British Journal of Political Science (2023), **53**, 441–459
doi:10.1017/S0007123422000321

British Journal of Political Science

ARTICLE

Network Competition and Civilian Targeting during Civil Conflict

Cassy Dorff[1]*, Max Gallop[2] and Shahryar Minhas[3]

[1]Department of Political Science, Vanderbilt University, Nashville, TN, USA, [2]Department of Politics and International Relations, University of Strathclyde, Glasgow, UK and [3]Department of Political Science, Michigan State University, East Lansing, MI, USA
*Corresponding author. Email: cassy.dorff@vanderbilt.edu

(Received 23 September 2021; revised 4 April 2022; accepted 14 June 2022; first published online 3 November 2022)

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.

Keywords: civilian victimization; network analysis; civil conflict

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 (Arjona 2017; Kalyvas 2006), or profitable commodities like oil (Lujala 2010). However, 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 exploring the dynamics of competition itself to identify meso-level, dynamic mechanisms that capture

[1]All estimates are calculated using the Armed Conflict Location and Event Dataset (ACLED) developed by Raleigh et al. (2010).

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 fluctuations in the 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 do 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 article, 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 and conflict networks (Dorff, Gallop, and Minhas 2020) 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 micro-foundations 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. Secondly, 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 a function not just of the total level of violence in a conflict or the number of violent actors, but also of 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 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 toward 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]:

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

where$N$ 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 in which most civilians support the groups in control of their territory and no victimization occurs.

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 toward victimization. In this case, there is likely a fluid control of territory. Frequent changes in the system increase incentives for violence against civilians, which is an assumption supported by existing research (Wood and Kathman 2015). Some of the most intractable and dynamic conflicts—such as the modern wars in Somalia—are likely to exhibit this network structure. Our theoretical model (explained later) 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]

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, 612) explains: "Unraveling these dynamics is particularly important if scholars wish to fully understand the dense web of interactions that guide insurgents' 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

[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), as well as the competitiveness of party systems (Alfano and Baraldi 2015).

[4]König et al. (2017) similarly use 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 (that is, 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.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

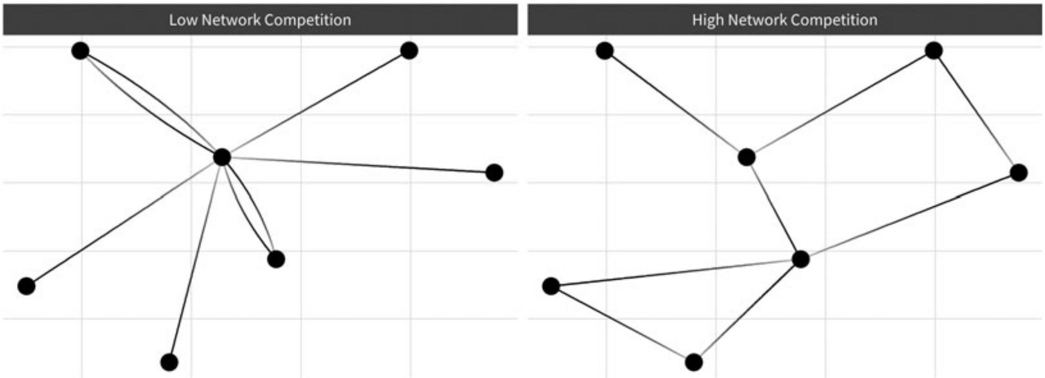

Figure 1. Conceptual networks illustrating scenarios of low and high network competition.
Note: Network competition is low in the left panel and high on the right, while the number of conflictual events and actors stay constant.

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 in the following. 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 in our model allows us to innovate and follow research on rebel–civilian relationships that underscores civilian agency in conflict areas (Arjona 2017; Kasfir 2015; Mampilly 2012). 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.

[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.

[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.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

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 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, since a non-supporter of the group requires coercion to yield 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 that 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 (Azam and Hoeffler 2002; Kalyvas 2006; Valentino 2014; 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 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 (see Kalyvas 2006). The probability of successful victimization (targeting a non-supporter) is a nonlinear 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 one's own supporters) is counterproductive. When an actor targets a supporter, the range of ideologies that will provide support to the actor shrinks

[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).

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

[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 because there are no supporters to target.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

(as the safety provided by supporting the actor is illusory) and when they target a non-supporter, the range of ideologies grows.[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, 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 tradeoff 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 can also 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 figures, territories are represented by rectangles and 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 in Figure 2. In Row 2 (left panel), we illustrate an armed group's 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 figure 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 and the possible consequences of victimization. In the following, we discuss the intuition behind the decision rules for each group in Figure 3 (for the explicit mathematical criterion for each choice, see Section A.1 in the Online Appendix).

(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, that is, 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

[10]Fjelde and Hultman (2014) show 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.

