Networks of Violence and Civilian Targeting During Civil Conflict

Abstract

Increasingly, scholarship demonstrates that armed groups' decision to victimize civilians is a political, strategic choice. Most examinations of this choice assume a simple environment where the main conflict is between a government and a unified opposition. Yet, we know that civil conflicts are more complicated than this and often involve three or more actors. Using an innovative computational model, we investigate the strategic incentives for victimization in a complex multi-actor conflict environment that incorporates civilian behavior. We find that dense strategic environments – where conflict between any two actors is more likely – lead to higher rates of civilian victimization, irrespective of the overall intensity of conflict. We test this hypothesis in multi-actor civil conflicts using ACLED to generate measures of both conflict intensity and network density. Empirical analysis supports our model's finding that more dense strategic environments are associated with a higher level of violence against the civilian population.

Introduction

Why do armed groups victimize civilians during civil conflicts? For years, political scientists considered the violent targeting of unarmed civilians “irrational, random, or the result of hatreds between ethnic groups." (Valentino, 2014, see summary on p. 91). More recently, however, a consistent body of research shows that violence against civilians is a highly rational and well-coordinated strategy used by armed groups in both dyadic and multi-actor conflicts to gain resources, territory, or to achieve broad military and political goals (Condra and Shapiro, 2012; Berman and Matanock, 2015; Kathman and Wood, 2015; Stanton, 2016). Under many of these strategic frameworks, information and competition play a critical role in armed groups' choice to victimize. Groups who target civilians are disadvantaged because civilian targeting produces incentives for civilians to share information with a group's rivals. Consequently, armed groups must weigh the potential costs of targeting civilians, such as losing supporters and control of information, against the benefits, such as punishing rival constituencies and gaining territory. Despite the meaningful implications of this strategic framework, prior approaches predominantly rest on the assumption that civil wars and intrastate conflicts are defined by violence between governments and a unified opposition.

Recent developments in research on intrastate conflicts, however, now confirm what policy experts and qualitative analysts have often reported, which is that conflicts are typically not dyadic in nature (Cunningham, Bakke and Seymour, 2012; Dowd, 2015, 2019) and help to move the literature beyond a dyadic framework. These works show how conflicts are driven by intense fragmentation and competition across multiple warring parties (Cunningham, Bakke and Seymour, 2012; Christia, 2012). Consider for example, Nigeria, where multiple armed groups compete over oil resources and interethnic rivalries in the southern Niger Delta region alone (Obi, 2009; Dorff, Gallop and Minhas, 2020). The northeast region of Nigeria is shaped by Boko Haram's insurgent violence, which by 2013 had led to the development of both government tasks forces and local vigilante groups fighting for territory (Mustapha, 2014). In the Democratic Republic of Congo–where conflict dynamics have led to the death of nearly 20,000 civilians in the last two decades–there were at least 20 armed actors in 2001 and upwards of over 50 by 2011.[1] To further illustrate this point, we use data from the Armed Conflict Location & Event Dataset (ACLED). We subset the dataset to only include battle events and then for each year we count the number of countries that had four actors or less, five to nine actors, or 10 actors or more.[2] The results are presented in Figure 1. The data clearly show that many intrastate conflicts[3] are 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.

[1]Counts of armed actors are based on event data from ACLED. For a deeper understanding of dominant conflict narratives and summaries of the DRC case see (Autesserre, 2012).

[2]We also make a few important decisions that necessarily decrease the reported number of total actors over time. We consolidate government actors into one group, such as different branches of the military, and we remove actors with vague name labels such as 'unidentified' or 'opposition' group labels.

[3]We broadly define 'intrastate conflict' as violence by organized political groups within the borders of a state.

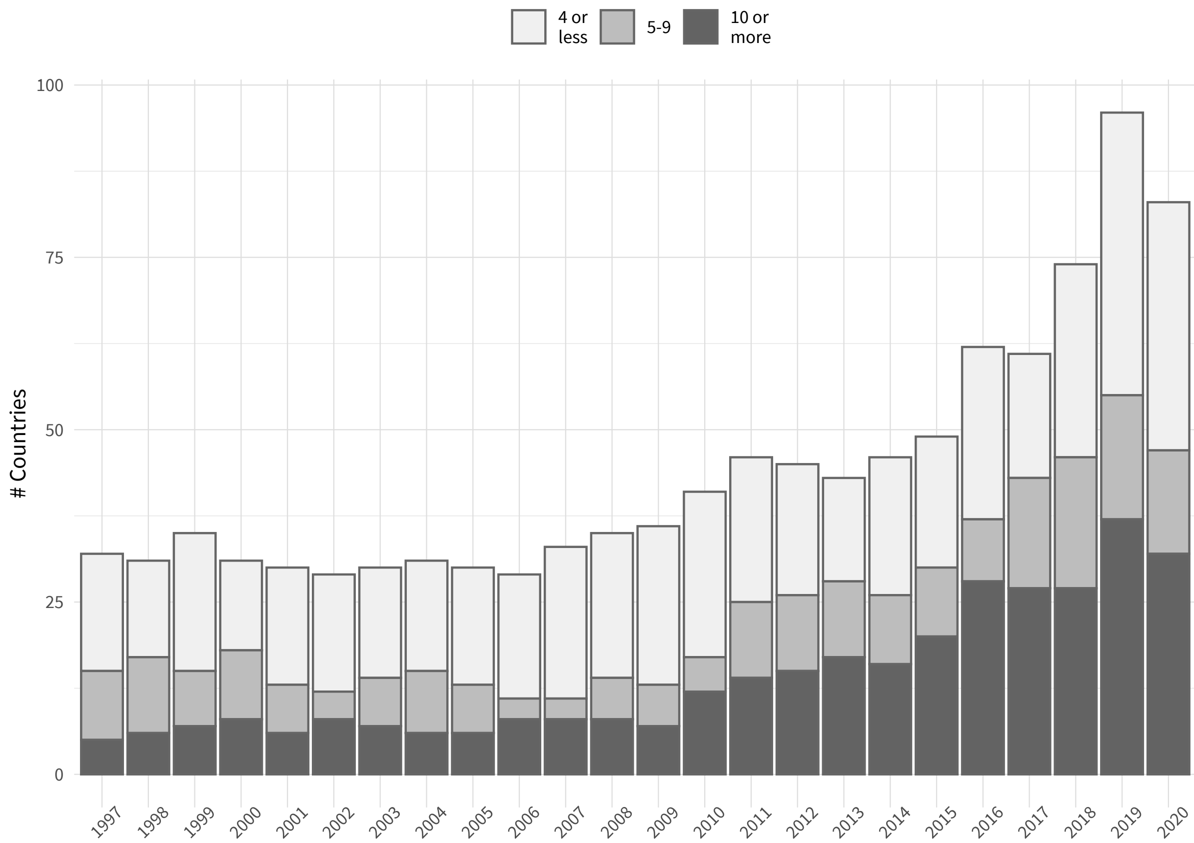

Figure 1: Number of active armed groups in countries from the ACLED dataset between 1997 to 2020. Dark grey represents armed conflicts with 4 or less active armed groups, light grey represents armed conflicts with 5-9 active armed groups, and white represents armed conflicts with 10 or more armed groups.

How does such complexity affect civilian welfare? To understand the risk to civilian life during the course of war, we need to better understand the logic of victimization in multi-actor settings. A natural starting point is to apply existing strategic victimization theories to multi-actor conflicts. We build on recent literature on multi-actor conflicts and victimization by formalizing the relationship between network structures and victimization strategies. Doing so results in at least two plausible conclusions. First, in a traditional dyadic conflict, civilians might have to face tradeoffs between groups that treat civilians well and those whose political aims civilians support (see Lyall, Blair and

Imai 2013). In a multi-actor environment, however, we can expect to observe more competition for civilian support between an array of ideologically motivated armed groups. Civilians, in these settings, are more likely to identify, and, consequently, support groups that both treat civilians well and are ideologically attractive. If this relationship holds, we would then expect to observe armed groups refrain from victimization in contexts where they fight against many ideologically similar armed groups in order to win civilian support.

