that a country must have at least three years of observations to be included. In the appendix, we examine the results when we set no minimum year requirement and when we set a five year requirement, in either case the results for network competition remain robust.

Future Research

In this paper, we assert that civilian decision making is central to the competitive environment in which armed groups operate. Despite our inclusion of civilian behavior into our theoretical model, our project is limited in its ability to empirically test outcomes related to civilian agency. We view this as a meaningful, yet necessary, limitation of our study in order to focus on explaining the general relationship between network competition and violence against civilians across country cases. In addition, while the theoretical implications of our model claim we should observe important civilians behaviors–like fleeing–as a response to violence, our model also suggests that a suite of behaviors are possible, such as protest or self-defense, and does not specify which type of civilian behavior we should actually observe. Thus, empirically testing these outcomes is beyond the current study. Future research, however, can build on this work by both better clarify specific expectations of civilian behavior within this a networked theoretical framework and collect new fine-grained intrastate data to test these expectations. The study of civilians during conflict would greatly benefit from data on both collective civilian acts and the target of civilian resistance.

Discussion

We have shown that civilian victimization depends, in large part, on the competitive dynamics of the strategic environment. If violence is concentrated around a single actor, where one actor dominates conflict initiation towards many others or receives conflict from many challengers, then civilian victimization will be less likely. If, however, all actors are likely to fight one another – in an all against all competition – civilian victimization will be at its highest. This result holds even when accounting for the number of belligerents and the total volume of fighting. There are two primary reasons for this pattern of victimization. First, groups are more likely to victimize civilians in a territory if that territory is at risk of an attack and a more competitive network leads to more changes in territorial control. Second, if a group faces a more ideologically diverse array of potential opponents, a larger swathe of the civilian population has suspect loyalties and so armed groups are more likely to turn to victimization. Both of these conditions are most intense in highly competitive conflict networks.

We test these dynamics in a cross-national analysis of multi-actor civil conflicts using ACLED data to construct conflict networks. We find a consistent positive effect of network competition on civilian victimization even when controlling for other characteristics of the conflict network. Our study makes an important contribution to the literature on civilian victimization by theoretically uniting distinct threads of research on civilian agency, competition in multi-actor conflicts, and the network dynamics of conflict. In doing so, we provide a theoretical framework that demonstrates how group-level decisions influence the conflict system as a whole. Our innovative approach then provides testable empirical implications in a cross-national setting.

In sum, our study models the choice for armed groups to victimize civilians as a strategic decision conditional on the multi-actor nature of the conflict environment. Importantly, our findings have implications for both policymakers and the civilian population. We have shown that a conflict setting with multiple moderately violent rival groups presents a situation that is at least as risky as a setting in which there is only one, extremely violent group. Armed groups choose to victimize civilians to improve their ability to mobilize resources and to maximize their chances to defend themselves if their territory is attacked. Civilians can decide to provide or withhold support, as well as flee, out of self-preservation and to achieve ideological goals. Our study unites the strategic decision-making of both armed groups and civilians into a single multi-actor framework of civil conflict that reveals how actors' incentives change according to the network dimensions of their strategic environment. Of course, our study is not the final word on this complex question. In the future, additional research can better incorporate other important factors into our model, such as the ability for armed groups to endogenously enter and leave the model and the possibility that armed groups' reliance on foreign support or loot-able goods influences patterns of victimization inside the conflict network. Further, additional empirical research is needed to examine how geography shapes competition in multi-actor contexts and the consequences of geography for victimization in these environments. To operationalize the role of geography within the empirical model from our study, we would require cross-national and time-varying measures of armed actors' control of geographic units. While accurately incorporating this information is beyond the scope of our study, an emerging body of research measuring the geography of armed conflict and territorial control (Anders, 2020; Haass, 2021; Kikuta, 2020) provides a promising next step in the accumulation of knowledge on this important topic.

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Contents

A.1. Details on Computational Model

A.1.1. Ideology and Utility

We define the distance between any two groups as:

$$D(a,b) = ||z_a - z_b|| \tag{A1}$$

where $z_a = x_a$ if a is an armed group. If a is a civilian, $z_a = \eta_a$. We define the ideological benefit that armed group i gets from changes to group j's utility as:

$$\alpha_{i,j} = 2\phi_i(.5 - D(i,j)) \tag{A2}$$

We use $2\phi_i$ so that a group that is both maximally ideological ($\phi_i = 1$) and extreme ($x_i = 0$ or 1) will be indifferent between a gain for themselves and a loss for a group at the other end of the spectrum.

A.1.2. Probability of Victimization Success

We define the probability of successful victimization by group i in territory q (denoted ζ_{iq}) as:

$$1 - \zeta_{iq} \equiv \epsilon\left(\frac{n_{\text{supp},i,q}}{n_{\text{civilians},i,q}}\right) + \left(\frac{n_{\text{civilians},i,q} - n_{\text{supp},i,q}}{n_{\text{civilians},i,q}} \times \left(\frac{n_{\text{supp},i,q}}{n_{\text{civilians},i,q}}\right)\right) \tag{A3}$$

Where $n_{\text{supp},i,q}$ is the number of supporters of group i in territory q, and $n_{\text{civilians},i,q}$ is the total number of civilians in territory q. The first term here is the probability (ϵ) of unsuccessful victimization given information times the probability of receiving information. The second term is the probability of unsuccessful victimization (the proportion of supporters in the territory) given no information times the probability of not receiving information.

A.1.3. Resources and Victory

We call the local resources of group i in territory L:

$$\Gamma_{i,L} = \sum_l \delta^{d_{l,L}}(n_{s,i,l} + \psi n_{ns,i,l} - k n_{o,i,l}) \tag{A4}$$

where δ is the spatial discount factor – how much less useful distant resources are than proximate ones – and $d_{l,L}$ is the distance from region l to L. $n_{s,i,l}$ denotes the number of supporters of group i in territory l and $n_{ns,i,l}$ are non-supporters of i in l. $n_{o,i,l}$ are the number of opponents of group i in territory l as long as territory l is part of the "battlefield" – the set of territories that are either the source or the target of the battle in question. Finally, ψ and k are the resources you get from non supporters, and those you lose from supporters of your opponent respectively.

For each group in the battle, the probability of winning is:

$$p_{i,L} \equiv P(i \text{ wins in territory L}) = \frac{\Gamma_{i,L}}{\sum_j \Gamma_{j,L}} \tag{A5}$$

where a group's probability of winning in territory (L) is determined by the group's local resources within the territory relative to the sum of all combatant's local resources in the same territory.

A.1.4. Decision to Attack

A group decides which territory to attack by looking at all territories they border, and compares their utility for attacking that territory compared to doing nothing. In particular, for each territory q, they look at:

$$U_i(q|G) = \sum_{g \in G} E[p_{g,L}|G]\alpha_{i,j}(R_q - c) \tag{A6}$$

where G are the groups already committed to battle within a territory, R is the number of civilians within a territory, c is the cost of war. We include the expectation here because at the time of the decision, civilian support is unknown,[32] For comparison, the utility for group i of the status quo in territory q, held by group j is:

$$U_i(j \text{ controls } q) = \alpha_{j,i} R_q \tag{A7}$$

A.1.5. Decision to Support

Civilians cannot observe what other civilians do in their support decisions, but they know their utility, and so their belief is that:

$$E[P(\text{Civilian l supports Group } i)] \equiv \text{max}(\text{min}(1 - D(i,l) + v\chi_j, 1), 0) \tag{A8}$$

Here χ_i is the net discriminacy of victimization by group i, which decreases when they victimize a supporter and v is the penalty for indiscriminately victimizing civilians.

If no battle is taking place in territory q, civilian l will support an armed group i if:

$$\frac{E[\bar{n}_{s,i,q}]}{2} > D(i,l) + v\chi_i \tag{A9}$$

where the expected number of supporters is calculated as discussed in Equation A8.

On the other hand, when a battle is taking place in a territory q, civilian h will support group g such that:

$$\text{argmax}_{(g \in G)} E[p_{g,q}](1 - D(g,h) + v\chi_g) \tag{A10}$$

[32]We will determine this in Equations A9 and A10 in the next stage.

It is worth highlighting here that $E[p_{g,q}]$ is determined by using beliefs from Equation A8 to calculate the values in Equations A4 and A5.

A.1.6. Decision to Victimize

The first thing a group must ascertain when deciding whether or not to victimize, is whether a given territory is at risk of imminent attack. This means a group i will evaluate, for each neighbor j and territory they control q, whether:

$$\alpha_{j,i}R_q < E[p_{i,q}]\alpha_{j,i}(R_q - c) + E[p_{j,q}](R_q - c) \tag{A11}$$

Note that these are the same utilities from Equation A6 and A7.

Armed groups believe that the proportion of the preference space made by their supporters is $s \equiv \frac{x_{s,i,q}}{n_{ns_i,q}+n_{s,i,q}} + v\chi_i$. The proportion believed to be composed by non-supporters is of course $1-s$. If the territory is not at risk of attack, the group will victimize if:

$$\zeta_q\left(\frac{v(1-c)n_{ns,i,q-1}}{(1-s)} - c\right) - (1-\zeta_q)\left(\frac{v(1-c)n_{s,i,q-1}}{s} - 1\right) > 0 \tag{A12}$$

Here $\frac{(vn_{ns,i,q-1})}{1-s}$ is the expected number of non-supporters coerced to support the armed group in the event of selective victimization, $(1-c)$ is the benefit of coercing non-supporters into support, and $\frac{(vn_{s,i,q-1})}{s}$ are the number of supporters pushed to non-support in the event of indiscriminate victimization. In addition, victimization has a direct effect of either killing a supporter or a non-supporter.