[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 Equations A4 and A5 in the Online Appendix.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

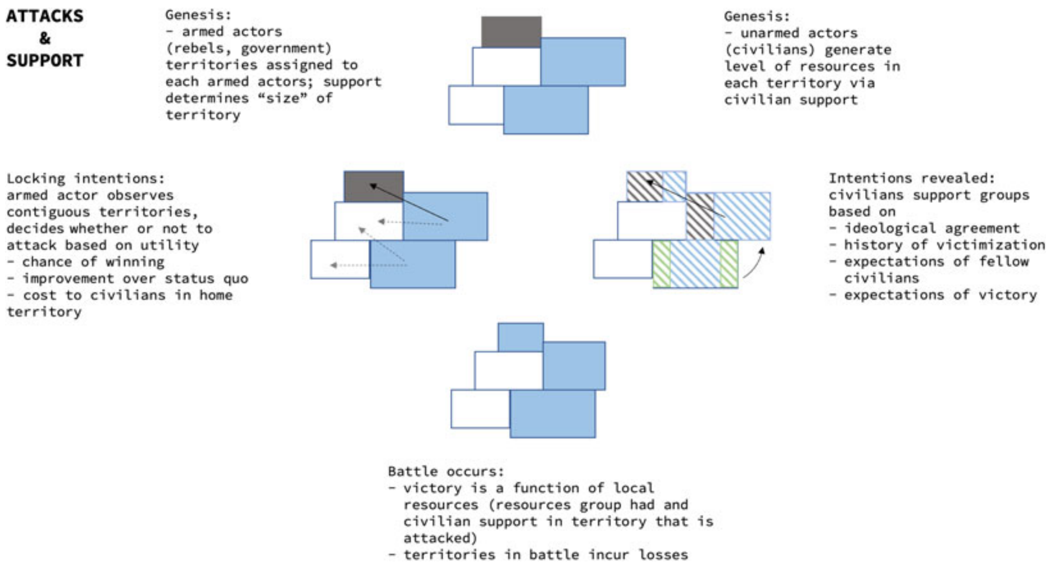

Figure 2. The choice of an armed actor to attack, and the choice of civilians to support the actor or not.
Notes: Rectangles represent territory, with territory size based on the size of the civilian population. For the solid colors, color represents the group controlling the territory. The arrows illustrate 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, the 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.

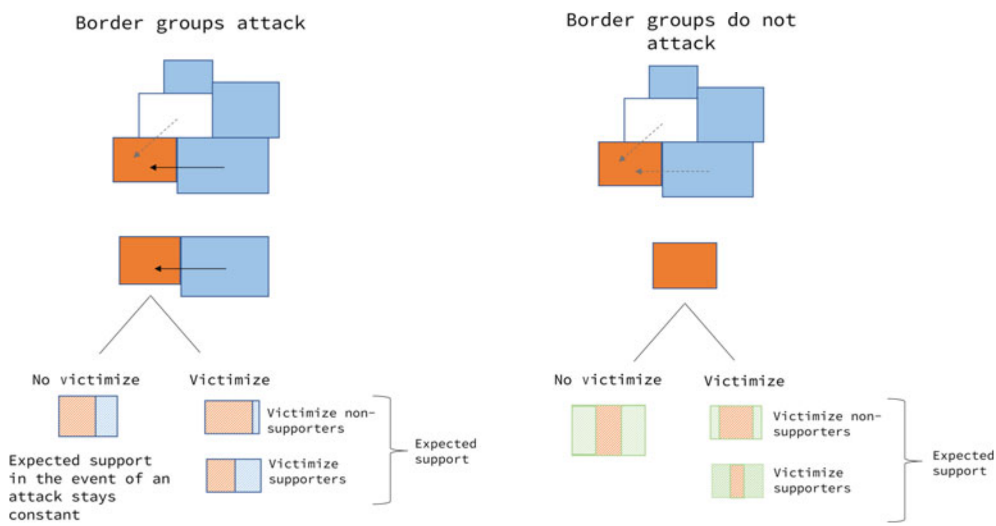

Figure 3. Graphic illustrating the choice of an armed actor to victimize civilians.
Notes: The orange group first determines whether any of their neighbors are likely to attack. If they are likely to attack, the orange group decides whether to victimize to maximize their support and chance of winning 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 its aims, the ideological range of support for the incumbent group increases; if it fails, the range contracts.

preferences or the past actions taken by civilians in a territory toward 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

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

factors is the payoff for attacking a given territory. Groups choose to attack 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

Civilians' decisions are conditioned not just on the characteristics of armed actors, but also 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 in the Online Appendix). Civilians who are ideologically close to the armed group are assumed to be highly likely to support them, and civilians who 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 (as 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 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, on random chance. When a civilian is victimized, there is 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, meaning that the civilian's support can thereby 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. However, when the territory is at risk of attack, the incentives to victimize are higher because the direct effect, that is, 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.