Alternatively, one could argue that in a traditional dyadic civil war the sides are clear, and civilians can always seek redress from the opposition [government] following victimization by the government [opposition]. In a more dense strategic environment, we would then observe shifting alliances and multilateral conflicts. In this context, civilians will have no guarantee that the the support they lend would be used against the victimizing group, rather than an unrelated third party. Hence, we would expect that civilians are less likely to punish perpetrators of victimization and thus suffer higher levels of victimization in these contexts.

Both of these scenarios are drawn from the literature on civilian victimization and plausibly follow what we know about network structure in civil conflict. Given the complexity of civil conflict networks and what they entail for civilian victimization, we require a principled way of generating network hypotheses, rather than simply choosing a story that fits our empirical results. To do so, we develop a formal, computational model to better investigate the link between network structure and victimization. This allows us to posit a set of assumptions about actors' incentives and possible actions, and discern how these assumptions affect our outcome of interest.

In addition to network complexity, we incorporate another layer of behavior into our study. Preexisting work tends to overlook the role that civilians' own choices might play in affecting the strategic logic of armed groups (Dorff, 2019). Modern day warfare is fought on battlegrounds shaped by civilian behavior and their willingness to support armed actors. The interactive nature of conflict, wherein civilians assess their likelihood of survival by balancing the risks and benefits of supporting armed groups, is a fundamental feature of conflict. Unpacking the intricate relationship between civilians, their experience with violence, and armed actors has been a growing trend in conflict and peace studies with an emphasis on rebel governance (Mampilly, 2012; Arjona, 2016), civilian victimization (Eck and Hultman, 2007; Wood, 2014), civilian displacement (Steele, 2011), and civilian organization and resistance (Kaplan, 2013; Arjona, 2017; Dorff and Braithwaite, 2018; Masullo, 2020). Our study contributes to recent scholarship on both sides of the civilian victimization puzzle by directly addressing the strategic implications of multi-actor armed conflicts and their relationship to civilian behavior during war.

We investigate the strategic incentives for civilian victimization in a complex multi-actor conflict environment using a novel computational model. Our model's key finding is that a more dense conflict network–one in which any two actors are more likely to fight–leads to more civilian victimization *irrespective* of the overall level of violence or the number of armed 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 important because it reveals that civilian casualties are not just a function of total levels of violence in a conflict, but are a function of network density. Next we describe the conceptual intuition behind our theory followed by our computational model and its results; then we proceed to test our hypotheses on data from ACLED. In both simulations from our computational model and the empirical data, we find strong support for the relationship between the network density of violence 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 computation model. As we model it, the decision for armed groups to victimize civilians is a strategic action. Armed groups target civilians to help extract resources from the population and to increase their likelihood of prevailing in expected conflicts with other groups. Civilians likewise act strategically to minimize their personal likelihood of being killed by armed groups. Thus, to understand when and where civilian victimization is likely to take place, we need to evaluate the strategic environment.

To do 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. Density measures the number of edges (or connections) proportional to the total number of possible edges. To understand the strategic environment, we illustrate stylized conflict networks shown in Figure 2. In each network the number of battles (edge thickness) and the number of actors (nodes) stay the same, but the distribution of these events change across actors. Our conceptual illustration demonstrates that even though the number of actors and battles are constant across all three networks, the third network exhibits the highest density.

Moving from left to right, the far left network is the sparse network. Here, conflict occurs between a few distinct dyads. In this network, the strategic decision to victimize civilians is simple – victimization takes place if the coercive effect (causing more non-supporters to begrudgingly support the group in charge) outweighs the resources that could be mobilized from non-supporters. In this environment, while there may be some initial low levels of victimization, we will pretty quickly approach an equilibrium where most civilians support the groups in control of their territory, and no victimization occurs. Intrastate conflict in Chad during the early 2000s might reflect this network

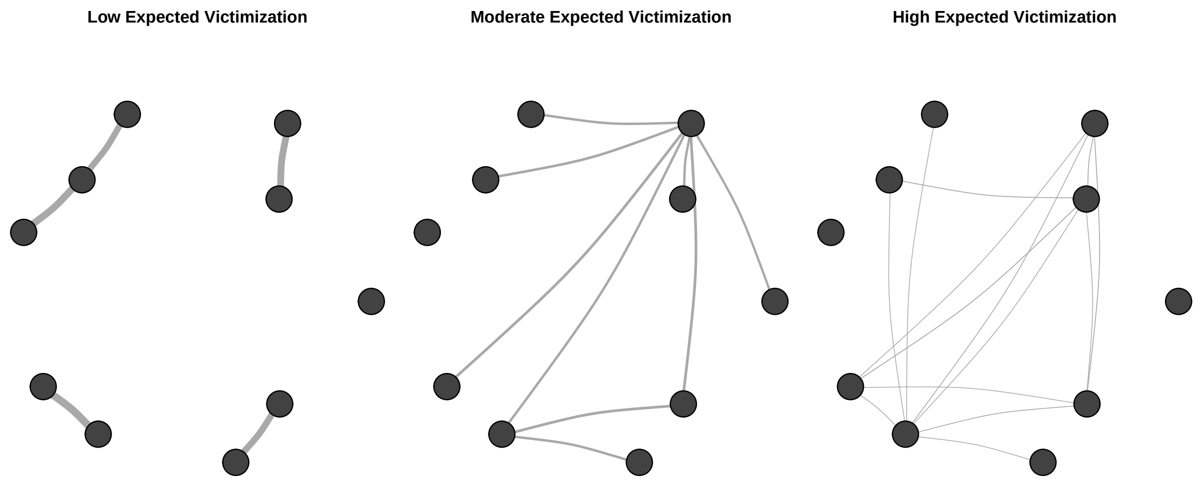

Figure 2: Conceptual networks demonstrate the expected relationship between density and civilian victimization. Conflict density increases as we go from left to right while the number of conflictual events and the number of actors stay constant.

structure, where conflict was largely split between a sparse number of warring rebel groups in the north and the south.

The far right network reveals a different picture. This complex conflict network functions as a Hobbesian war of all against all, where each armed group is ready to attack each other armed group. In these cases, the dynamics that led to victimization in the polarized network are intensified. Almost all territories are at risk of an attack, and they are at risk of an attack from multiple sources leading to even stronger incentives towards victimization, since even if victimization is counterproductive against some opponents, it will be beneficial against others. In this case, there would also likely be a fluid control of territory and frequent changes in ruling groups, which generates even more incentives for violence against civilians. Some of the most intractable and dynamic conflicts–like the modern wars in Somalia– are likely to exhibit this network structure.

Civilian Victimization During War

Extant research into the underlying logic of civilian victimization has focused on key characteristics of armed groups, such as a group's fighting capability (Wood, 2010), resource base (Azam and Hoeffler, 2002*a*) and external support (Salehyan, Siroky and Wood, 2015). Yet, these studies also acknowledge 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." We draw on the intuition that the networked dynamics of armed groups influence violence against civilians to support each turn of our modeling decisions described below.

Model Environment

In this model a country is composed of territories comprised of two types of actors: civilians and armed groups. 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. In general, armed groups' primary motivation is to gain territory containing resources that can be mobilized (Kalyvas, 2006), where resources in our game are represented by civilians. Failing this, actors prefer that territory is held by groups with similar preferences.

The other main actors in this model are civilians. Civilians are primarily motivated by their personal safety; their secondary motivation is ideological. The inclusion of civilian preferences follows 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 ideal point (x_i) on a one-dimensional preference space (bounded between 0 and 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.[4] 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. We define the distance between any two groups as:

$$D(a,b) = ||z_a - z_b|| \tag{1}$$

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

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

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.

In this game, armed groups draw resources from civilian mobilization. This "instru-

[4]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.

mentalist" perspective follows from research conceptualizing victimization as a strategic choice shaped by the desire to control resources and territory while capturing civilian support and undermining support for opponent groups (Wood, 2014).[5] To extract resources, armed groups try to mobilize support from the civilian population and they 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 other armed groups in order to conquer additional territory and gain more resources; and armed groups can victimize civilians in territory they control. Civilians choose whether to support an armed group in their territory and which group to support. 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. 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 coercin 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

[5]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).