When considering whether to victimize in a territory at risk of an attack, the armed group needs to separate civilians into potential supporters of the attacker and non-supporters. Their belief is that the division for support for groups i and j, defined such that $x_i > x_j$ is that a civilian, f, will support group i if:

$$\eta_f > x_i E[p_{i,q}] + x_j E[p_{j,q}] \equiv \lambda_q \tag{A13}$$

This, combined with their beliefs about the distribution of supporters and non-supporters, allows an armed group to estimate the number of supporters both for themselves and the attacking group, as well as the range of preferences occupied by each group, which are of length λ_q and $1-\lambda_q$, respectively. They then victimize if:

$$\zeta_q\left(\frac{v(1+k)E[n_{o,i,q}]}{\lambda_k} + k\right) - (1-\zeta_q)\left(\frac{v(1+k)E[n_{s,i,q}]}{(1-\lambda_k)} + 1\right) > 0 \tag{A14}$$

A.1.7. Decision to Flee

Civilian k will choose to flee a territory controlled by group i for a territory controlled by group j if these territories are contiguous and:

$$D(i,l) + v\chi_i < e^{3-t3/T}D(j,l) + v\chi_j \tag{A15}$$

The exponential decay function is such that in the first turn of a game (t) another group needs to be at least e^3 times better than the incumbent in a civilians territory for the civilian to move, but by the final turn of the game (T) the group will move to whichever territory has a more congenial incumbent.

A.2. Sample Information

A.2.1. Countries in the Sample

Table A1 list the countries that we are able to include based on data availability in each of our models. The "Base" model includes 42 countries (an "X" denotes the countries included in the model), the "Base + Controls (1997-2018)" includes 38, and the "Base + Controls (1997-2015)" includes 19.

	Base	Base + Controls (1997-2018)	Base + Controls (1997-2015)
Algeria	X	X	X
Angola	X	X	X
Benin	X	X	
Burkina Faso	X	X	
Burundi	X	X	X
Cameroon	X	X	
Central African Republic	X	X	X
Chad	X	X	X
Congo, Republic Of	X	X	X
Congo, The Democratic Republic Of	X	X	X
Cote D'ivoire	X	X	X
Egypt	X	X	X
Eritrea	X	X	
Ethiopia	X	X	X
Gambia	X		
Ghana	X	X	
Guinea	X	X	X
Guinea-Bissau	X	X	
Kenya	X	X	
Liberia	X	X	X
Libyan Arab Jamahiriya	X	X	X
Madagascar	X	X	
Mali	X	X	X
Mauritania	X	X	
Morocco	X		
Mozambique	X	X	
Namibia	X		
Niger	X	X	
Nigeria	X	X	X
Rwanda	X	X	X
Senegal	X	X	X
Sierra Leone	X	X	X
Somalia	X		
South Africa	X	X	
South Sudan	X	X	X
Sudan	X	X	X
Tanzania, United Republic Of	X	X	
Togo	X	X	
Tunisia	X	X	
Uganda	X	X	X
Zambia	X	X	
Zimbabwe	X	X	

Table A1: List of countries in each model, "X" indicates country was included.

A.2.2. Descriptive Statistics

Below we show descriptive statistics for each of the models presented in the paper.

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	638	0	35	291.53	9337	753.8
Num. Actors	638	3	8	20.17	168	28.18
Num. Conflicts	638	1	23.5	90.77	1534	182.09
Network Competition	638	0	0.75	0.72	0.98	0.18

Table A2: Descriptive statistics for variables in Base model.

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	544	0	27	301.55	9337	800.65
Num. Actors	544	3	8	17.25	148	21.55
Num. Conflicts	544	1	21	69.24	1185	114.22
Network Competition	544	0	0.75	0.71	0.97	0.18
Polity	543	4	11	12.36	20	4.47
Log(Pop.)	542	13.94	16.74	16.75	19.07	0.99
Log(GDP Cap.)	536	5.23	6.74	6.85	9.4	0.87
Excl. Pop.	543	0	0.09	0.19	0.85	0.25
Peacekeepers	544	0	0	0.2	1	0.4

Table A3: Descriptive statistics for variables in Base + Controls (1997-2018) model.

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	293	0	63	457.57	9337	1027.52
Num. Actors	293	3	10	18.8	108	20.66
Num. Conflicts	293	1	48	88.44	1185	122.51
Network Competition	293	0	0.77	0.73	0.96	0.16
Polity	292	4	11	11.34	19	4
Log(Pop.)	293	14.59	16.64	16.72	18.99	1.08
Log(GDP Cap.)	289	5.23	6.61	6.74	9.4	0.92
Excl. Pop.	292	0	0.18	0.26	0.85	0.27
Peacekeepers	293	0	0	0.3	1	0.46
Reb. Stronger Govt.	177	0	0	0.01	1	0.11
Reb. Supp. by Foreign Govt.	177	0	0.4	0.41	1	0.4
Govt. Supp. by Foreign Govt.	177	0	1	0.62	1	0.47

Table A4: Descriptive statistics for variables in Base + Controls (1997-2015) model.

A.3. Alternative Modeling Strategies

A.3.1. Fixed Effect Regression Results when Including Controls

Below we show results from our two models with controls when using fixed effects instead of random effects. Similar to the random effects results we present in the paper these models are estimated using a ten randomly sampled datasets from the posterior of our imputation model and results are combined using Rubin's rules.

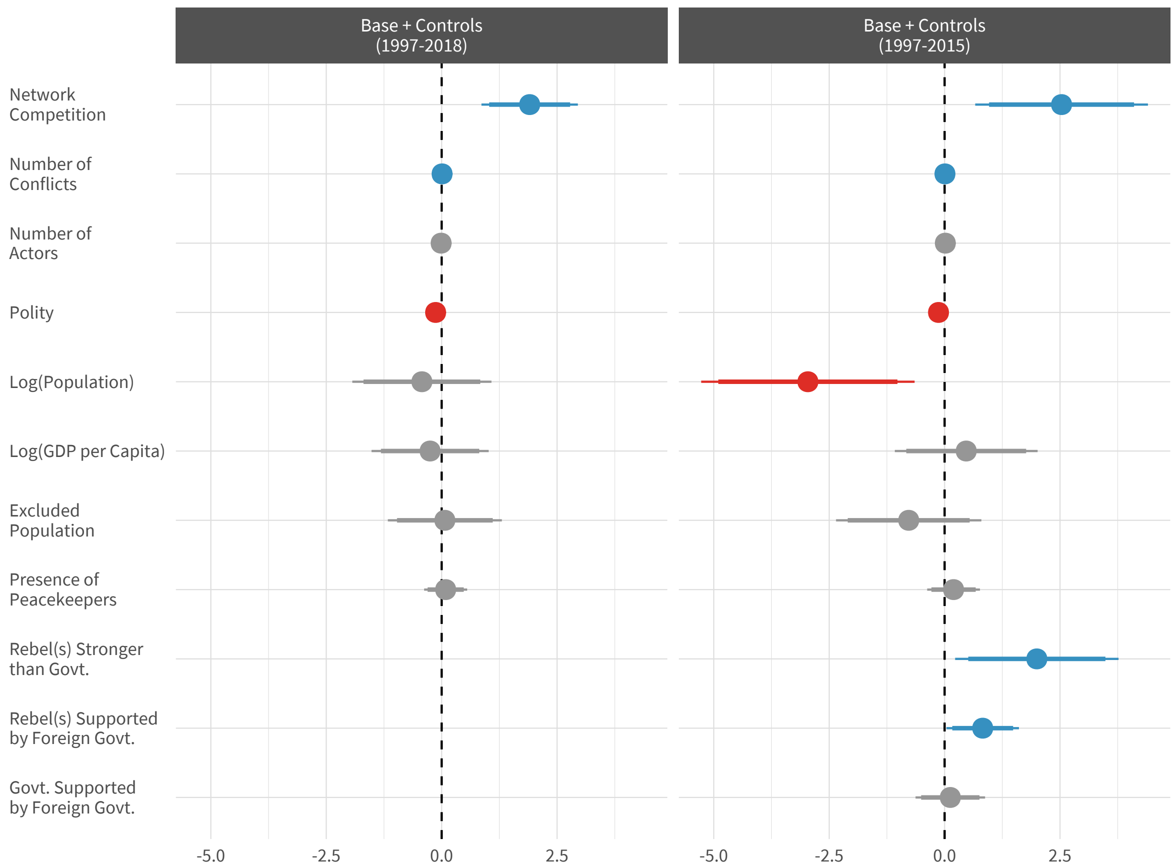

Figure A1: Regression results from multiply imputed datasets when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average value of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.3.2. Results without Multiple Imputation

Here we show results from our models with controls when utilizing listwise deletion. The "Base" specification results remain the same as for those covariates there is no missing data to impute.

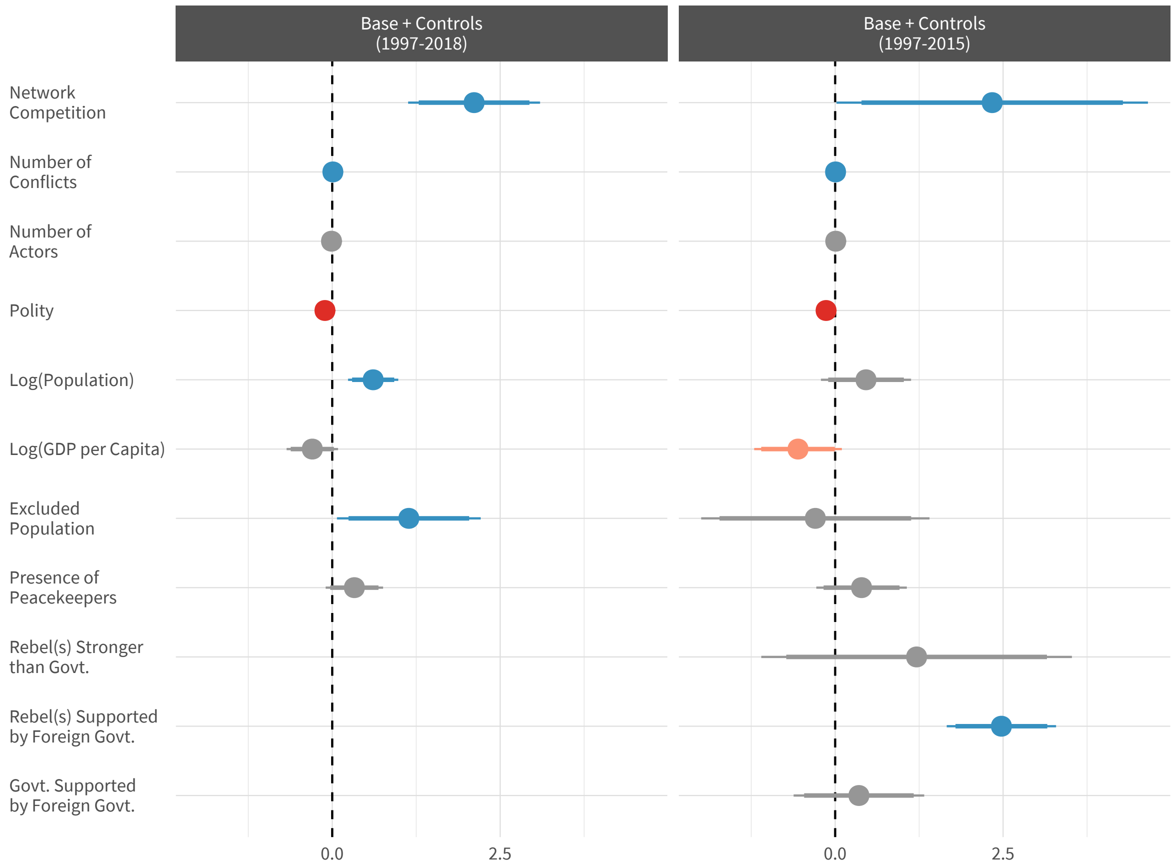

Figure A2: Regression results from unimputed data when pairing Base specification with controls using random effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