[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 in the Online Appendix.

(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: (1) the government controls all the territories; (2) the government controls no territories; or (3) 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; rather, it is the product of strategic choices by different actors in the game that profoundly influence other choices, in particular, the choice to use violence against civilians. At the same time, violence against civilians can also influence future strategic decisions and thus endogenously affect levels 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 also the targets of an 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 (as they are more likely able to support an ideologically congenial invading group). When network competition is low, we will also see fewer territories changing hands, as 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 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 the Computational Model

To determine the macro-level effects of the micro-actions described earlier, 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.

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.*

[15]Secondly, 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).

[16]It is worth noting here that in the Agent Based Model (ABM) victimization refers to both 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.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

Table 1. Summary of the parameters in our computational model

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)

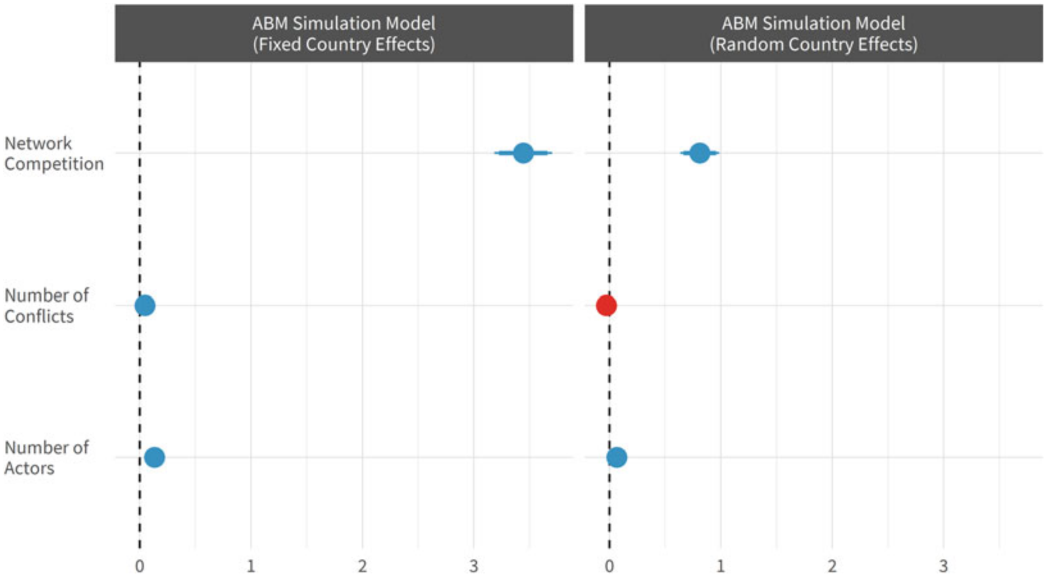

Figure 4. Analysis of determinants of victimization in computational model.
Notes: The left panel visualizes coefficient estimates when using fixed effects on conflict scenarios and the right uses random effects. Points represent average values of parameters. Thicker lines represent the 90 per cent confidence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

Empirical Analysis

To investigate the implications of our computational model empirically, we use the Armed Conflict Location and Event Dataset (ACLED) developed by Raleigh et al. (2010). The 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 the ACLED. Battles are defined by the 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

[17]As defined by the 2019 ACLED codebook, available at: https://www.acleddata.com/wp-content/uploads/dlm_uploads/2019/04/General-User-Guide_FINAL.pdf

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

study are those actors that have been involved in a battle event as either a primary or an 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 1 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 in the 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 the actors in our analysis reflect 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 ten or more active armed groups in a given year, are on the rise—as shown in the top panel of Figure 5. The bottom panel of Figure 5 depicts the distribution of network competition across our sample of countries from 1997 to 2020.[22]

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.[23] Importantly, 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 the excluded population variable into the model, for example, is important because the number of excluded groups is shown to affect conflict mobilization and would thus 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 (Eck and Hultman 2007; Harff 2003).

[18]To account for potential COVID-19 impacts on our results, in Figure A16 of the Online 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 article.

[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 would be recorded in this case.

[21]In Figure A15 in the Online 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, secondly, we tighten the restriction by requiring countries to have at least five years of non-empty adjacency matrices. In both cases, our results remain consistent with what we present in the article.

[22]Figure A1 in the Online Appendix depicts the level of variance in our network competition measure for every country in our sample.