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*b*; 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.[6] 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 also choose to victimize civilians in territories they control. These groups' ability to be selective in victimization relies on their access to resources and 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. This probability is a combination of the probability of successful victimization given information and with no information. 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 will target a supporter. We define the probability of successful

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

victimization by group i in territory q (denoted ζ_{iq}) as: [7]

$$1 - \zeta_{iq} \equiv \epsilon \left(\frac{n_{\text{supp},i,q}}{n_{\text{civilians},i,q}} \right) + \left(\frac{n_{\text{civilians},i,q} - n_{\text{supp},i,q}}{n_{\text{civilians},i,q}} \times \left(\frac{n_{\text{supp},i,q}}{n_{\text{civilians},i,q}} \right) \right) \tag{3}$$

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. In this model selective violence is effective at coercing civilians into giving support, whereas indiscriminate violence (targeting ones' own supporters) is counter-productive. 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.[8]

Civilian Preferences

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 for who to support is based on their expectation of who other civilians will support. This is because if they believe other civilians will support the incumbent power in a region, it becomes more effective to "go along" with it in order to avoid the risk of violence.

[7] 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.

[8] 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.

Civilians are assumed to support the incumbent with a probability that is based on their ideological proximity to the group. Civilians will support the group if their ideological distance, modified by the effect of past victimizations, is less than half of the expected number of other supporters of the armed group.[9] 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. 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, the decision to flee begins with a high threshold in the model and becomes more plausible over the course of the conflict.

Sequential Order of Events

We depict the main stages of the game in Figures 3 and 4. 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 3. 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 4 we depict how a third actor represented in this conflict environment would choose to victimize civilians. This

[9] All else equal, civilians will support a maximally close group regardless of the number of other supporters. If a civilian is half the preference space away, then she will only support the armed group if they are supported by the rest of the population, or if they have a history of very effective victimization.

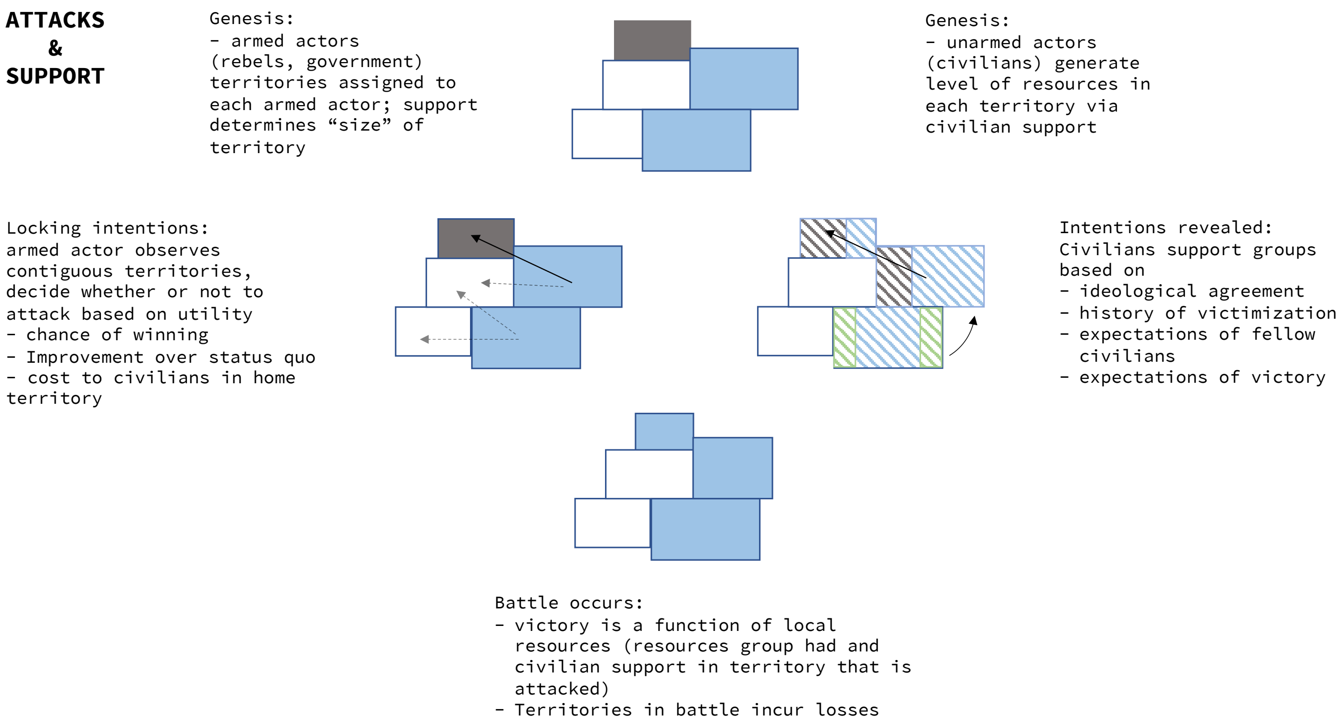

Figure 3: Graphic illustrating the choice of an armed actor to attack, and the choice of civilians to support the actor or not. Rectangles represent territory, with its size based on the size of the civilian population. For the solid colors, color represents the group controlling the territory. The arrows 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.

actor's calculus depends on both whether an attack is likely, as well as the possible consequences of victimization. Below, we discuss the specific decision rules for each group in the graphic.

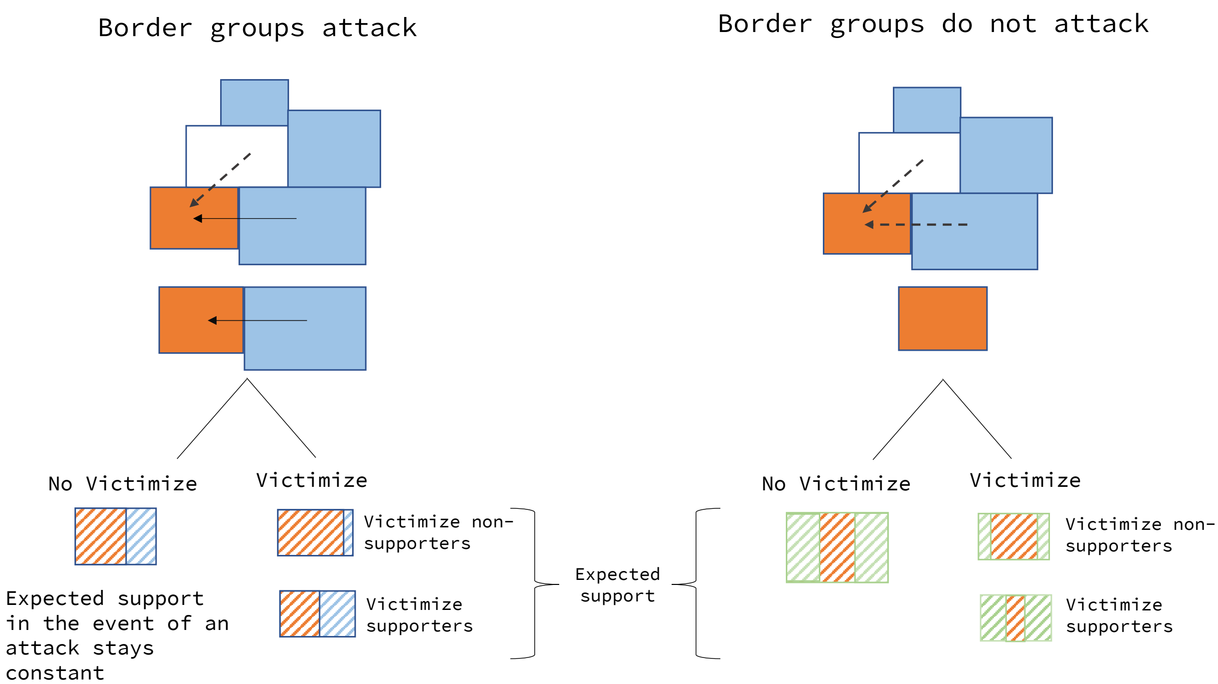

Figure 4: Graphic illustrating the choice of an armed actor to victimize civilians. The orange group first determines whether any of their neighbors are likely to attack. If they are likely to attack, the orange group decides whether to victimize to maximize their support and chance of winning in a battle, 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 succeeds, 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.[10] 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. In particular, we call the local resources of group i in territory L:

$$\Gamma_{i,L} = \sum_{l} \delta^{d_{l,L}} (n_{s,i,l} + \psi n_{ns,i,l} - k n_{o,i,l}) \tag{4}$$

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.