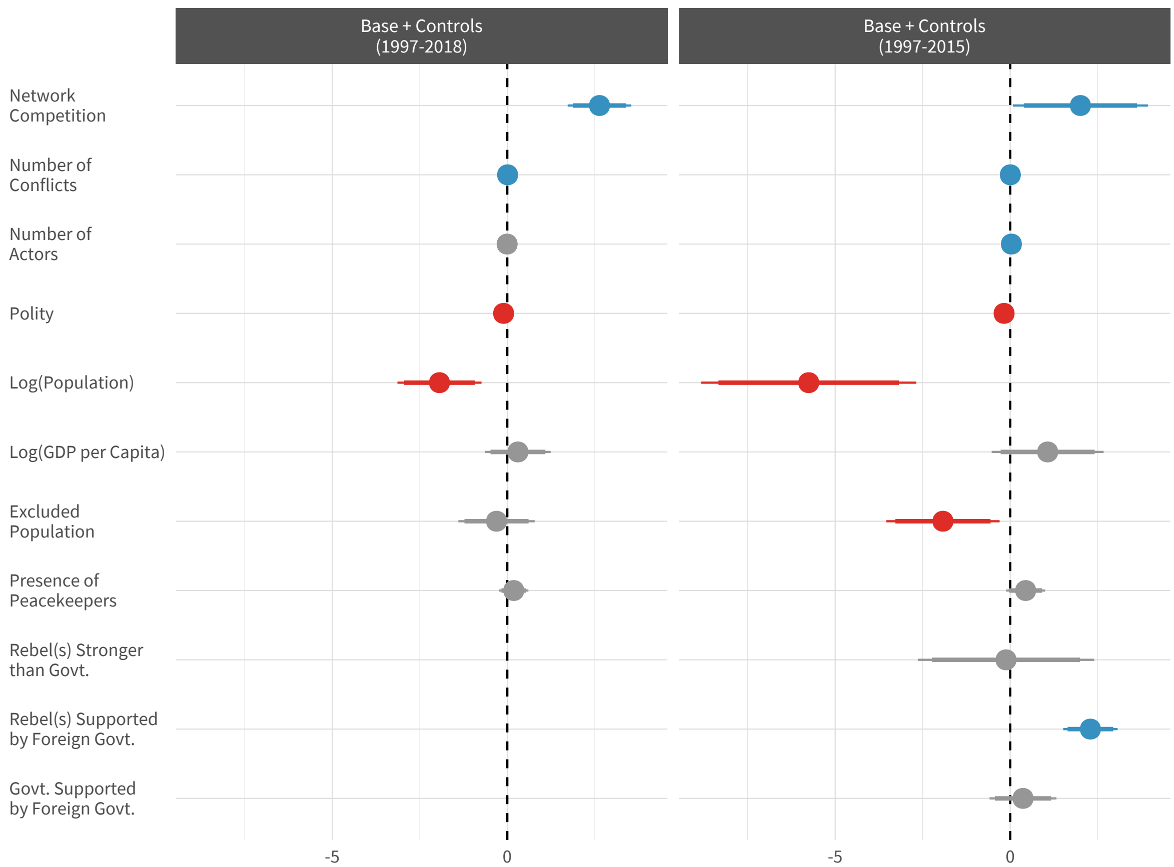

Figure A3: Regression results from unimputed data when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.4. Alternative Model Specifications

A.4.1. Results with a Lagged Dependent Variable

Below we show that results for network competition, our parameter of theoretical interest, are similar when controlling for a lagged dependent variable in both the random and fixed effects specifications.

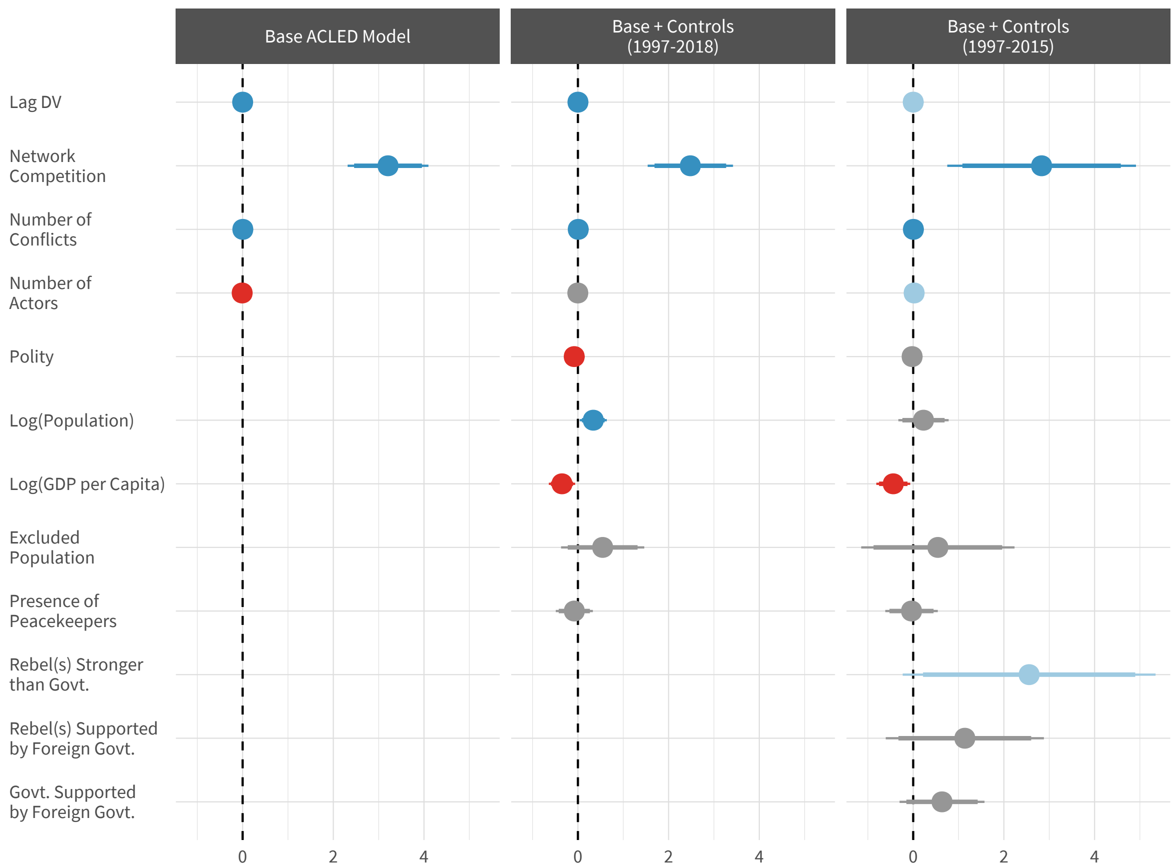

Figure A4: Random effect regression results when including a lagged dependent variable. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

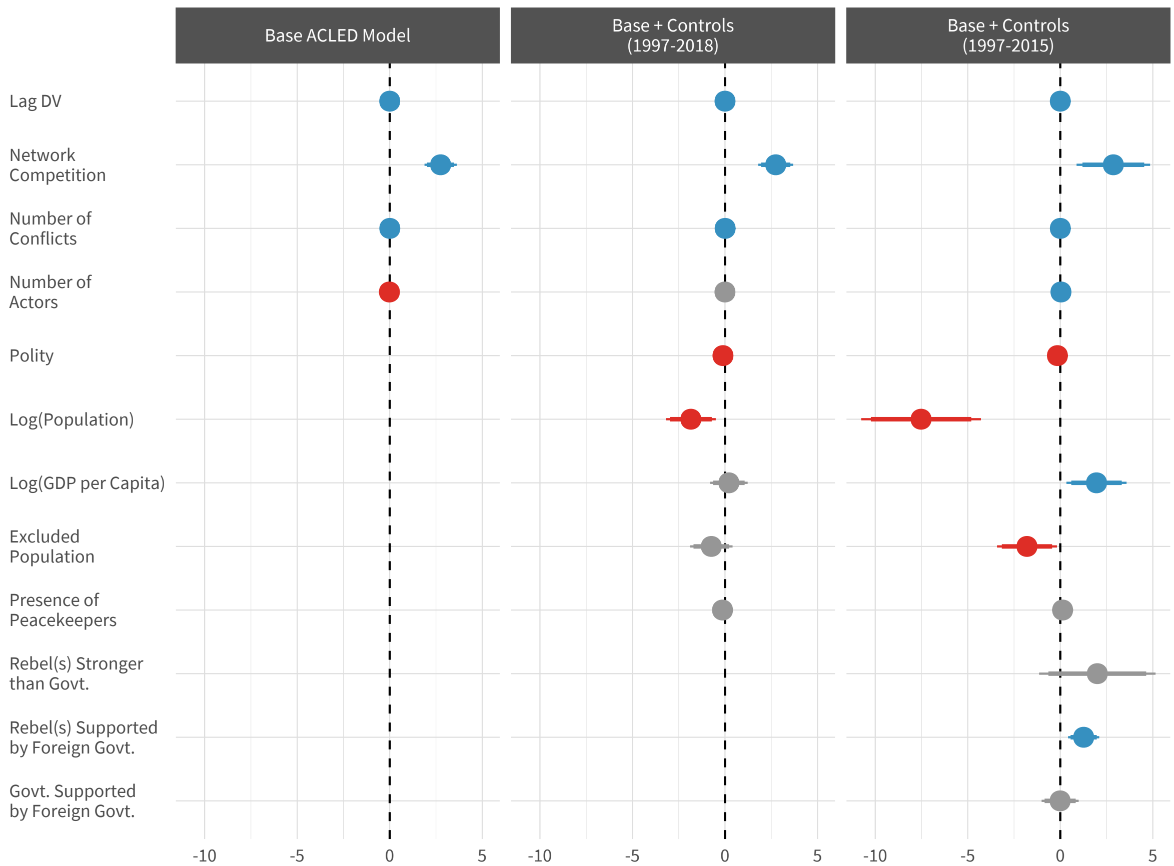

Figure A5: Fixed effect regression results when including a lagged dependent variable. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.4.2. Incorporating Geographic Spread of Actors

Controlling for the geographic proximity of actors in an armed conflict is an important robustness check for our analysis. High levels of victimization could be a result of actors in an armed conflict being geographically concentrated rather than being a function of network competition. To estimate the geographic concentration of armed actors in a country-year we calculate the centroid positions of armed actors for every country-year based on all the events that they were involved in,[33] next we calculate the distance between each actor centroid, and last take the average of those distances as a measure of how spread out actors are from one another.[34] Results when including this control for the geographic spread of actors are shown in Figures A6 and A7 below. In both the random and fixed effects specifications, the effect of the network competition measure matches our theoretical expectations.