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

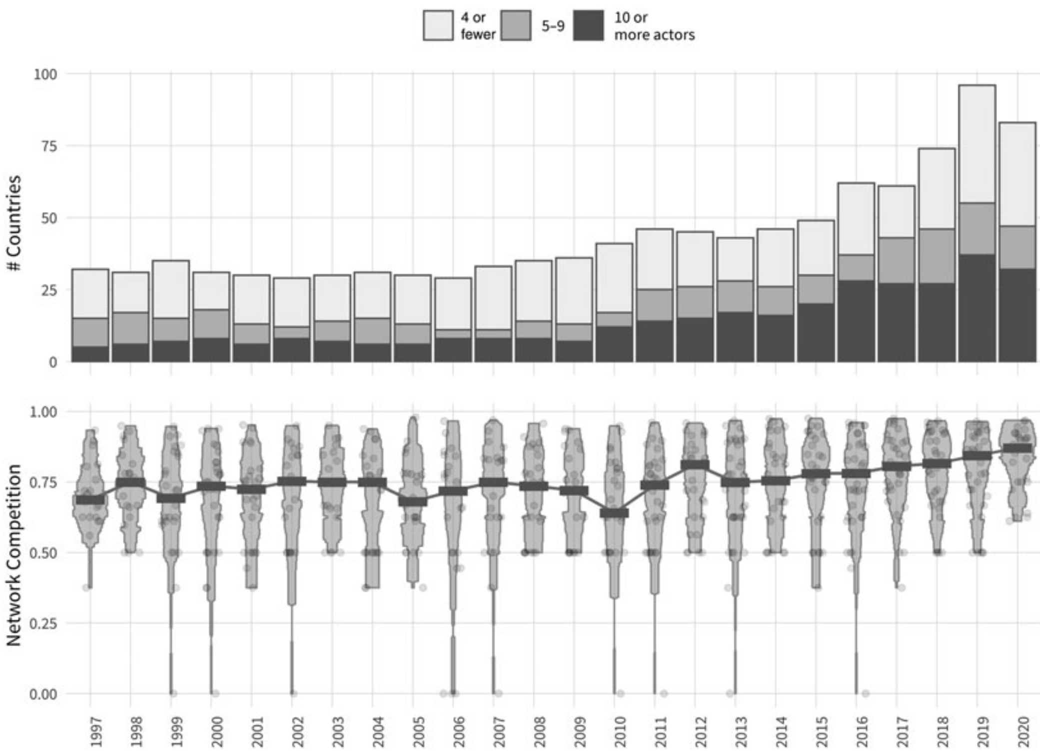

Figure 5. The number of active armed groups and distribution of network competition in countries from the ACLED between 1997 and 2020

Notes: Top panel shows the number of active armed groups in countries from the ACLED between 1997 and 2020. Dark grey represents armed conflicts with four or fewer active armed groups; light grey represents armed conflicts with five to nine active armed groups; white represents armed conflicts with ten or more armed groups. Bottom panel uses violin plots to showcase the distribution of network competition across our sample of countries over time. Thick, horizontal bars through each violin plot designate the median.

Table 2. Summary of data used in our empirical analysis

Variable	Source	Last year of data	Base	Base + controls (1997–2018)	Base + controls (1997–2012)
Network competition	Raleigh et al. (2010)	2020	X	X	X
Number of actors	Raleigh et al. (2010)				
Number of conflicts	Raleigh et al. (2010)				
Polity	Marshall, Jaggers, and Gurr (2009)	2018		X	X
Log(population)	World Bank Group (2016)	2019		X	X
Log(GDP per capita)	World Bank Group (2016)				
Excluded population	Vogt et al. (2015)	2017		X	X
Presence of peacekeepers	Kathman (2013)	2012			X
Rebel(s) stronger than government	Cunningham, Gleditsch, and Salehyan (2013)	2014			X
Rebel(s) supported by foreign government	Cunningham, Gleditsch, and Salehyan (2013)				
Government supported by foreign government	Cunningham, Gleditsch, and Salehyan (2013)				

Notably, however, there is no annually updated available data on the attributes of armed actors that span across both space and time at the actor level. To overcome this, we rely on Cunningham, Gleditsch, and Salehyan's (2013) "Non-state actors in civil wars" (NSA) data. The NSA data extend the Uppsala Conflict Data Program (UCDP)/ Peace Research Institute Oslo (PRIO) Armed Conflict Dataset (Themnér and Wallensteen 2013) and cover all internal armed conflicts from 1945 to 2011.[24] The NSA data contain information about rebel–government dyads and only include 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. Secondly, the NSA data are based on different event data than our study and necessarily include a number of restrictions on which actors are included in the data. This means that the actors in the NSA data do 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.

While the ACLED data are available from 1997 to 2020, the availability of other data sources varies markedly. 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 the ACLED, which gives us a sample of 42 countries from 1997 to 2020.[25] The next model we run includes polity, population, gross domestic product (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 NSA database for rebel strength relative to the government and whether rebels or governments receive support from foreign countries (Cunningham, Gleditsch, and Salehyan 2013).[26] 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. 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. (Raleigh et al. 2021)." To model this, we utilize a negative binomial framework. We report the results for our "base" models of civilian victimization in Figure 6. The left panel shows results using fixed effects on countries and the right uses random effects.