[10] 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.)

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

$$p_{i,L} \equiv P(i \text{ wins in territory L}) = \frac{\Gamma_{i,L}}{\sum_j \Gamma_{j,L}} \tag{5}$$

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. Next, 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:

$$U_i(q|G) = \sum_{g \in G} E[p_{g,L}|G]\alpha_{i,j}(R_q - c) \tag{6}$$

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,[11] so 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. For comparison, the utility for group i of the status quo in territory q, held by group j is:

$$U_i(j \text{ controls } q) = \alpha_{j,i} R_q \tag{7}$$

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

[11] We will determine this in Equations 9 and 10 in the next stage.

from attacking compared to the status quo (or if none of these are positive, they attack nowhere). This decision is illustrated in Figure 3.

(2) Civilians choose whether to support armed groups

Civilians' decisions are conditioned not just on the characteristics of armed actors, but on the behavior of other civilians.[12] When civilians choose who to support, they assume that other civilians will make support decisions probabilistically based on their proximity to armed groups, such that:

$$E[P(\text{Civilian l supports Group } i)] \equiv \text{max}(\text{min}(1 - D(i,l) + v\chi_j, 1), 0) \tag{8}$$

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. 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 a group has a history of killing supporters, all civilians are perceived as less likely to support the group.

Civilian behavior is also conditioned on the actions of armed groups in the territory and battle occurrence, as determined in the previous stage. If no battle is taking place in territory q, civilian l will support an armed group i if:

$$\frac{E[\bar{n}_{s,i,q}]}{2} > D(i,l) + v\chi_i \tag{9}$$

where the expected number of supporters is calculated as discussed in Equation 8.

[12] 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.

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

$$\text{argmax}_{(g \in G)} E[p_{g,q}](1 - D(g,h) + \upsilon\chi_g) \tag{10}$$

It is worth highlighting here that $E[p_{g,q}]$ is determined by using beliefs from Equation 8 to calculate the values in Equations 4 and 5. Civilians try to meet both their goals by choosing the group that gives them the best combination of plausibly winning the battle and ideologically congruence.

(3) Battles take place and winners are determined

This occurs as discussed above in Equation 5, in each territory involved in the battle, c civilians at random are removed.

(4) Armed groups choose which territories to victimize.

Armed groups first determine if each territory is at risk of an attack next period. This means a group i will evaluate, for each neighbor j and territory they control q, whether:

$$\alpha_{j,i} R_q < E[p_{i,q}]\alpha_{j,i}(R_q - c) + E[p_{j,q}](R_q - c) \tag{11}$$

Note that these are the same utilities from Equation 6 and 7. In any territory where this is true for all neighbors j, the armed group will victimize to maximize their potential of winning in a future period. If it is not true, they will victimize in order to maximize resources in a future period.

Armed groups believe that the proportion of the preference space made by their supporters is $s \equiv \frac{x_{s,i,q}}{n_{ns_i,q} + n_{s,i,q}} + \upsilon\chi_i$. 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:

$$\zeta_q \left(\frac{v(1-c)n_{ns,i,q-1}}{(1-s)} - c \right) - (1-\zeta_q) \left(\frac{v(1-c)n_{s,i,q-1}}{s} - 1 \right) > 0 \tag{12}$$

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:

$$\eta_f > x_i E[p_{i,q}] + x_j E[p_{j,q}] \equiv \lambda_q \tag{13}$$

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:

$$\zeta_q \left(\frac{v(1+k)E[n_{o,i,q}]}{\lambda_k} + k \right) - (1-\zeta_q) \left(\frac{v(1+k)E[n_{s,i,q}]}{(1-\lambda_k)} + 1 \right) > 0 \tag{14}$$

Similar to the case where there is no risk of battle, this is the net effect of victimization on local resources, which is the probability of gaining new supporters and the negative effect of civilian death on resources. The tradeoffs for the armed group in each of these cases is illustrated in Figure 4.

(5) Civilians Choose to Flee

After victimization civilians choose whether or not to flee from a territory into an adjacent territory. 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:

$$D(i,l) + v\chi_i < e^{3-t3/T} D(j,l) + v\chi_j \tag{15}$$

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.[13]

(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.

Computational Model Simulation Results

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 network statistics – the number of armed groups in the network, the overall level of violence in the network, and the density of the conflict network. We also capture the frequency of civilian victimization in each run of the game.

[13]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).

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.

To estimate the effect that our three network 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 5, the left plot shows the result with fixed effects and the right with random effects.

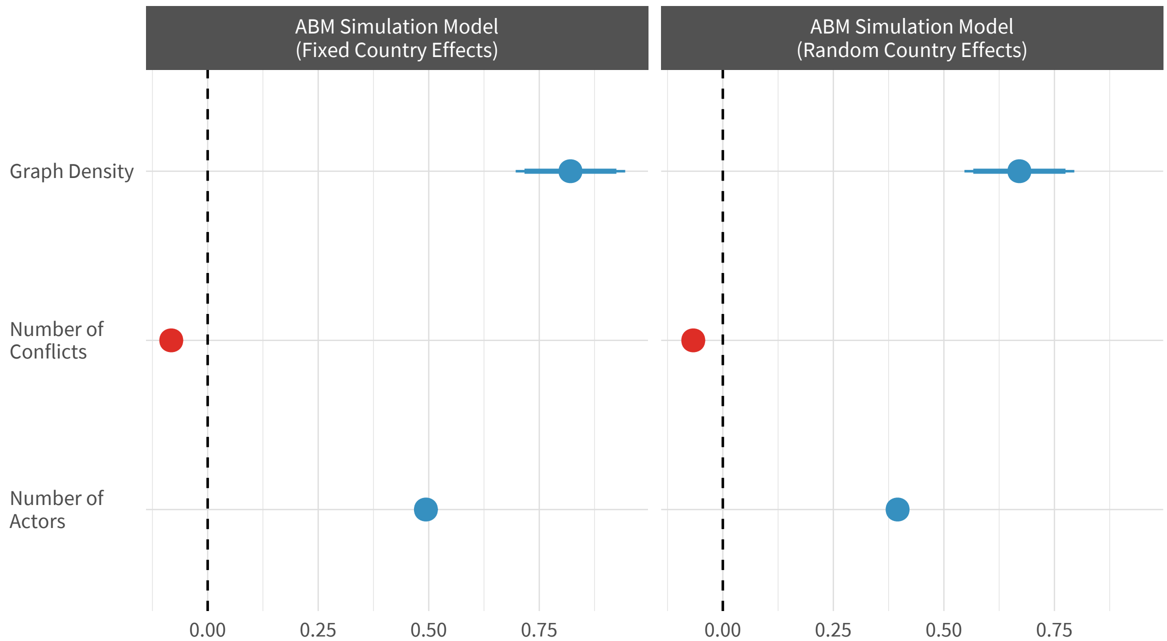

Figure 5: Analysis of determinants of victimization in computational model. The left panel visualizes coefficient estimates when using fixed effects on conflict scenarios and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

Here we can see that more dense conflict networks have a higher expected frequency of civilian victimization.[14] This finding generates our main hypothesis for empirical investigation: *Even when controlling for the overall level of violence, a more dense 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.

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

(2010). Our first step is to calculate conflict network densities for countries experiencing intrastate conflict according to the *battles* data provided by ACLED. Our sample ranges from 1997 to 2020 and includes 42 countries.[15]

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. 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 goverment actor. Additionally, we exclude international actors such as peacekeepers, militaries from other countries, and election observers from our analysis. In some cases, these actor cleaning steps lead to empty adjacency matrices with no actors.[16] For inclusion in our sample, we impose a restriction that a country must have at least three years of non-empty conflict adjacency matrices.[17]

Once we have generated our set of adjacency matrices for every country-year we then calculate the number of actors and the graph density of the conflict networks. We control for the overall level of violence by counting the number of battle events a coun-

[15] To account for potential COVID-19 impacts on our results, in Figure A5 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.