[33] We subset to only events that had an ACLED precision code of 1 or 2. Results for network competition are the same, however, if we subset to only events that had a precision of 1.

[34] Using the median distance produces the same result.

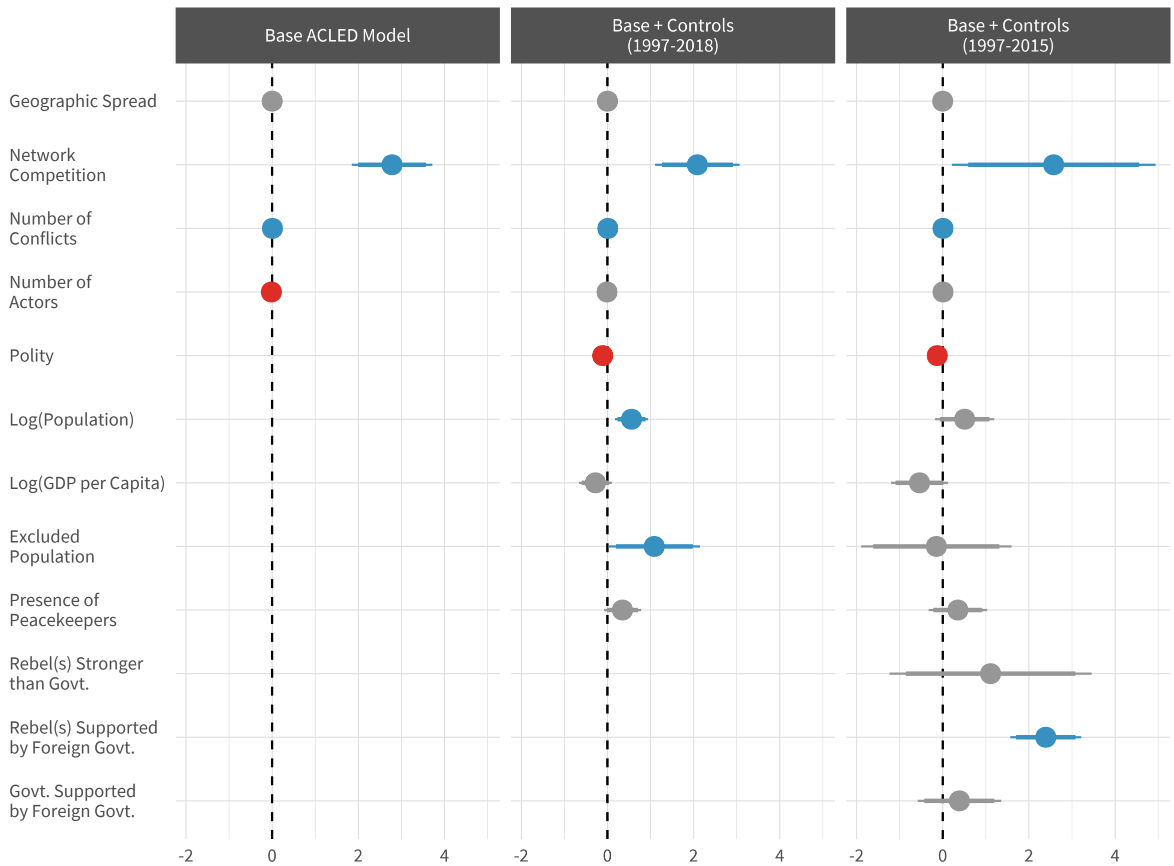

Figure A6: Regression results with random effects including a control for the geographic dispersion of actors. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

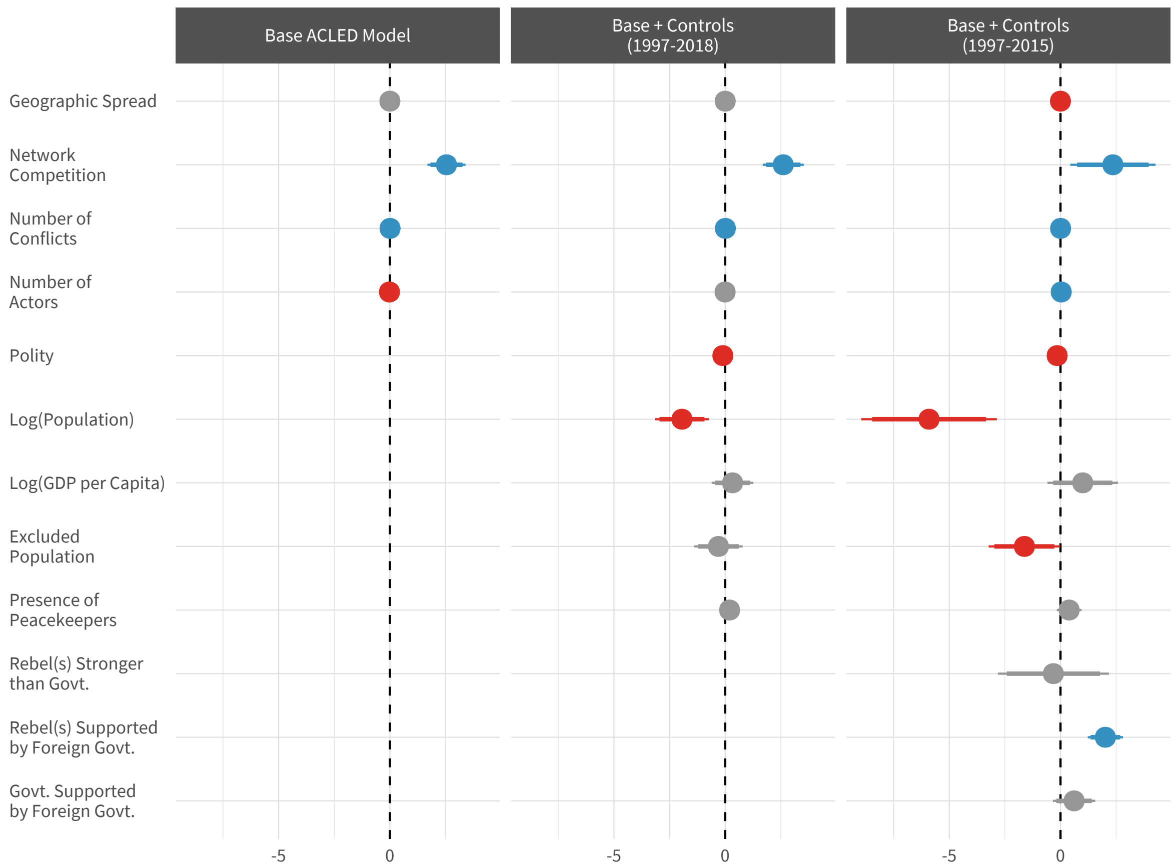

Figure A7: Regression results with fixed effects including a control for the geographic dispersion of actors. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.4.3. Controlling for proportion of potential allies

As the reviewer rightly points out, binary measures of conflict are often plagued by issues of left censoring. In other words, we know two actors are enemies if they experience conflict, but if they experience no conflict, we are not sure whether they are apathetic towards each other, or if they are actually friends and allies. There have been a number of recent works discussing how we can leverage the relational nature of conflict data to infer levels of amity (Cheng and Minhas, 2021; Gallop and Minhas, 2021; Dorff, Gallop and Minhas, 2021). To that end, we posit three principles for actors that are not just indifferent to each other, but possible allies:

1. If i and j are allies, i never attacks j, and j never attacks i.
2. If i attacks a third party k, j is more likely to attack k as well.
3. If i allies themselves with a third party k, j is less likely to attack k.

In both the simulation results for our ABM, and our cross-national empirical work, we use these principles to generate the following algorithm, to determine which armed actors are allies.

1. Generate a network containing cumulative counts of conflict between all actors until time $t - 1$.
2. Center and standardize this network, then use a singular value decomposition to obtain a vector for each group (groups will have vectors pointing in similar directions if they have similar patterns of conflict with third parties).
3. Calculate the cosine similarity for each pair of groups.
4. For all isolates (groups that never send or receive conflict from any other state), assume that they are not allied with any other groups.
5. If any pair of states ij have fought in the past, set their alliance level to 0.
6. Find the proportion of dyads with cosine similarity above a sufficiently high threshold, and treat this as the proportion of groups in a system with alliances.

We then include the proportion of groups in a country-year that are allied in both our statistical analysis of the ABM results and our empirical work. Results when including this measure in our ABM model are shown in Figure A8. The network competition measure remains significant and in the expected direction in both the fixed and random effect specifications.