In both cases, we find strong support for the effect of network competition on civilian victimization, even after controlling for 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

[24]Since Cunningham, Gleditsch, and Salehyan (2013) base their data collection on the UCDP database, their criteria for case inclusion are different than ours. Specifically, 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."

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

[26]Variables from the NSA 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 still in line with our expectations but less precisely measured.

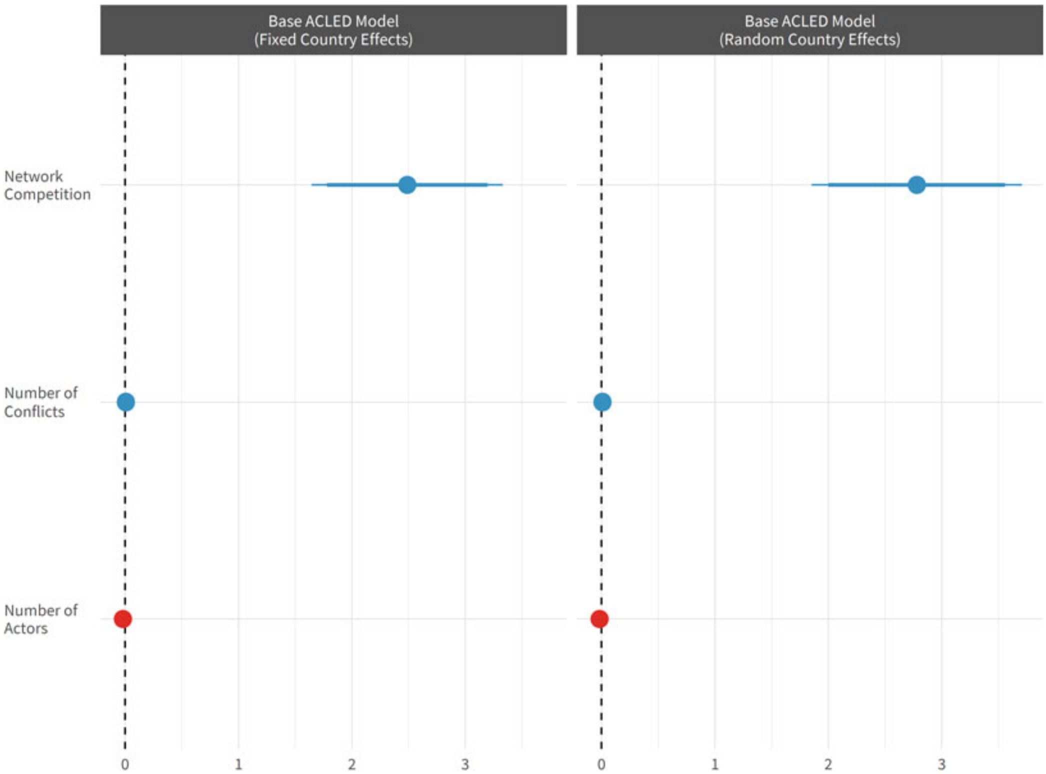

Figure 6. Regression results for the base model specification for 42 countries from 1997 to 2020.
Notes: The left panel visualizes coefficient estimates with country-level fixed effects and the right visualizes the results with random effects. Points represent average values of parameters. Thicker lines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

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.[27] Additionally, many of the control variables that we include have a notable quantity of missing data. As detailed in Honaker and King (2010), simply employing listwise deletion can lead to inferential issues.[28] 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.[29] 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.

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 Figure 8 corresponds with a model from Figure 7.

[27]Results with fixed effects are presented in Figure A2 in the Online Appendix and are consistent with regard to the effect of network competition.

[28]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 A3 and A4 in the Online Appendix.

[29]Specifically, we employ a semiparametric copula estimation scheme that has been shown to have equivalent or better performance to alternatives such as MICE = Multivariate Imputation by Chained Equations and Amelia by Hollenbach et al. (2021).