[16] 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.

[17] In Figure A4 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.

try 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. These are listed in Table 2.[18]

Variable	Source	Last Year of Data	Base	Base + Controls (1997-2018)	Base + Controls (1997-2012)
Graph Density 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)	2011			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.[19] The next model we run includes 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

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

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

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 are receiving support from foreign countries (Cunningham, Gleditsch and Salehyan, 2013). The sample for this final model ranges from 1997 to 2012 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. 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.

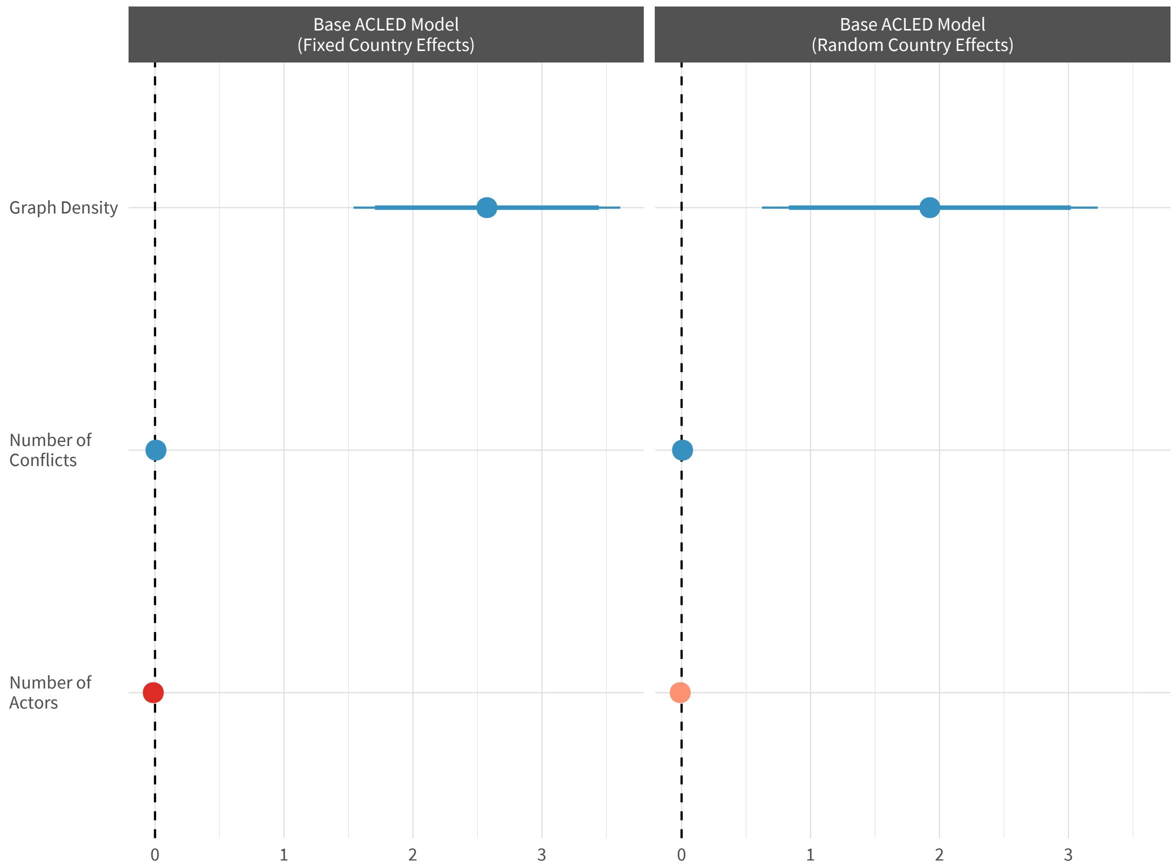

Figure 6: Regression results for the Base model specification includes 42 countries from 1997 to 2020. The left panel visualizes coefficient estimates with country-level fixed effects and the right visualizes the results with random effects. Points represent average values of parameters. Thicker lines 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 graph density 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.[20] Additionally, many of the control variables that we include have

[20]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.[21] 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.[22] The results from this analysis show that the effect of graph density continues to have a substantive impact on civilian victimization even after accounting for the control variables listed in Table 2.[23]

to the effect of graph density.

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

[22]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).

[23]We also conduct a sensitivity analysis in Figure A6 to ensure that our results are not being driven by any particular country in our sample.

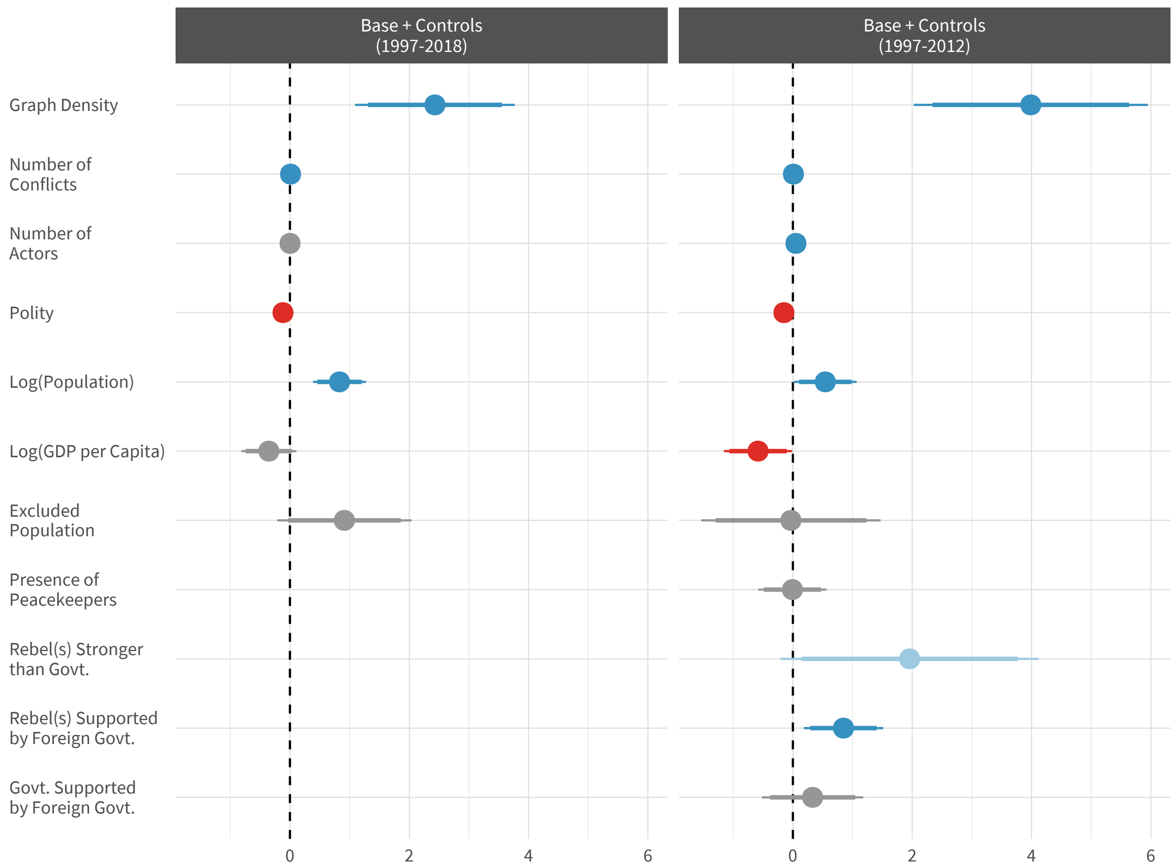

Figure 7: Regression results from multiply imputed datasets when pairing Base specification with controls using random effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2012. Points represent average values 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.