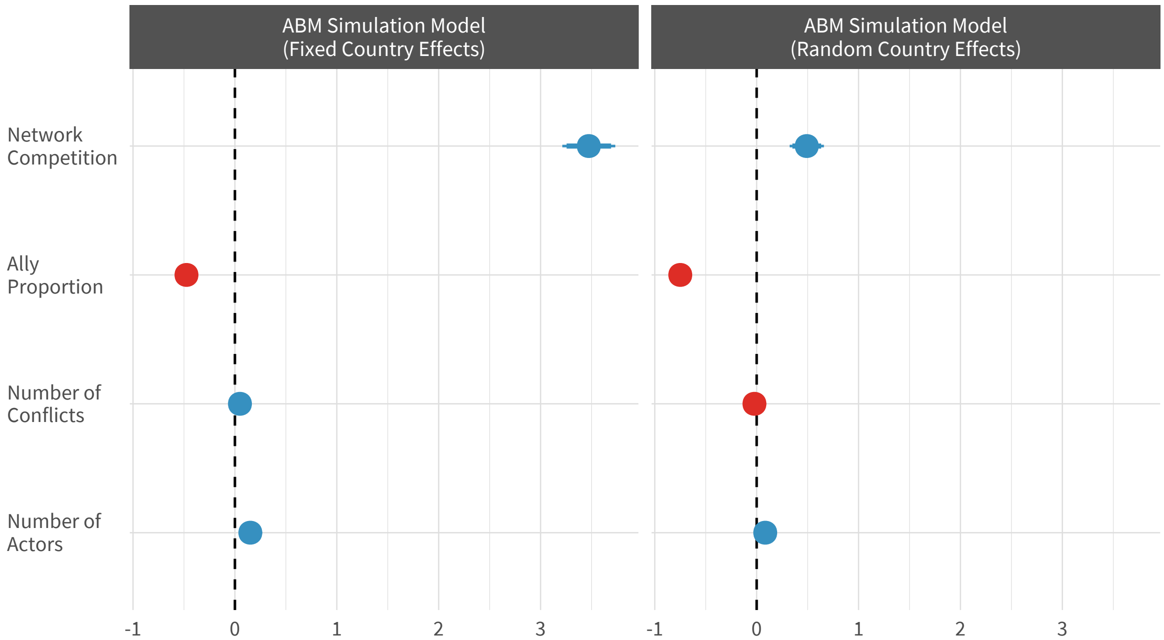

Figure A8: Analysis of determinants of victimization in computational model controlling for proportion of allies. The left panel visualizes coefficient estimates when using fixed effects on conflict scenarios and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

Figure A9 and A10 show the results when including this measure in our empirical models, and there as well we find that the network competition measure continues to align with our theoretical expectations.

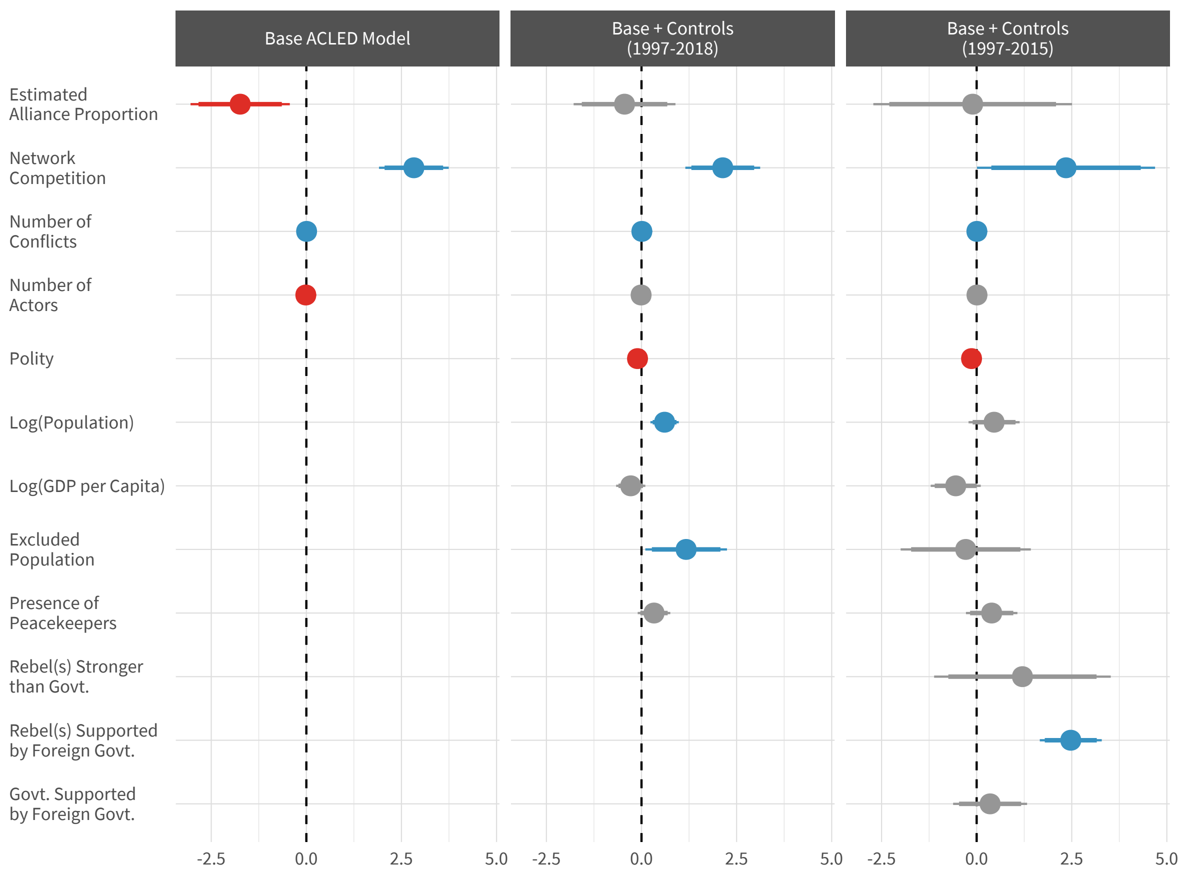

Figure A9: Regression results with random effects including a control for the proportion of actors allied in a country-year. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

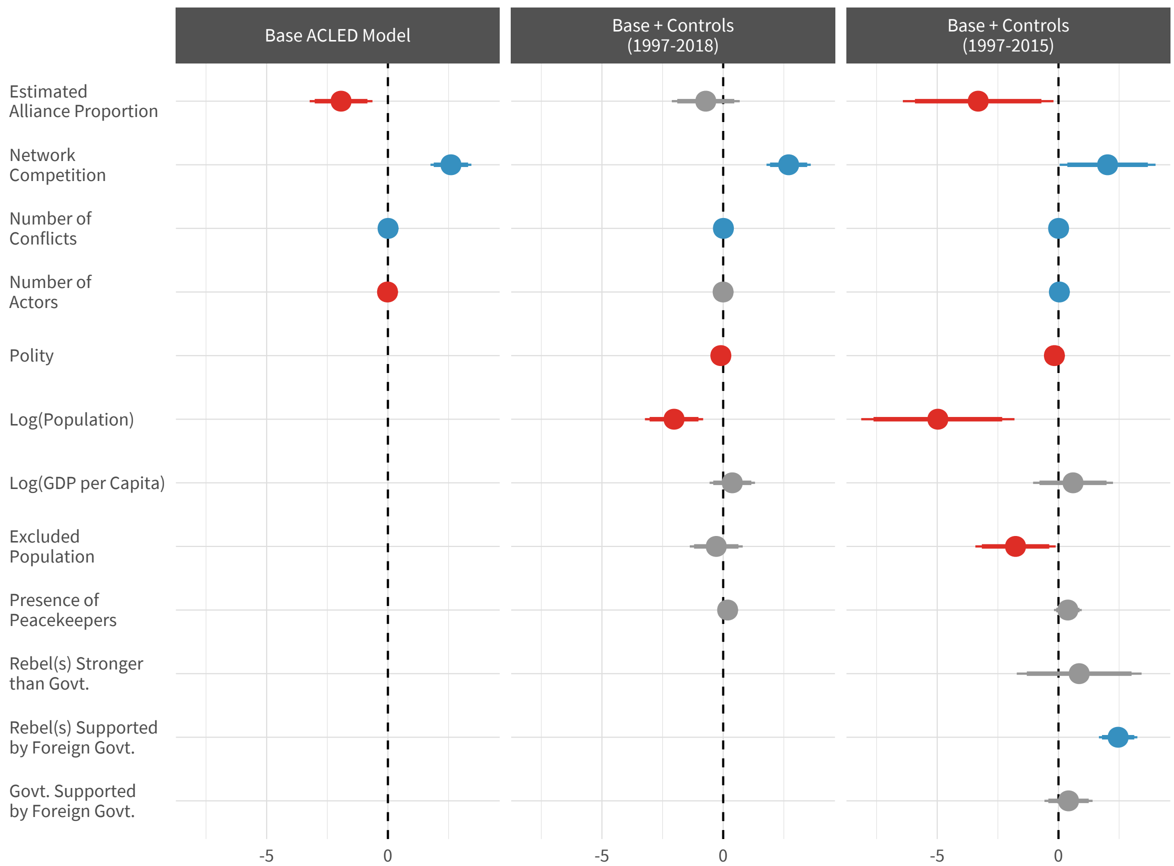

Figure A10: Regression results with fixed effects including a control for the proportion of actors allied in a country-year. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.4.4. Conditional Effect of Government Strength

Here we examine whether the effect of network competition is conditional on the strength of either the government or the rebel. Within the ABM, we do this by measuring the allocation of the territory held by the government relative to rebel groups. Specifically, we create a binary measure, called rebel strength, that has a value of 1 when rebels hold more territory than the government and 0 if less. To test whether or not there is a conditional effect, we add the rebel strength variable to the model specification and also include an interaction between it and the network competition measure. Figure A11 shows predicted levels of victimization for the effect of network competition conditional on rebel strength. In cases where rebels are stronger (government is weaker), the effect of network competition is more muted, whereas in cases where rebels are weaker (government is stronger) the effect of network competition is increasing with network competition. Given that empirically, the government almost always begins a civil conflict more powerful than various rebel groups, we find it reassuring that our main mechanism holds in the more common circumstance.