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

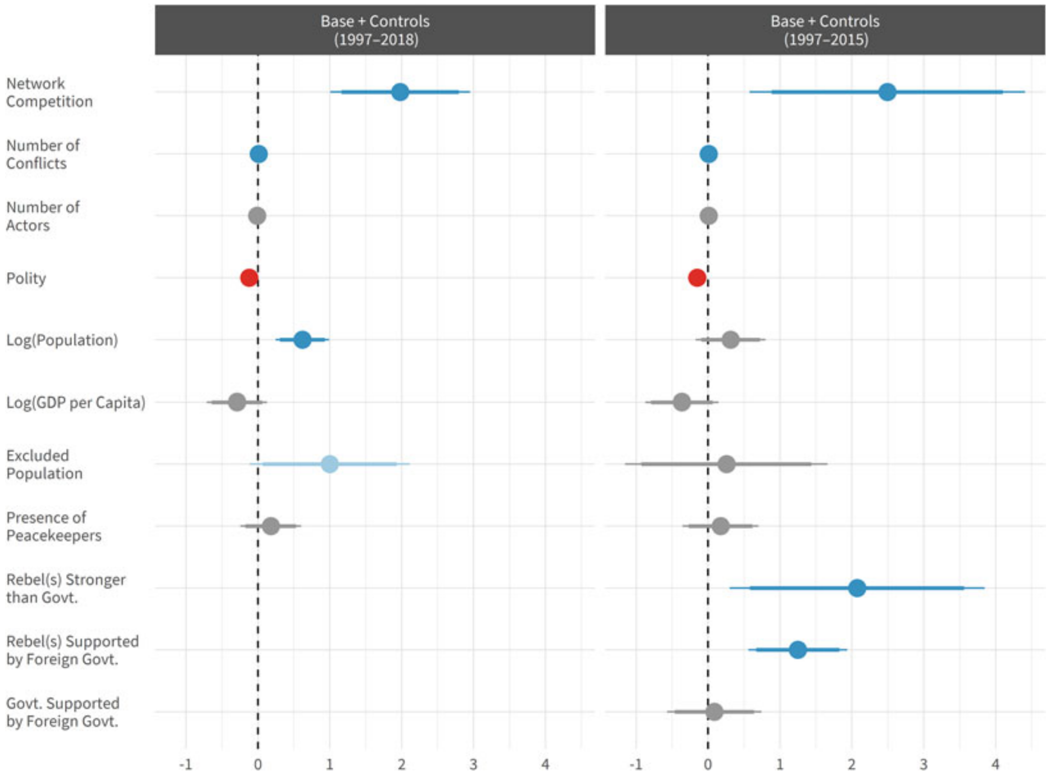

Figure 7. Regression results from multiply imputed datasets when pairing base specification with controls using random effects for countries.

Notes: 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 per cent confidence interval and thinner lines the 95 per cent interval. A darker shade of red (blue) indicates significant positive (negative) values.

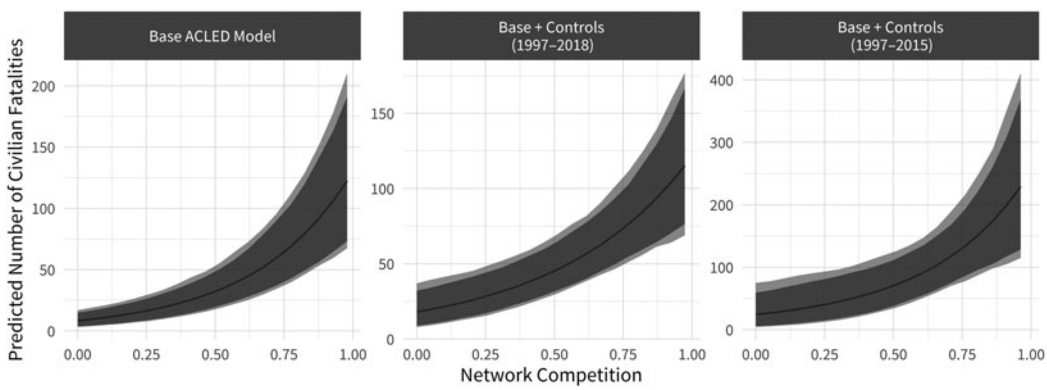

Figure 8. Simulated substantive effect of our measure of network competition across each model.

Irrespective of the controls included, we can see that there is considerable variation in predicted levels of victimization as network competition increases.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

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. 2019), but such a task would require building a dictionary that can bridge actor-level information between UCDP and the ACLED. Nonetheless, when using information from UCDP, our network competition measure remains positive and significant.[30]

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.[31] A 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; Dorff, Gallop, and Minhas 2021; Gallop and Minhas 2021).[32] When including a measure representing how many groups are allied 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 also even the reporting of conflict data in a number of ways. To ensure 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. Lastly, for the results presented in the article, the underlying sample had a requirement that a country must have at least three years of observations to be included. In the Online 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 article, 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

[30]For the article, we chose to focus on results using the ACLED. UCDP data record information only on groups that commit a specific threshold of violence during a battle, whereas ACLED data contain 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 the ACLED.

[31]For details on the calculation of this measure, see the Online Appendix.

[32]For details on the calculation of this measure, see the Online Appendix.

https://doi.org/10.1017/S0007123422000321 Published online by Cambridge University Press

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 civilian 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 clarifying specific expectations of civilian behavior within this networked theoretical framework and collecting 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 targets of civilian resistance.