Discussion

We have shown that the frequency of civilian victimization depends, in large part, on the strategic environment. If conflict between armed groups is rare, civilian victimization will similarly be rare; if we have a conflict where any two armed groups are highly likely to fight, then 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. Second, victimization is most common when groups are newly in control of territory, since a combination of past victimization, and civilians' choice to flee make territories more ideologically homogeneous and congruent with the ruling group over time. Both of these factors are at their most intense in dense conflict networks.

We test these dynamics in a cross-national analysis of multi-actor civil wars using ACLED data to construct conflict networks. We find a consistent positive effect of network density on civilian victimization even when controlling for other characteristics of the conflict network. Going forward, we aim to make a number of advances in both empirical and theoretical research. Theoretically, we will investigate whether other empirical regularities concerning civilian victimization, like the tendency for more violent battles to increase the risk of victimization, are borne out in our model. We also plan to 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.

While this paper has focused on civilian victimization during civil conflicts, we believe it has wider applications. First, it demonstrates the implications of moving from a relatively simple dyadic interaction or model to a more complex multi-actor model. We can see similar dynamics at play for example in the median voter theorem, where the equilibrium breaks down in the presence of a third candidate (Patty et al., 2009); in coalition bargaining, where circumstances with only two major parties are trivial, and appropriately modeling and measuring negotiations with three or more parties is fraught (Laver, De Marchi and Mutlu, 2011); and in the bargaining model of war, where the fundamental finding that war is irrational ceases to hold with more than two potential combatants (Gallop, 2017).

In sum, our study models the choice for armed groups to victimize civilians as a strategic one. Importantly, our findings have implications for 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 war that reveals how actors' incentives change according to the network dimensions of their strategic environment.

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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 (1997-2012)" includes 19.

	Base	Base + Controls (1997-2018)	Base + Controls (1997-2012)
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	
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	
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.

Descriptive Statistics

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

Base Model

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	638	0	35	291.53	9337	753.8
Graph Density	638	0	0.1	0.15	0.67	0.15
Num. Actors	638	3	8	20.17	168	28.18
Num. Conflicts	638	1	23.5	90.77	1534	182.09

Table A2: Descriptive statistics for variables in Base model.

Base + Controls (1997-2018)

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	544	0	27	301.55	9337	800.65
Graph Density	544	0	0.1	0.15	0.67	0.15
Num. Actors	544	3	8	17.25	148	21.55
Num. Conflicts	544	1	21	69.24	1185	114.22
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

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

Base + Controls (1997-2012)

	N	Min.	Median	Mean	Max.	Std. Dev.
Civ. Victimization	240	0	58.5	408.86	9337	964.97
Graph Density	240	0	0.1	0.15	0.67	0.15
Num. Actors	240	3	8	16.32	105	17.52
Num. Conflicts	240	1	44	74.9	1185	107.97
Polity	240	4	11	11.24	19	4.06
Log(Pop.)	240	14.59	16.67	16.69	18.91	1.09
Log(GDP Cap.)	236	5.23	6.52	6.66	8.42	0.87
Excl. Pop.	240	0	0.24	0.28	0.85	0.28
Peacekeepers	240	0	0	0.3	1	0.46
Reb. Stronger Govt.	149	0	0	0.02	1	0.12
Reb. Supp. by Foreign Govt.	149	0	0.5	0.43	1	0.4
Govt. Supp. by Foreign Govt.	149	0	1	0.66	1	0.46

Table A4: Descriptive statistics for variables in Base + Controls (1997-2012) model.

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.

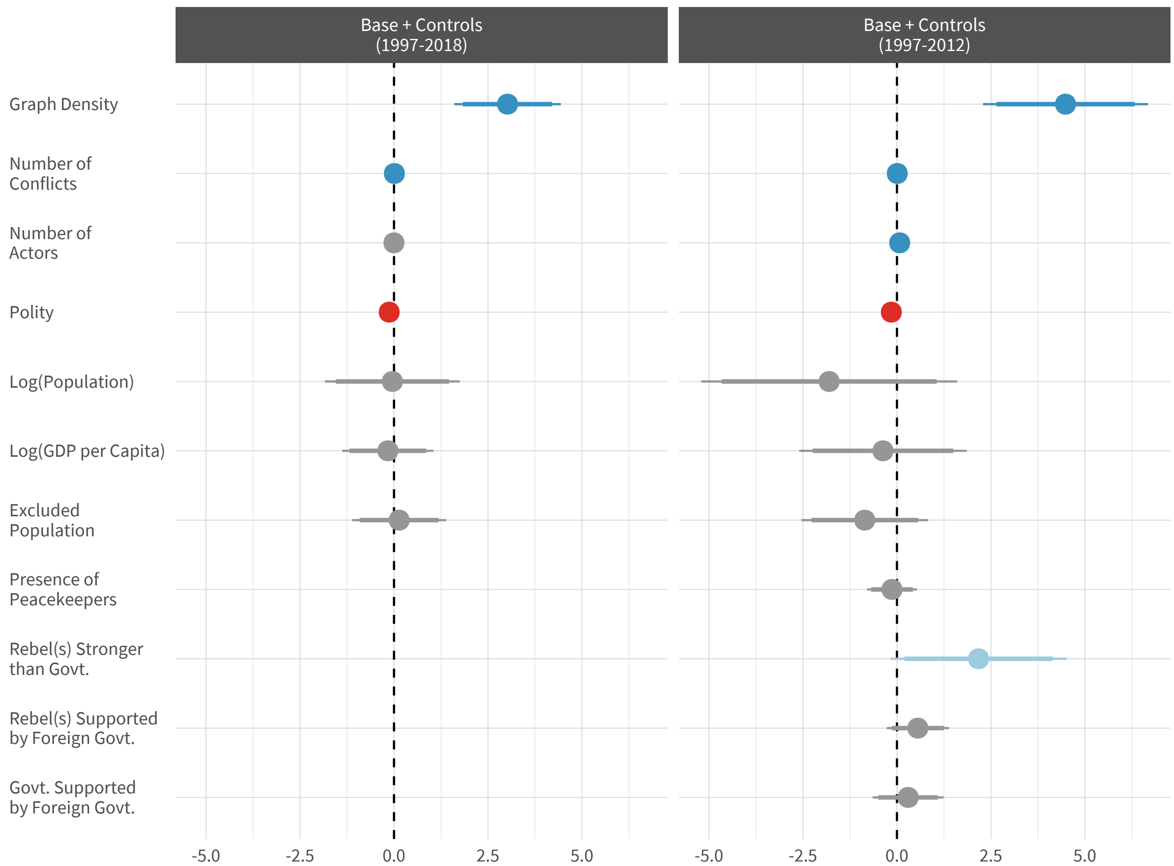

Figure A1: Regression results from multiply imputed datasets when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2012. Points represent average value of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

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 estimate.