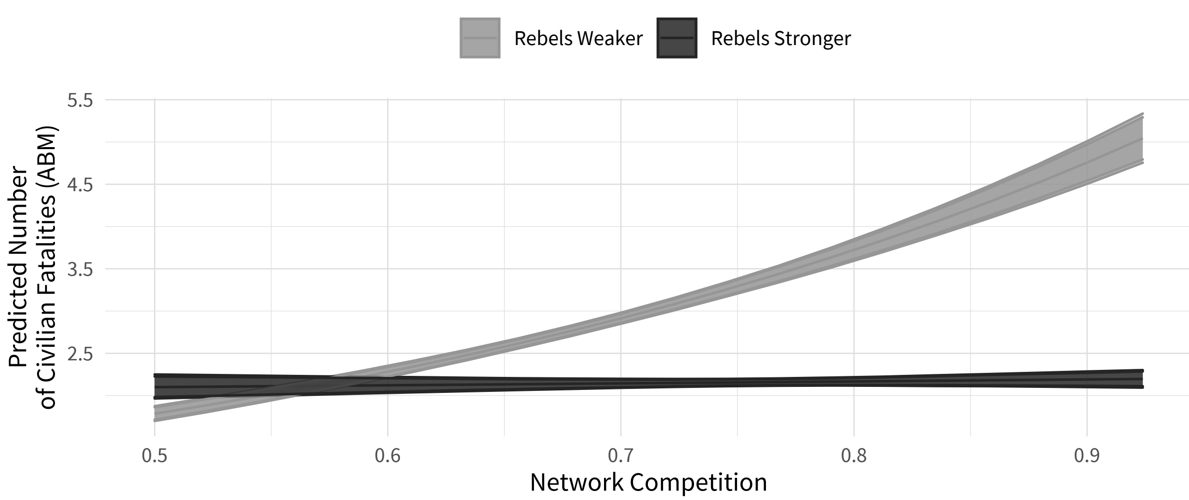

Figure A11: Simulation analysis of the ABM results of a random effects model that includes an interaction between government strength and network competition.

For the empirical analysis, we already have a variable measuring whether rebel forces are stronger than the government from the NSA database. We interact the rebel stronger variable from that database with our measure of network competition and conduct a simulation analysis to understand the conditional effect of network competition on victimization. The results of this analysis for the empirical model are shown in Figure A12. Here we see results that are generally in line with what we found in the ABM, though estimated with much less precision. Specifically, the left panel shows predicted levels of victimization by network competition when rebel groups are weaker, and the right for the case in which rebels are stronger. As with the ABM, we can see that higher levels of victimization are predicted as network competition increases when rebel groups are weak, and that there seems to be little effect when rebel groups are relatively stronger. We would caution drawing too much from the interaction analysis using the empirical data, however, given the imprecision of the estimates.

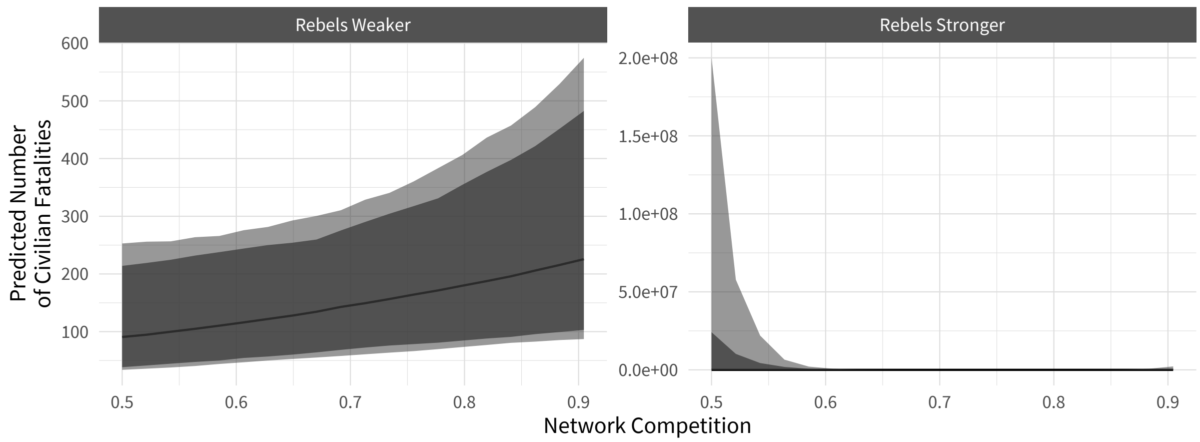

Figure A12: Simulation analysis of the empirical results of a random effects model that includes an interaction between an indicator variable for rebels stronger than governmentand network competition.

A.4.5. Effect of Number of Actors under Various Specifications

We acknowledge that there is a disconnect between our ABM results and the literature, where the number of actors has a positive effect on victimization, and our empirical results, where the number of actors has a negative or insignificant effect on victimization. After further examination of our empirical results, we find that these results can be somewhat explained by our research design. Specifically, two of our modeling choices jointly lead to a negative or insignificant effect of number of actors: (1) the use of fixed effects at the country level and (2) the inclusion of our main independent variable, network competition, into the model. If either modeling choice is made, our results disagree with previous literature. We show the variation in the results for the effect of number of actors below in Figure A13.

It is possible that, in previous studies, measurements representing changes in the number of actors over time actually capture both country-level conditions that might correlated with actor composition (demographic factors, political events) and conflict level dynamics (strategic incentives for violence) that affect one-sided violence. In our paper, fixed effects account for variation in country-level conditions, while our competition measure more accurately reflects strategic changes between actors. For these reasons, the effect of network competition has consistently positive effect across both our theoretical and empirical specifications while the effect of the number of actors changes depending on the model specification used.

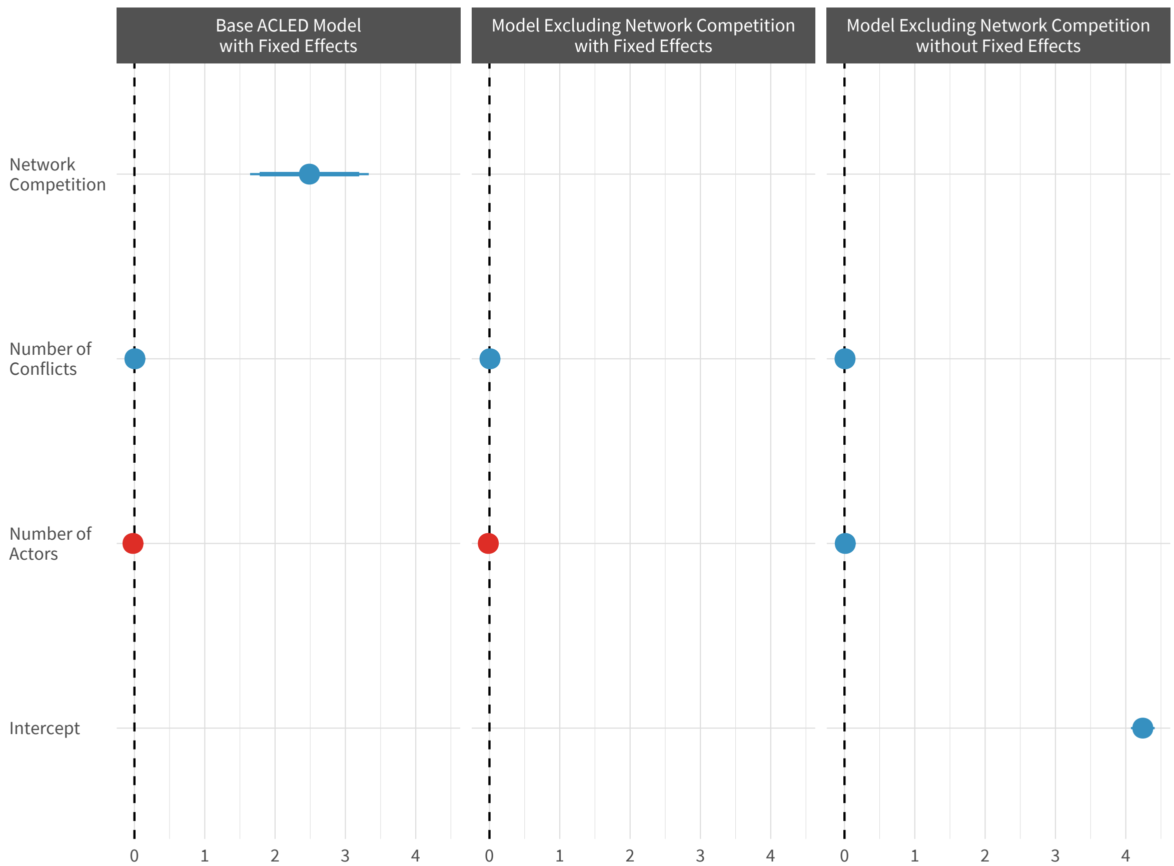

Figure A13: Regression results exploring the effect of Number of Actors: in the first column we show the results in our paper, in the second we exclude our measure of network competition, and in the third we exclude our measure of network competition and run the model without fixed effects for countries. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.5. Robustness to Sample Changes

A.5.1. Results using Various Thresholds to Include Countries

In the Base results presented in Figure 6 of the manuscript, the underlying sample had a requirement that a country must have at least three years of observations to be included in our analysis. This led to a sample of 42 countries from 1997 to 2020. Here we modify this three year minimum to test the robustness of our results. The first row in Figure A14 depicts our results when we employ no miminum and the second row when we employ a five year minimum per country. The former criterion leads to a sample of 45 countries and the latter 39. Our results in terms of network competition are robust to any of these minimum country year requirements.