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 lootable 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 2022) provides a promising next step in the accumulation of knowledge on this important topic.

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 toward 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. Secondly, if a group faces a more ideologically diverse array of potential opponents, a larger swath 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 tested 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 has modeled 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 has united the strategic decision making of both armed groups and civilians into a multi-actor framework of civil conflict that reveals how actors' incentives change according to the network dimensions of their strategic environment.

Supplementary material. Online appendices are available at: https://doi.org/10.1017/S0007123422000321

Data Availability Statement. Replication material and instructions are available on GitHub (available at: https://github.com/s7minhas/victimization) and in the *BJPS* Data Archive on Dataverse (available at: https://doi.org/10.7910/DVN/HGLHM5).

Acknowledgments. We are grateful for the helpful comments that we have received from Arturas Rozenas, Scott de Marchi, and Jennifer Larson. Earlier versions of this article were presented at the American Political Science Association in 2019. We would also like to thank the comments and suggestions we received from our three anonymous reviewers on how to strengthen this article.

Author Contributions. Alphabetical order signifies equal authorship; all mistakes are our own.

Financial Support. Cassy Dorff acknowledges support from National Science Foundation (NSF), Award 2017162, and Shahryar Minhas acknowledges support from the NSF, Award 2017180.

Competing interests. The authors declare no competing interests.

References

Alfano MR and Baraldi AL (2015) Is there an optimal level of political competition in terms of economic growth? Evidence from Italy. *European Journal of Law and Economics* **39**(2), 263–285.
Anders T (2020) Territorial control in civil wars: theory and measurement using machine learning. *Journal of Peace Research* **57**(6), 701–714.
Arjona A (2017) Civilian cooperation and non-cooperation with non-state armed groups: the centrality of obedience and resistance. *Small Wars & Insurgencies* **28**(4–5), 755–778.
Azam J-P and Hoeffler A (2002) Violence against civilians in civil wars: looting or terror? *Journal of Peace Research* **39**(4), 461–485.
Bagozzi BE, Koren O, and Mukherjee B (2017) Droughts, land appropriation, and rebel violence in the developing world. *Journal of Politics* **79**(3), 1057–1072.
Balcells L and Stanton JA (2020) Violence against civilians during armed conflict: moving beyond the macro- and micro-level divide. *Annual Review of Political Science* **24**, 45–69.
Cederman L-E, Wimmer A, and Min B (2010) Why do ethnic groups rebel? New data and analysis. *World Politics* **62**(1), 87–119.
Cheng C and Minhas S (2021) Keeping friends close, but enemies closer: foreign aid responses to natural disasters. *British Journal of Political Science* **51**(3), 940–962.
Cunningham D, Gleditsch KS, and Salehyan I (2013) Non-state actors in civil wars: a new dataset. *Conflict Management and Peace Science* **30**(5), 516–531.
Dawkins S (2021) The problem of the missing dead. *Journal of Peace Research* **58**(5), 1098–1116.
Donnay K et al. (2019) Integrating conflict event data. *Journal of Conflict Resolution* **63**(5), 1337–1364.
Dorff C, Gallop M, and Minhas S (2020) Networks of violence: predicting conflict in Nigeria. *The Journal of Politics* **82**(2), 476–493.
Dorff C, Gallop M, and Minhas S (2021) [W]hat lies beneath: using latent networks to improve spatial predictions. *International Studies Quarterly* **66**(1). Available from https://doi.org/10.1093/isq/sqab086
Dorff C, Gallop M, and Minhas S (2022) Replication code and data documentation for "Network Competition and Civilian Targeting during Civil Conflict". https://doi.org/10.7910/DVN/HGLHM5.
Eck K (2012) In data we trust? A comparison of UCDP GED and ACLED conflict events datasets. *Cooperation and Conflict* **47**(1), 124–141.
Eck K and Hultman L (2007) One-sided violence against civilians in war: insights from new fatality data. *Journal of Peace Research* **44**(2), 233–246.
Fearon JD (2003) Ethnic and cultural diversity by country. *Journal of Economic Growth* **8**(2), 195–222.
Fjelde H and Hultman L (2014) Weakening the enemy: a disaggregated study of violence against civilians in Africa. *Journal of Conflict Resolution* **58**(7), 1230–1257.
Fjelde H, Hultman L, and Nilsson D (2019) Protection through presence: UN peacekeeping and the costs of targeting civilians. *International Organization* **73**(1), 103–131.
Gallop M and Minhas S (2021) A network approach to measuring state preferences. *Network Science* **9**(2), 135–152.

Haass F (2021) Insurgency and ivory: the territorial origins of illicit resource extraction in civil conflicts. *Comparative Political Studies* **54**(8), 1327–1361.
Harff B (2003) No lessons learned from the Holocaust? Assessing risks of genocide and political mass murder since 1955. *American Political Science Review* **97**(1), 57–73.
Hollenbach FM et al. (2021) Multiple imputation using Gaussian copulas. *Sociological Methods & Research* **50**(3), 1259–1283.
Honaker J and King G (2010) What to do about missing values in time-series cross-section data. *American Journal of Political Science* **54**, 561–581.
Kalyvas S (2006) *The Logic of Violence in Civil War*. New York, Cambridge: Cambridge University Press.
Kaplan O (2017) *Resisting War: How Communities Protect Themselves*. Cambridge: Cambridge University Press.
Kasfir N (2015) Rebel governance—constructing a field of inquiry: definitions, scope, patterns, order, causes. *Rebel Governance in Civil War*, 21–46.
Kathman J (2013) United Nations peacekeeping personnel commitments, 1990–2011. *Conflict Management and Peace Science* **30**(5), 532–549.
Kathman J and Benson M (2019) Cut short? United Nations peacekeeping and civil war duration to negotiated settlements. *Journal of Conflict Resolution* **63**(7), 1601–1629.
Kikuta K (2022) A new geography of civil war: a machine learning approach to measuring the zones of armed conflicts. *Political Science Research and Methods* **10**(1), 97–115.
King G, Tomz M, and Wittenberg J (2000) Making the most of statistical analyses: improving interpretation and presentation. *American Journal of Political Science* **44**(2), 341–355.
König MD et al. (2017) Networks in conflict: theory and evidence from the Great War of Africa. *Econometrica* **85**(4), 1093–1132.
Larson JM et al. (2019) Social networks and protest participation: evidence from 130 million Twitter users. *American Journal of Political Science* **63**(3), 690–705.
Lujala P (2010) The spoils of nature: armed civil conflict and rebel access to natural resources. *Journal of Peace Research* **47**(1), 15–28.
Lyall J, Shiraito Y, and Imai K (2015) Coethnic bias and wartime informing. *The Journal of Politics* **77**(3), 833–848.
Mampilly ZC (2012) *Rebel Rulers: Insurgent Governance and Civilian Life during War*. Ithaca, New York, USA: Cornell University Press.
Marshall MG, Jaggers K, and Gurr TR (2009) Polity IV Project: Political Regime Characteristics and Transition 1800–2007. CIDCM, University of Maryland, USA.
Raleigh C et al. (2010) Introducing ACLED: an armed conflict location and event dataset special data feature. *Journal of Peace Research* **47**(5), 651–660.
Raleigh C et al. (2021) Armed conflict location and event data project (ACLED) codebook. https://acleddata.com/acleddatanew/wp-content/uploads/2021/11/ACLED_Codebook_v1_January-2021.pdf (2021).
Ross M (2004) How do natural resources influence civil war? Evidence from thirteen cases. *International Organization* **58**(1), 35–67.
Salehyan I, Gleditsch KS, and Cunningham D (2011) Explaining external support for insurgent groups. *International Organization* **65**(4), 709–744.
Salehyan I, Siroky D, and Wood R (2015) External rebel sponsorship and civilian abuse: a principal–agent analysis of wartime atrocities. *International Organization* **68**(3), 633–661.
Steele A (2017) *Democracy and Displacement in Colombia's Civil War*. Ithaca, New York, USA: Cornell University Press.
Themnér L and Wallensteen P (2013) Armed conflicts, 1946–2012. *Journal of Peace Research* **50**(4), 509–521.
Uzonyi G and Demir B (2020) Excluded ethnic groups, conflict contagion, and the onset of genocide and politicide during civil war. *International Studies Quarterly* **64**(4), 857–866.
Valentino BA (2014) Why we kill: the political science of political violence against civilians. *Annual Review of Political Science* **17**, 89–103.
Vogt M et al. (2015) Integrating data on ethnicity, geography, and conflict: the ethnic power relations data set family. *Journal of Conflict Resolution* **59**(7), 1327–1342.
Wood RM (2010) Rebel capability and strategic violence against civilians. *Journal of Peace Research* **47**(5), 601–614.
Wood RM (2014) From loss to looting? Battlefield costs and rebel incentives for violence. *International Organization* **68**(4), 979–999.
Wood RM and Kathman JD (2015) Competing for the crown: inter-rebel competition and civilian targeting in civil war. *Political Research Quarterly* **68**(1), 167–179.
World Bank Group (2016) *World Development Indicators 2016*. Washington, DC, USA: World Bank Publications.

Cite this article: Dorff C, Gallop M, Minhas S (2023). Network Competition and Civilian Targeting during Civil Conflict. *British Journal of Political Science* **53**, 441–459. https://doi.org/10.1017/S0007123422000321