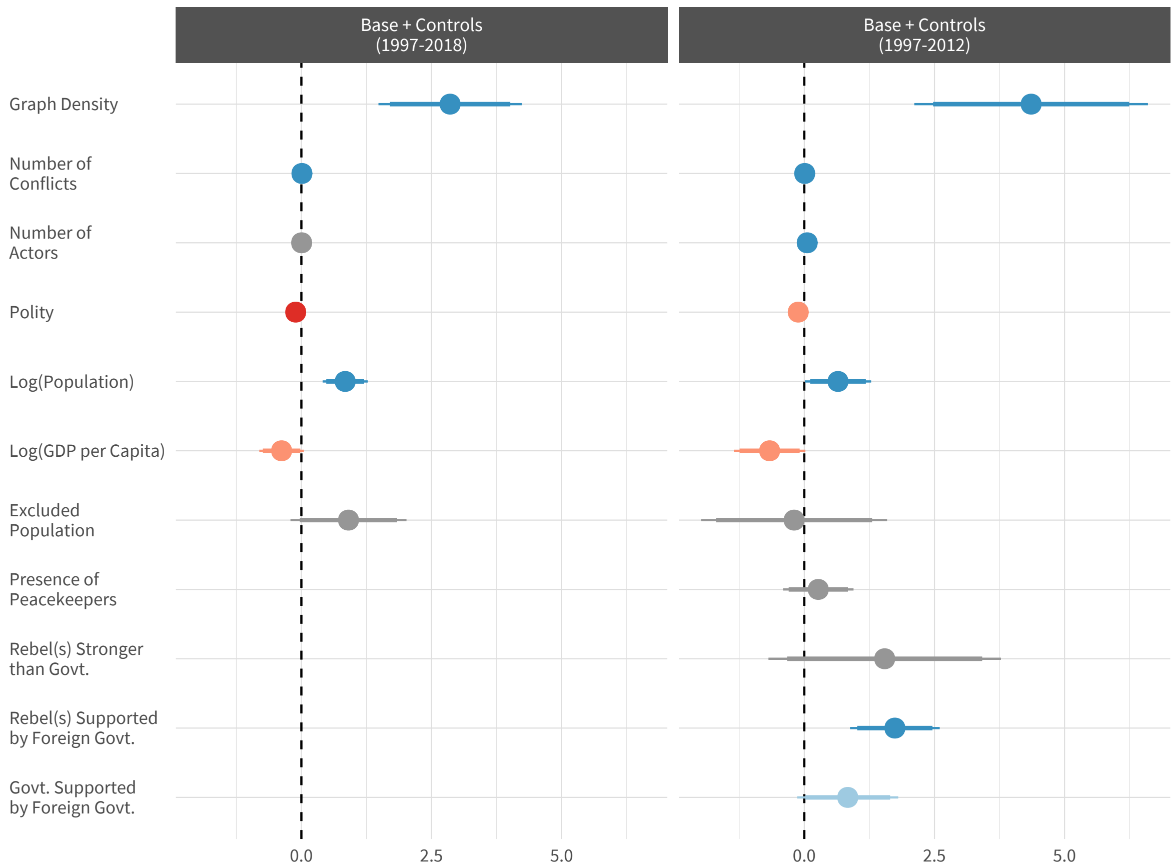

Figure A2: Regression results from unimputed data when pairing Base specification with controls using random effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2012. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

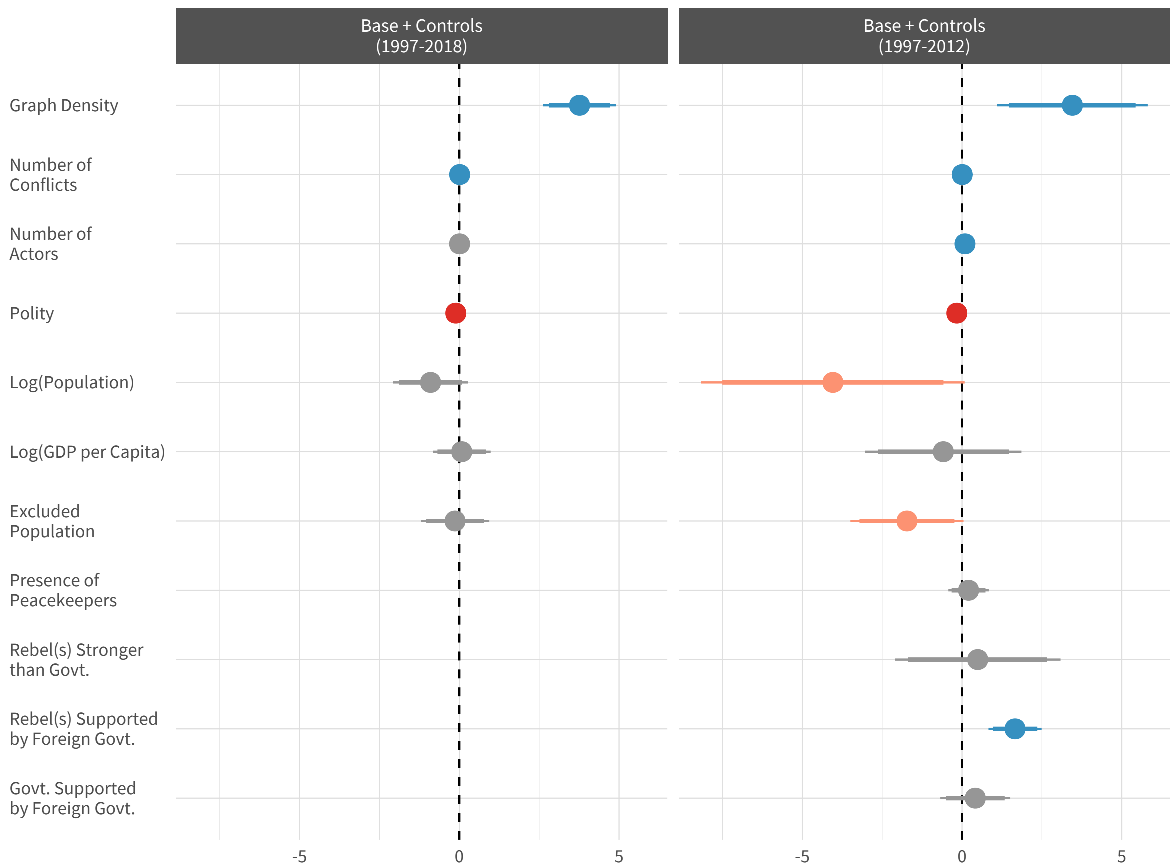

Figure A3: Regression results from unimputed data when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2012. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

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 observations to be included in our analysis. This led to a sample of 42 countries from 1997 to 2020. Here we modify this three observation minimum to test the robustness of our results. The first row in Figure A4 depicts our results when we employ no miminum and the second row when we employ a five observation minimum per country. The former criterion leads to a sample of 45 countries and the latter 39. Our results in terms of graph density are robust to any of these minimum country observation requirements.

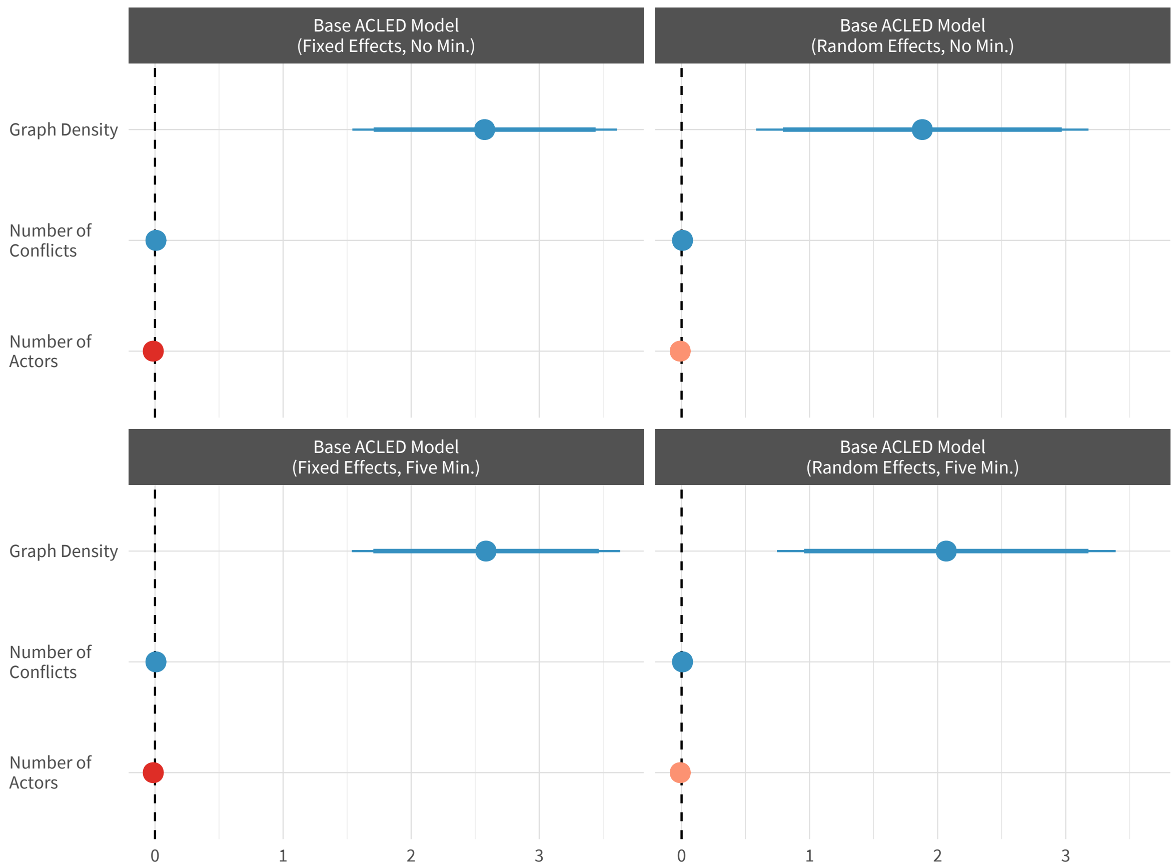

Figure A4: Regression results from unimputed data on Base specification when using various thresholds to include countries and estimations via fixed or random effects. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2012. Points 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.