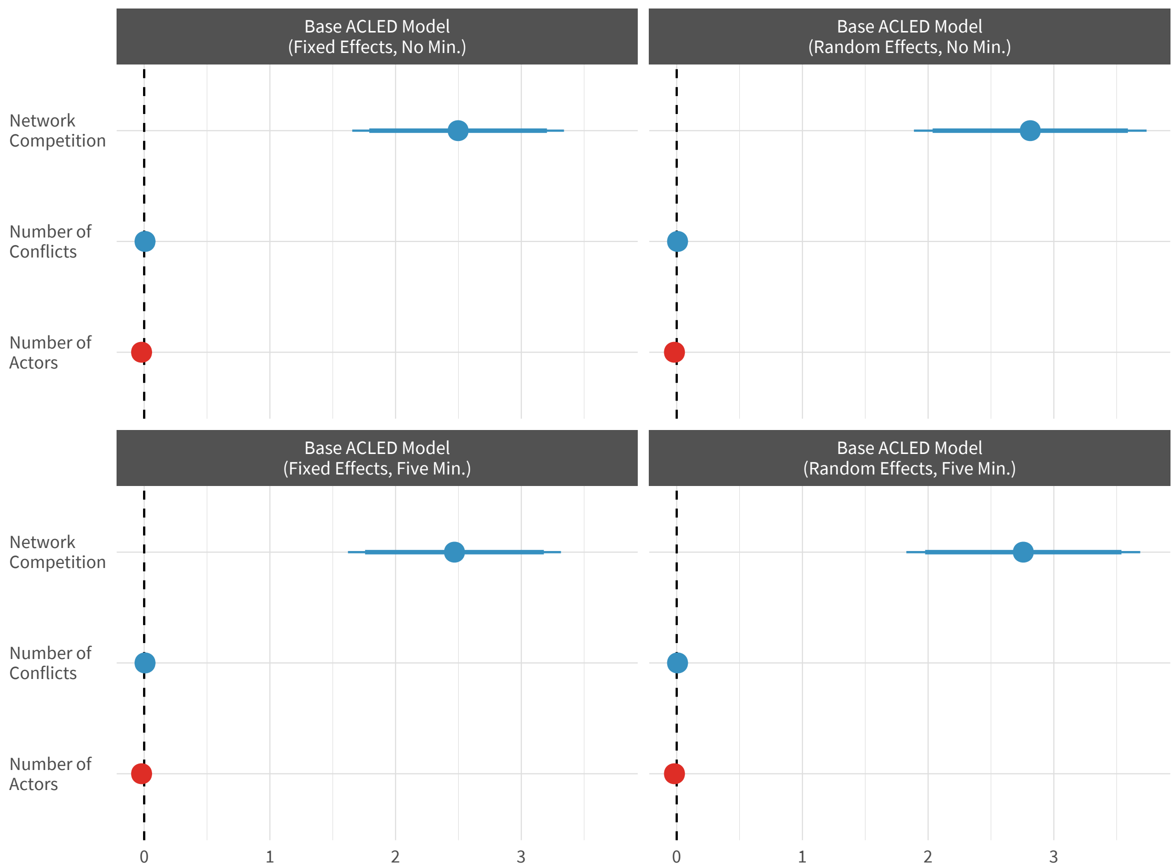

Figure A14: Regression results from unimputed data on Base specification when using various thresholds to include countries and estimations via fixed or random effects. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.5.2. Model Estimates when Limiting Sample to 1997-2019

COVID-19 may impact not only our results but even the reporting of conflict data in a number of ways. To insure that our results are not being affected by this type of exogenous dynamic, we limit our sample to 1997 and 2019. Figure A15 shows the results for our base model using fixed and random effects when we exclude 2020 from our sample. There is no need to rerun analyses for the models in which we include controls as they already end before 2020 because of data availability reasons.

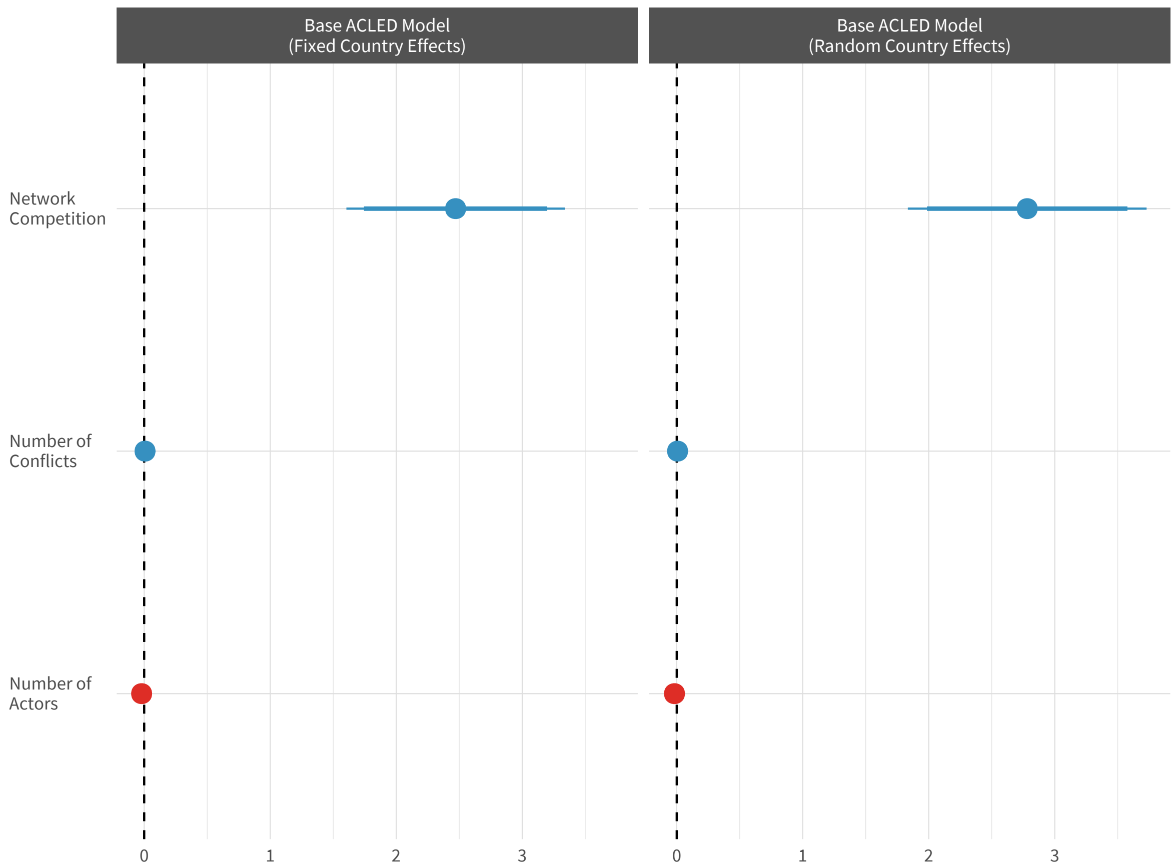

Figure A15: Regression results using Base specification that includes 42 countries from 1997 to 2019. The left panel visualizes coefficient estimates when using fixed effects on countries and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.5.3. Model Estimates with UCDP

Given that the information in various event datasets can vary widely across countries (Eck, 2012), we also run our analysis using information from UCDP. Ideally, we would like to integrate information from both data sources (Donnay et al., 2018), but such a task would require building a dictionary that can bridge actor level information between UCDP and ACLED. Figures A16 and A17 show the results when using data from UCDP instead of ACLED. Results for our network competition measure remain positive and significant when using information from UCDP. For the manuscript, we choose to focus on results using UCDP, however, because UCDP data records information only on groups that commit a specific threshold of violence during a battle, whereas ACLED data contains information about all groups relevant to all battles, regardless of the number of deaths incurred. Due to our focus on measuring network competition based on how groups are interacting with one another we focus on results with ACLED.

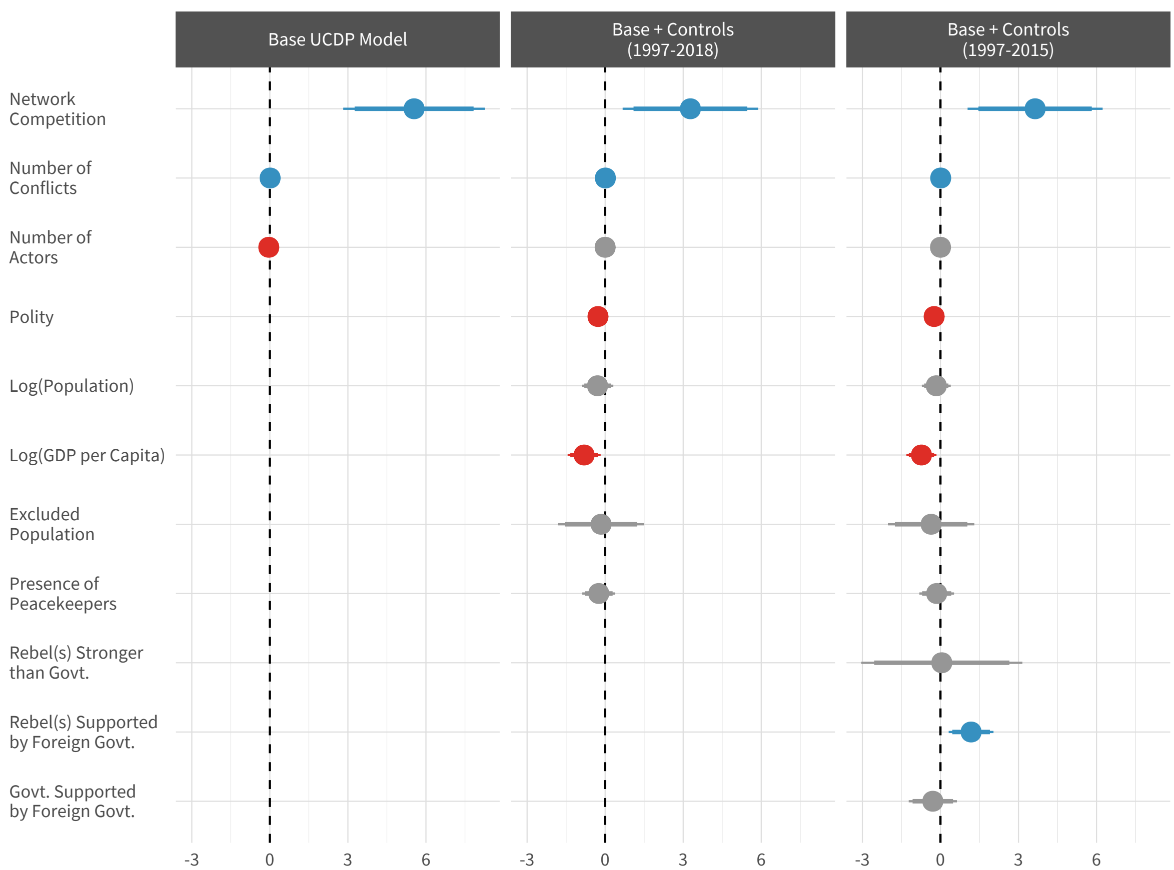

Figure A16: Regression results with random effects using UCDP data. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

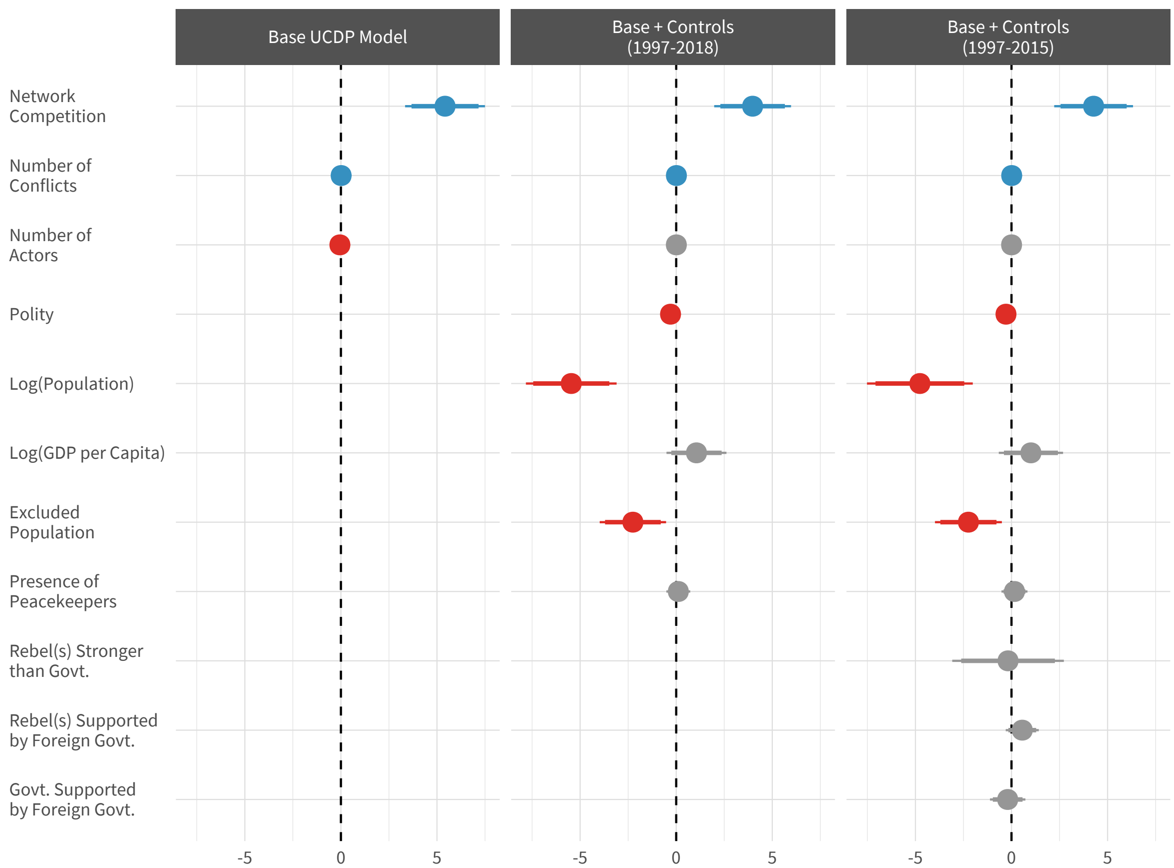

Figure A17: Regression results with fixed effects using UCDP data. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

A.6. Alternative Dependent Variable

A.6.1. Using Counts of OSV Events instead of Fatalities

Given the difficulties in accurately measuring fatality counts from conflict (Dawkins, 2021), we also reestimate our model using a count of one-sided violent events in a country-year as the dependent variable. The results are presented below in Figures A18 and A19. With this alternative dependent variable we find that our network competition measure has a positive and significant effect on the number of civilian victimization events in a given year using either a random or fixed effects framework.

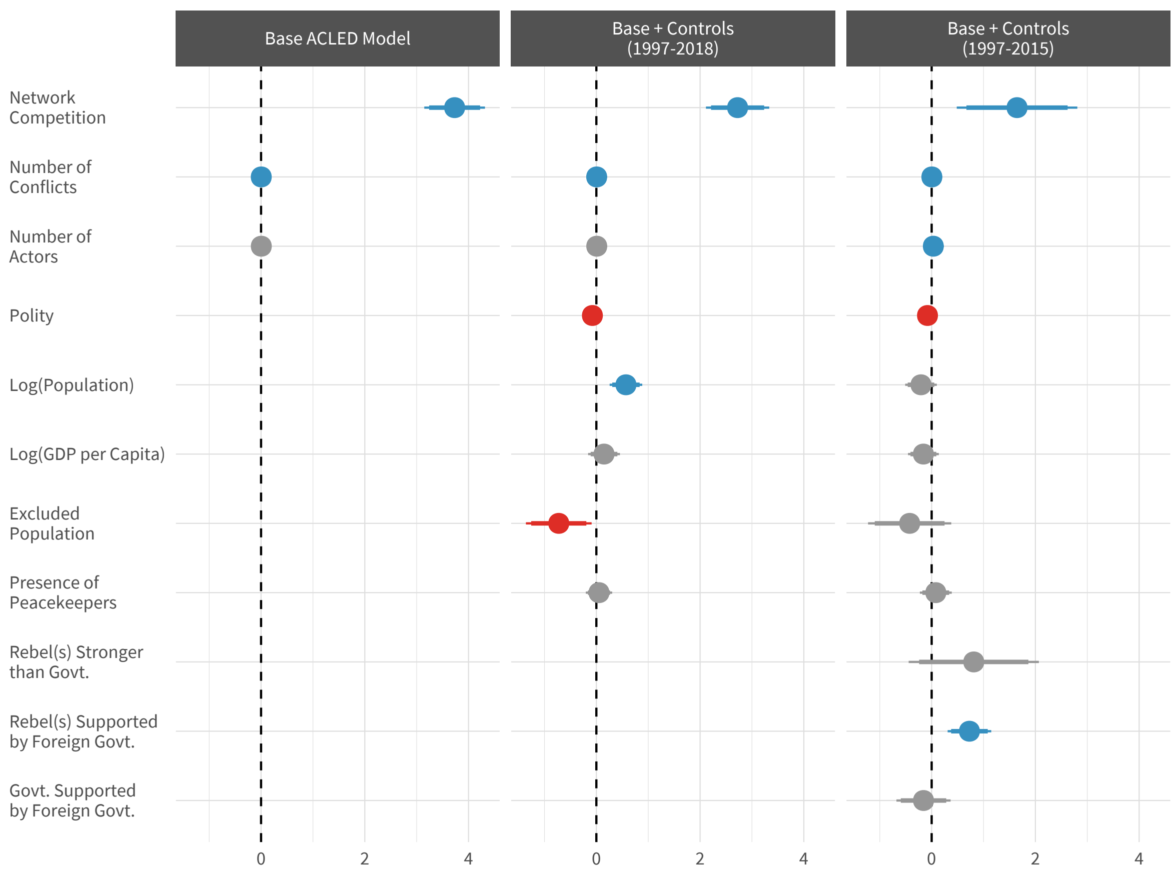

Figure A18: Regression results on count of OSV events with random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

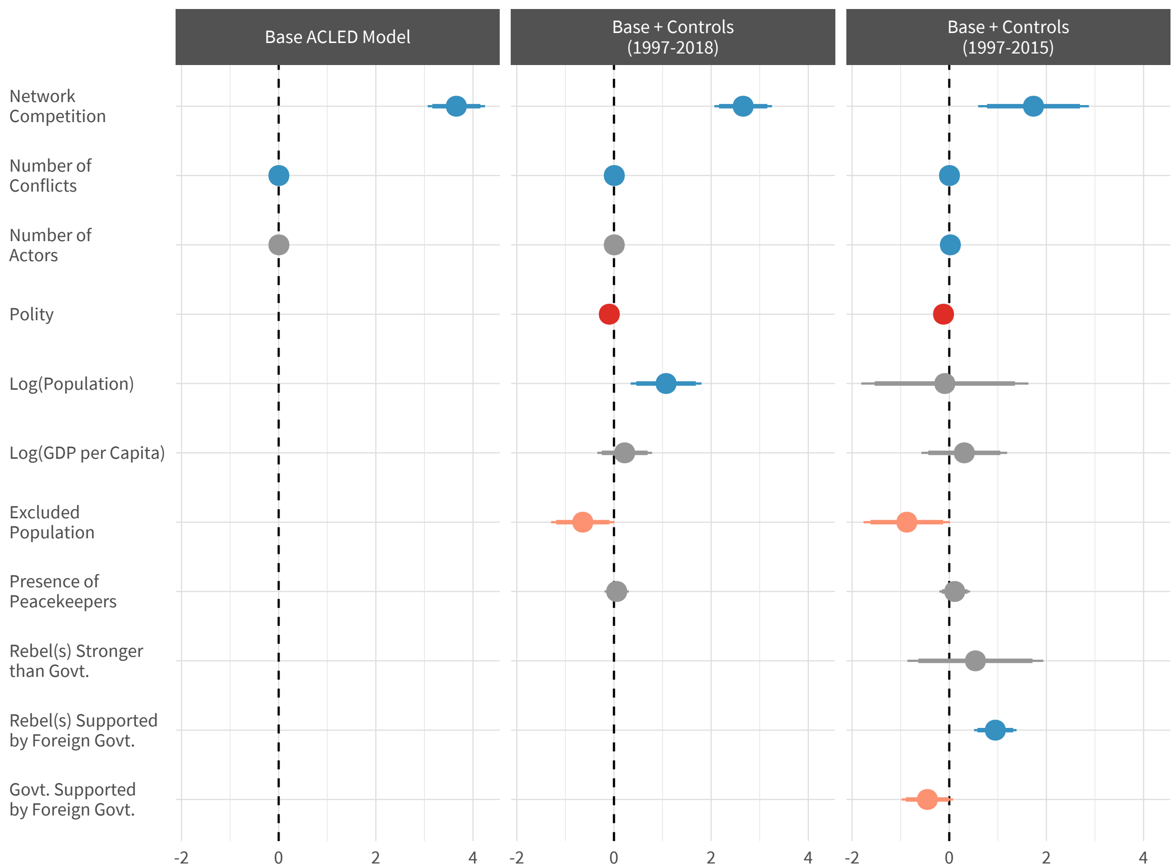

Figure A19: Regression results on count of OSV events with fixed effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.