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 A5 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.

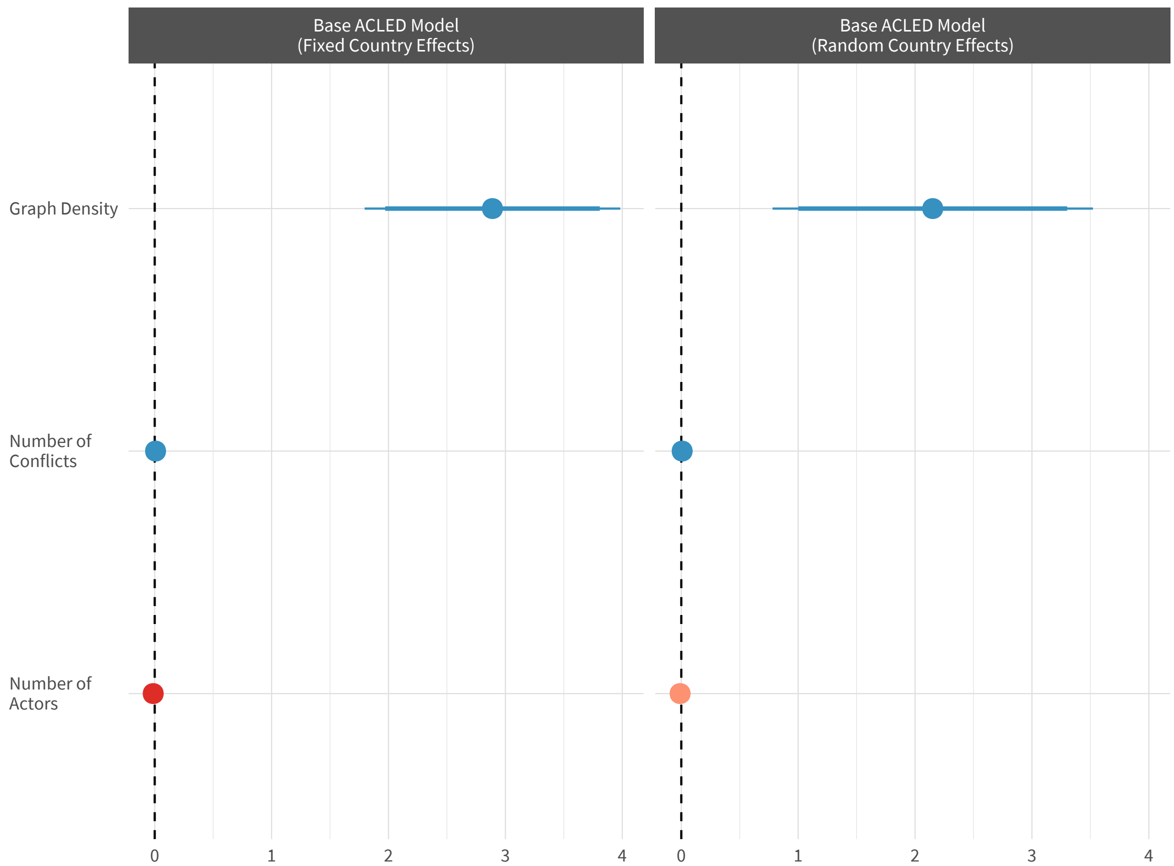

Figure A5: Regression results using Base specification that includes 42 countries from 1997 to 2019. The left panel visualizes coefficient estimates when using fixed effects on countries and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

Sensitivity of Results to Dropping Countries

Here we conduct a sensitivity analysis to ensure that our results are not being driven by any particular country in our sample. To do this, we estimate a model excluding the data from a particular country and save the regression estimate for our graph density measure. We conduct this analysis for the “Base” and two models with controls using unimputed data. Figure A6 shows the results of this analysis and we can see that dropping any one country from our sample does not meaningfully change the interpretation we would draw about the effect of graph density on civilian victimization.

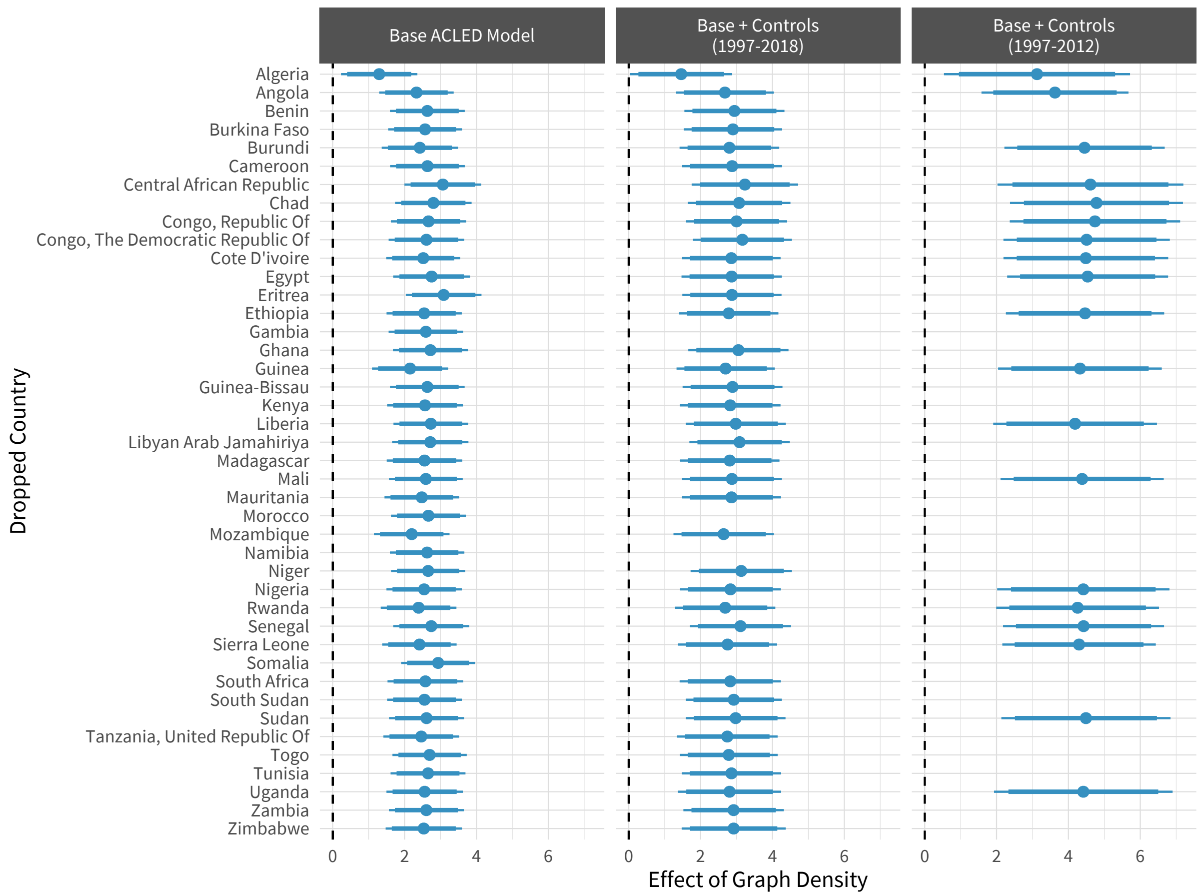

Figure A6: Effect of Graph Density in Base specification when dropping a country on the y-axis. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval.