# Network Competition and Civilian Targeting During Civil Conflict

Cassy Dorff[a], Max Gallop[b], Shahryar Minhas[c]

[a] *Department of Political Science, Vanderbilt University, Nashville, TN, USA*
[b] *University of Strathclyde, Glasgow, 16 Richmond St., Glasgow, UK G1 1XQ*
[c] *Department of Political Science, Michigan State University, East Lansing, MI 48824, USA*

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**Abstract**

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

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*Email addresses:* cassy.dorff@vanderbilt.edu (Cassy Dorff), max.gallop@strath.ac.uk (Max Gallop), minhassh@msu.edu (Shahryar Minhas)

## Contents

## A.1. Details on Computational Model

### *A.1.1. Ideology and Utility*

We define the distance between any two groups as:

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

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

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

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

### *A.1.2. Probability of Victimization Success*

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

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

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

*A.1.3. Resources and Victory*

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

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

where $\delta$ 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, $\psi$ and $k$ are the resources you get from non supporters, and those you lose from supporters of your opponent respectively.

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

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

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

*A.1.4. Decision to Attack*

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

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

where $G$ are the groups already committed to battle within a territory, $R$ is the number of civilians within a territory, $c$ is the cost of war. We include the expectation here because at the time of the decision, civilian support is unknown,[1] For comparison, the utility for group $i$ of the status quo in territory $q$, held by group $j$ is:

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

*A.1.5. Decision to Support*

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

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

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

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

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

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

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

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

It is worth highlighting here that $E[p_{g,q}]$ is determined by using beliefs from Equation

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

A8 to calculate the values in Equations A4 and A5.

*A.1.6. Decision to Victimize*

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

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

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

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

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

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

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

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

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

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

*A.1.7. Decision to Flee*

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

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

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

## A.2. Sample Information

### *A.2.1. Countries in the Sample*

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

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

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

### A.2.2. *Descriptive Statistics*

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

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

**Table A2:** Descriptive statistics for variables in Base model.

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

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

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

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

### *A.2.3. Network Competition Descriptives*

Here we present additional descriptive statistics on our network competition measure, specifically, Figure A1 depicts measurements for every country in our sample.

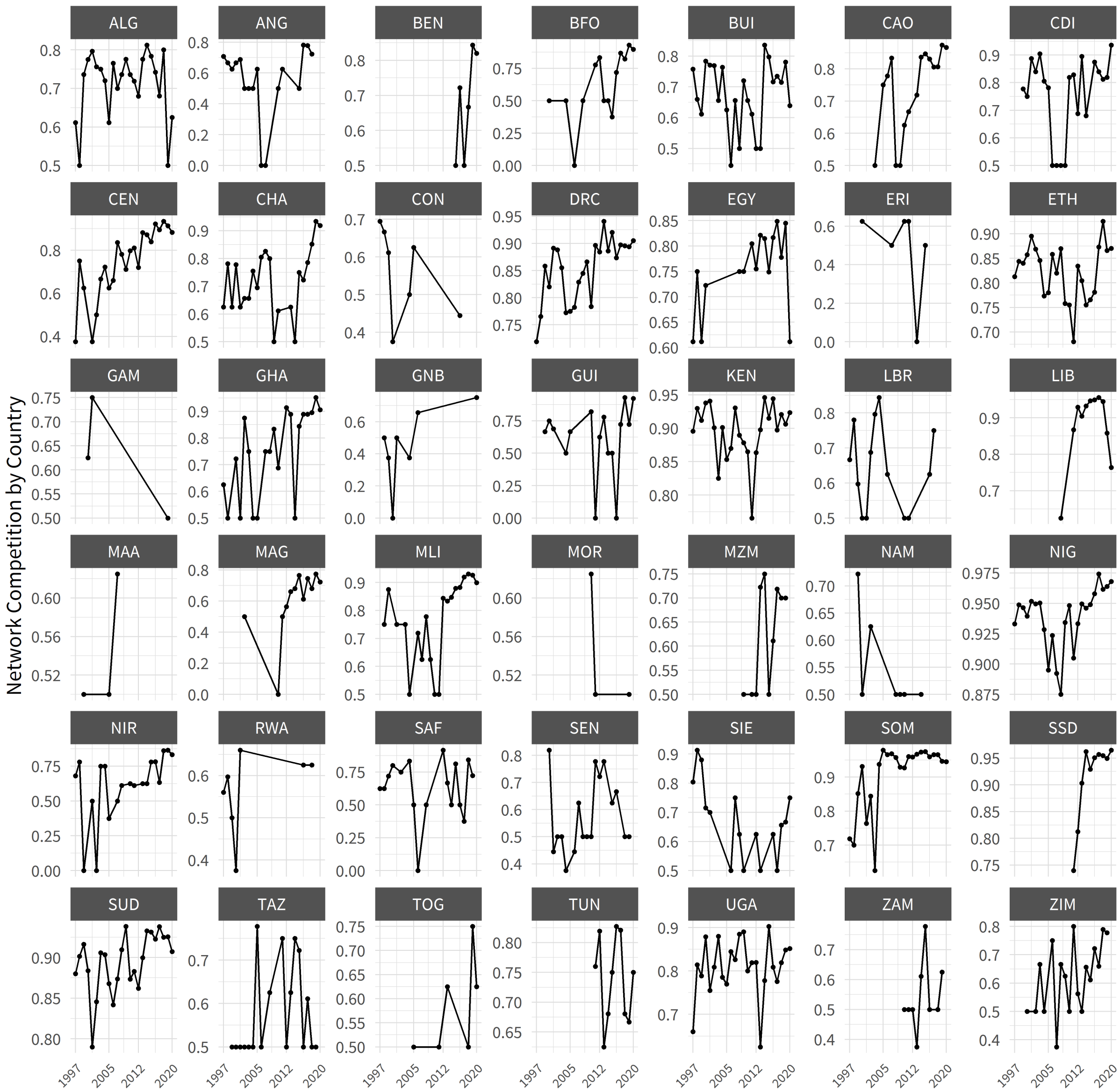


**Figure A1:** Network competition score for every country-year in our sample.

## A.3. Alternative Modeling Strategies

### *A.3.1. Fixed Effect Regression Results when Including Controls*

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

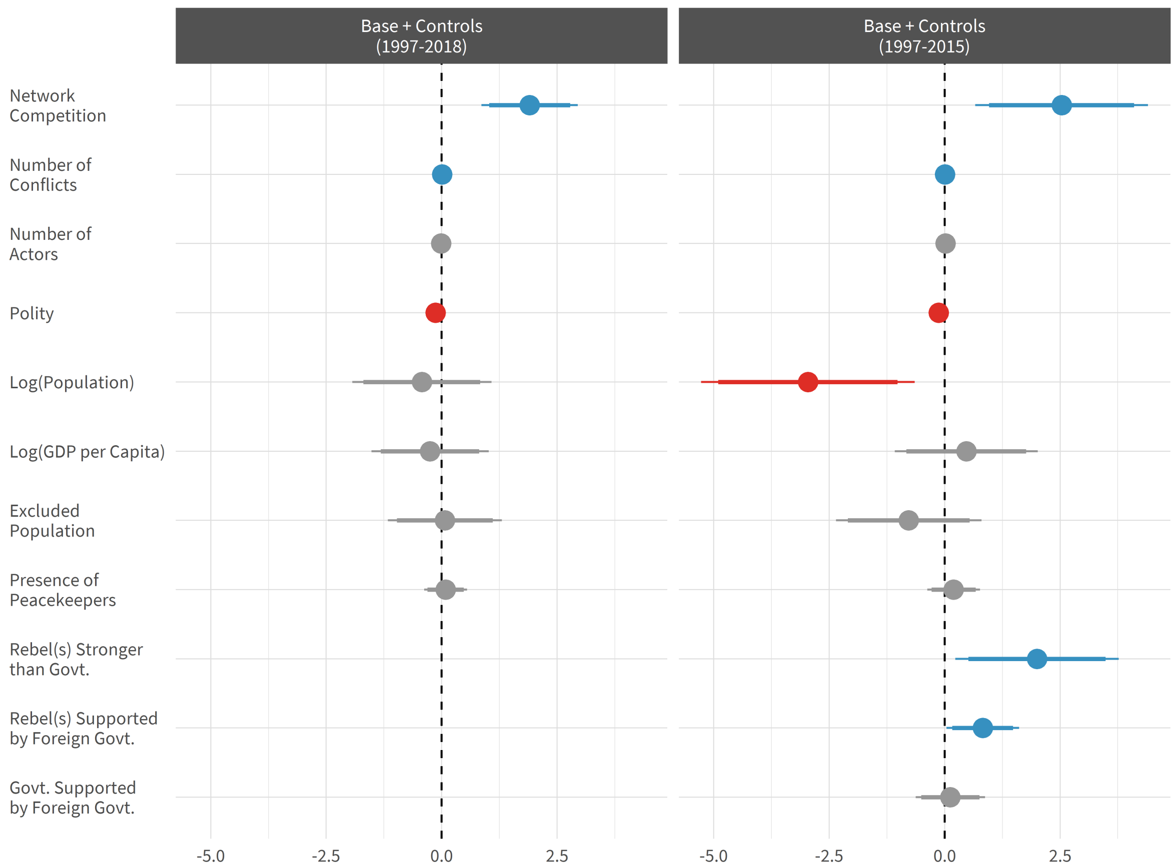


**Figure A2:** Regression results from multiply imputed datasets when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average value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

### *A.3.2. Results without Multiple Imputation*

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

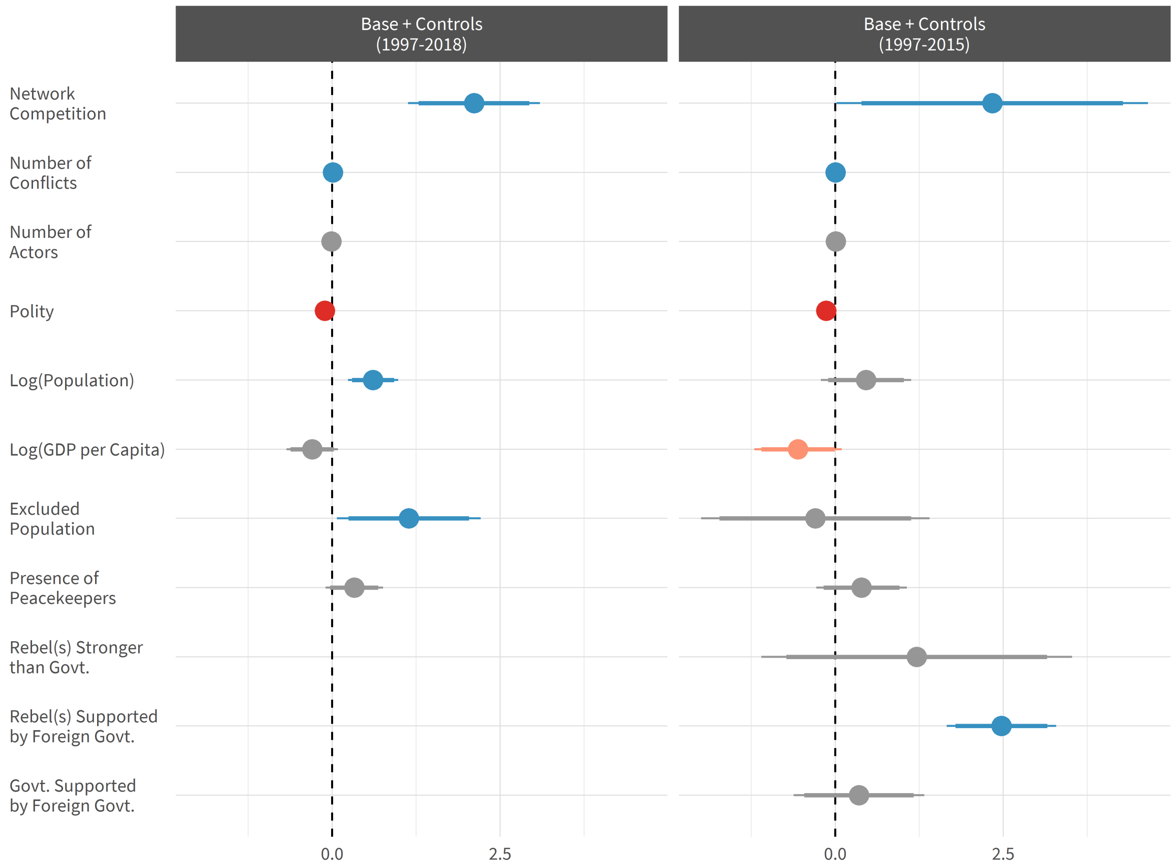


**Figure A3:** Regression results from unimputed data when pairing Base specification with controls using random effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters.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

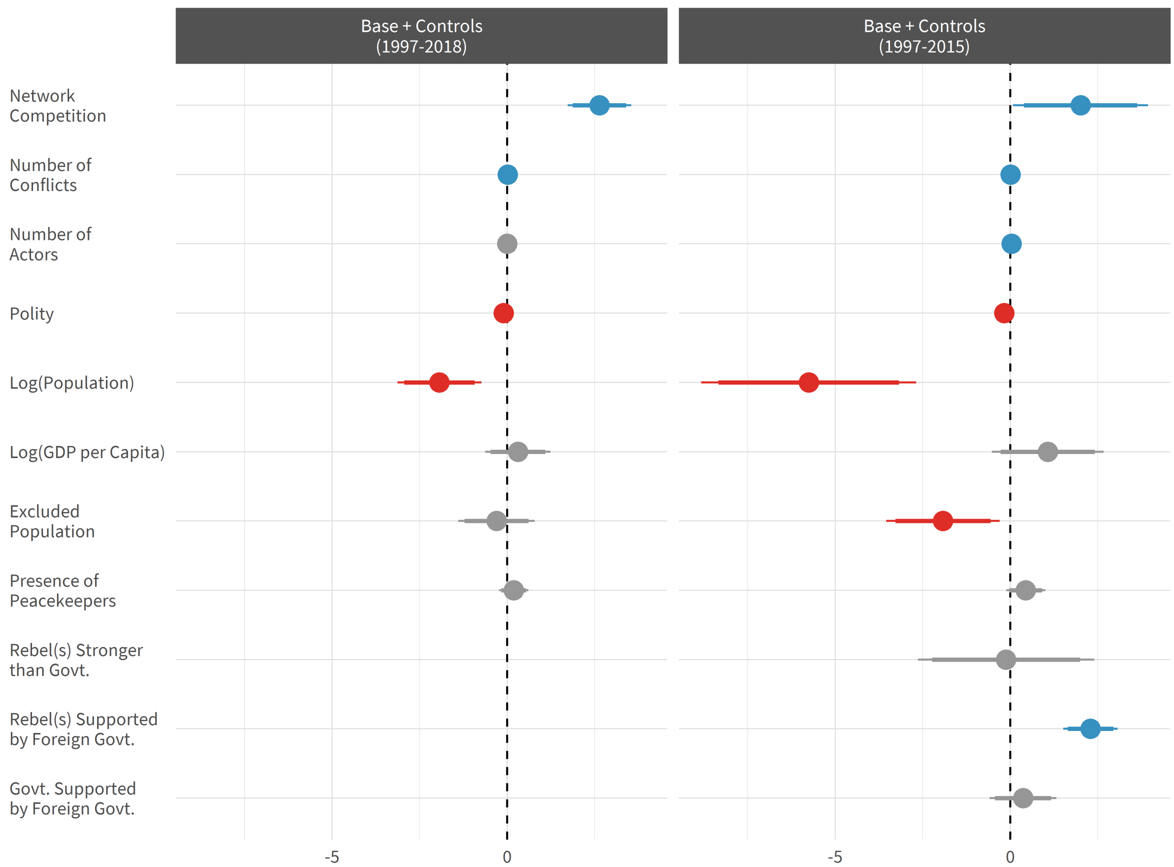


**Figure A4:** Regression results from unimputed data when pairing Base specification with controls using fixed effects for countries. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

## A.4. Alternative Model Specifications

### *A.4.1. Results with a Lagged Dependent Variable*

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

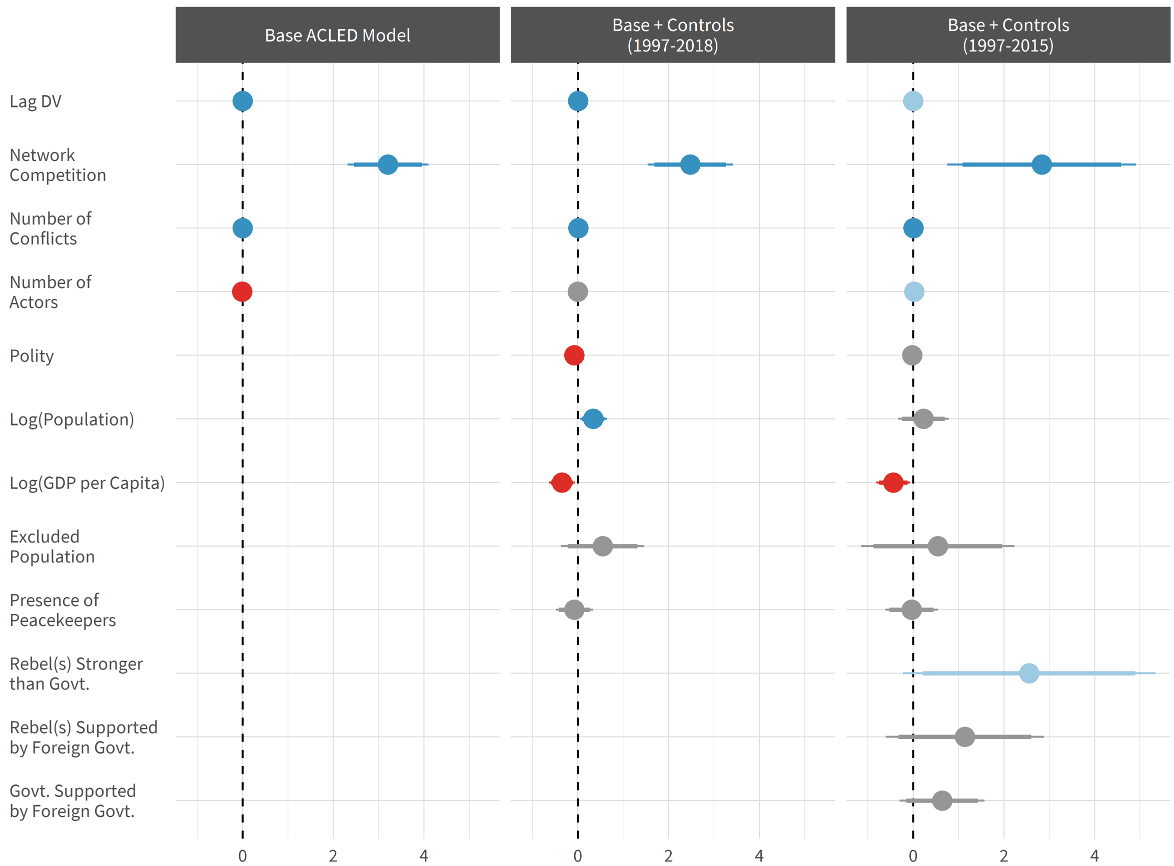


**Figure A5:** Random effect regression results when including a lagged dependent variable. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

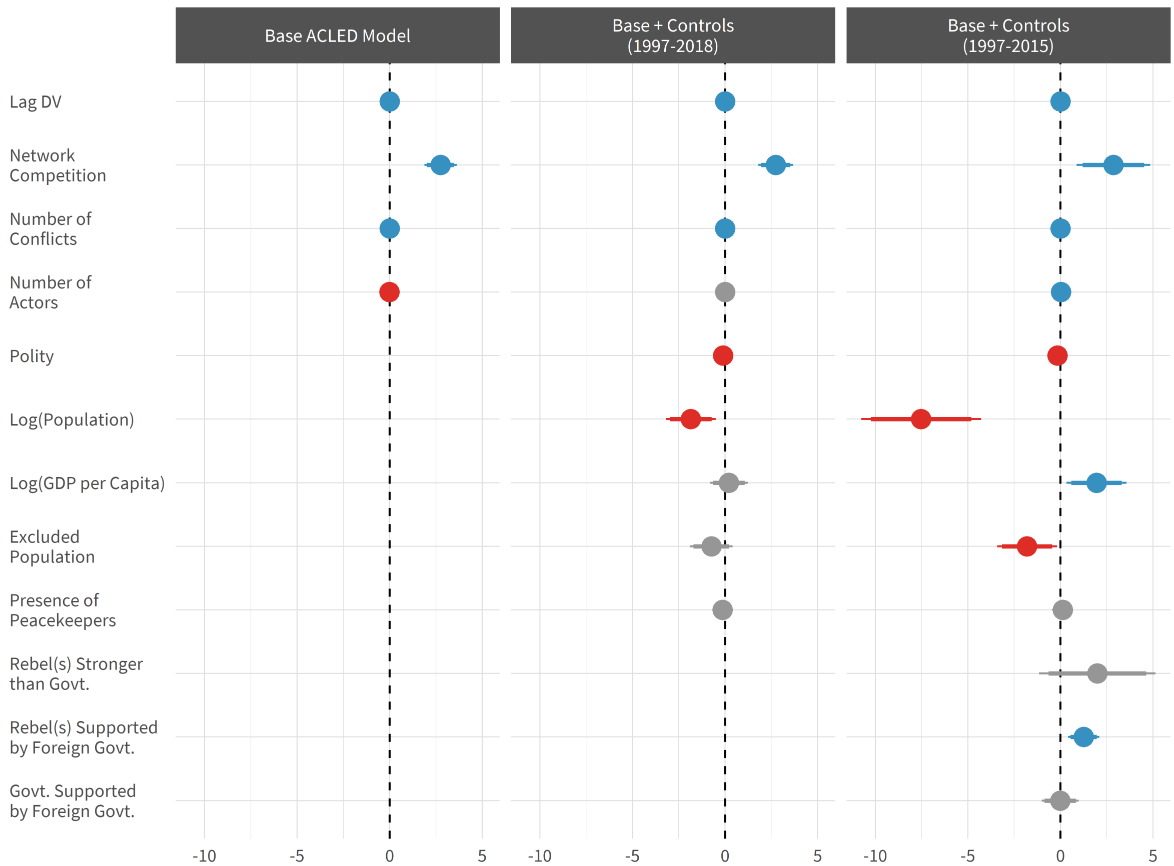


**Figure A6:** Fixed effect regression results when including a lagged dependent variable. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

*A.4.2. Incorporating Geographic Spread of Actors*

Controlling for the geographic proximity of actors in an armed conflict is an important robustness check for our analysis. High levels of victimization could be a result of actors in an armed conflict being geographically concentrated rather than being a function of network competition. To estimate the geographic concentration of armed actors in a country-year we calculate the centroid positions of armed actors for every country-year based on all the events that they were involved in,[2] next we calculate the distance between each actor centroid, and last take the average of those distances as a measure of how spread out actors are from one another.[3] Results when including this control for the geographic spread of actors are shown in Figures A7 and A8 below. In both the random and fixed effects specifications, the effect of the network competition measure matches our theoretical expectations.

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

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

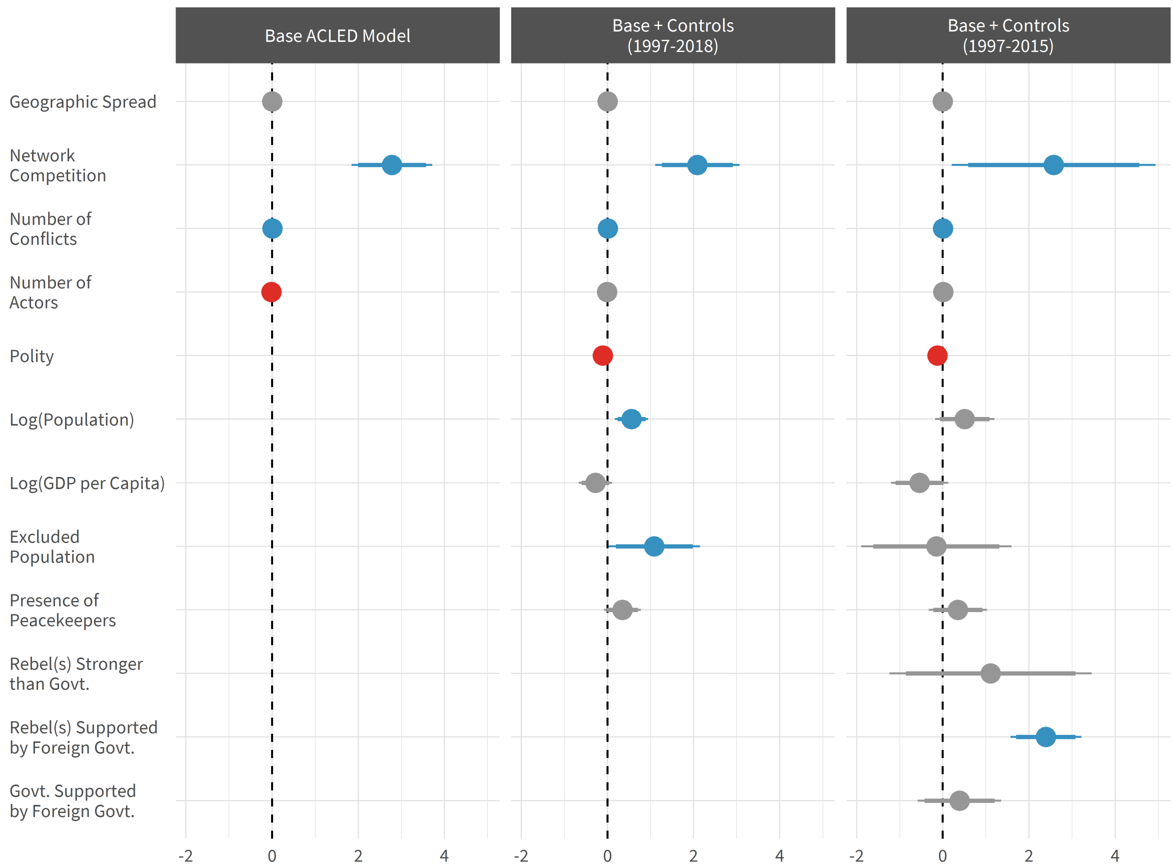


**Figure A7:** Regression results with random effects including a control for the geographic dispersion of actors. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive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

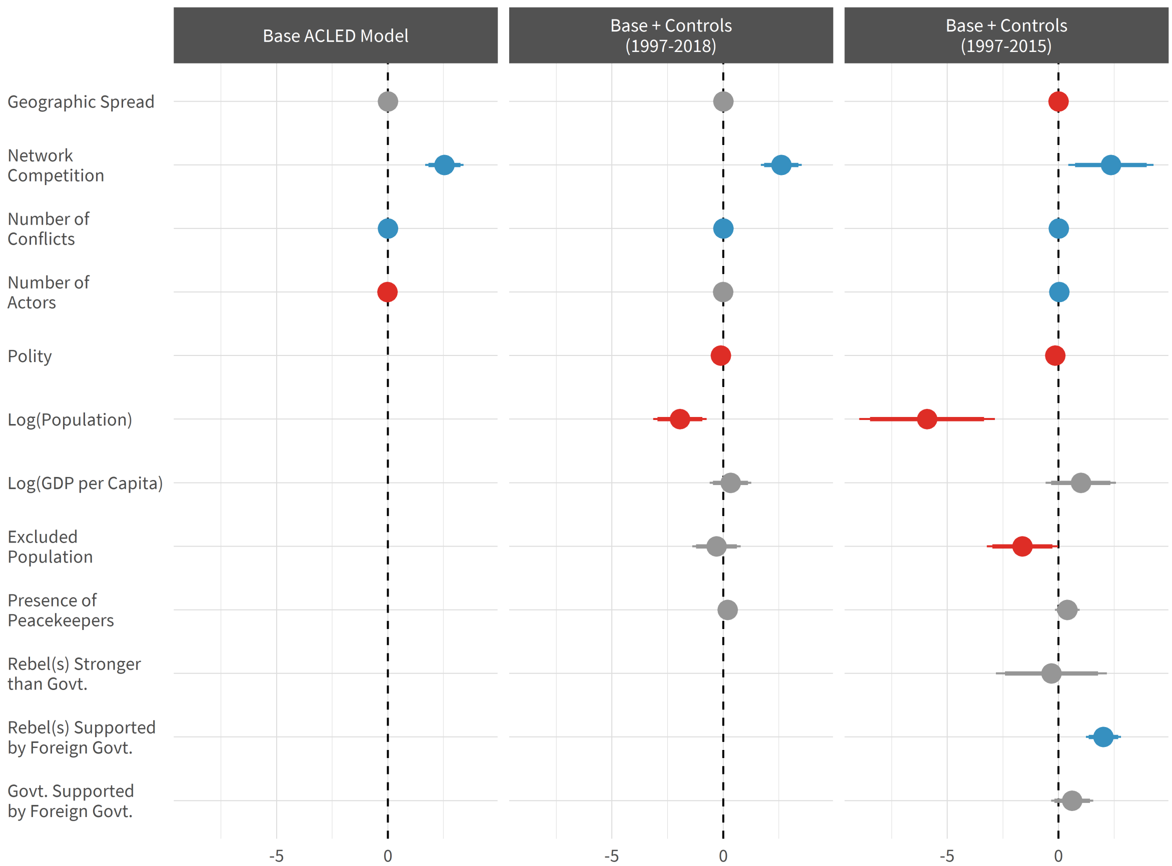


**Figure A8:** Regression results with fixed effects including a control for the geographic dispersion of actors. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

### *A.4.3. Controlling for proportion of potential allies*

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

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

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

1. Generate a network containing cumulative counts of conflict between all actors until time $t - 1$.
2. Center and standardize this network, then use a singular value decomposition to obtain a vector for each group (groups will have vectors pointing in similar directions if they have similar patterns of conflict with third parties).
3. Calculate the cosine similarity for each pair of groups.
4. For all isolates (groups that never send or receive conflict from any other state), assume that they are not allied with any other groups.

5. If any pair of states $ij$ have fought in the past, set their alliance level to $0$.

6. Find the proportion of dyads with cosine similarity above a sufficiently high threshold, and treat this as the proportion of groups in a system with alliances.

We then include the proportion of groups in a country-year that are allied in both our statistical analysis of the ABM results and our empirical work. Results when including this measure in our ABM model are shown in Figure A9. The network competition measure remains significant and in the expected direction in both the fixed and random effect specifications.

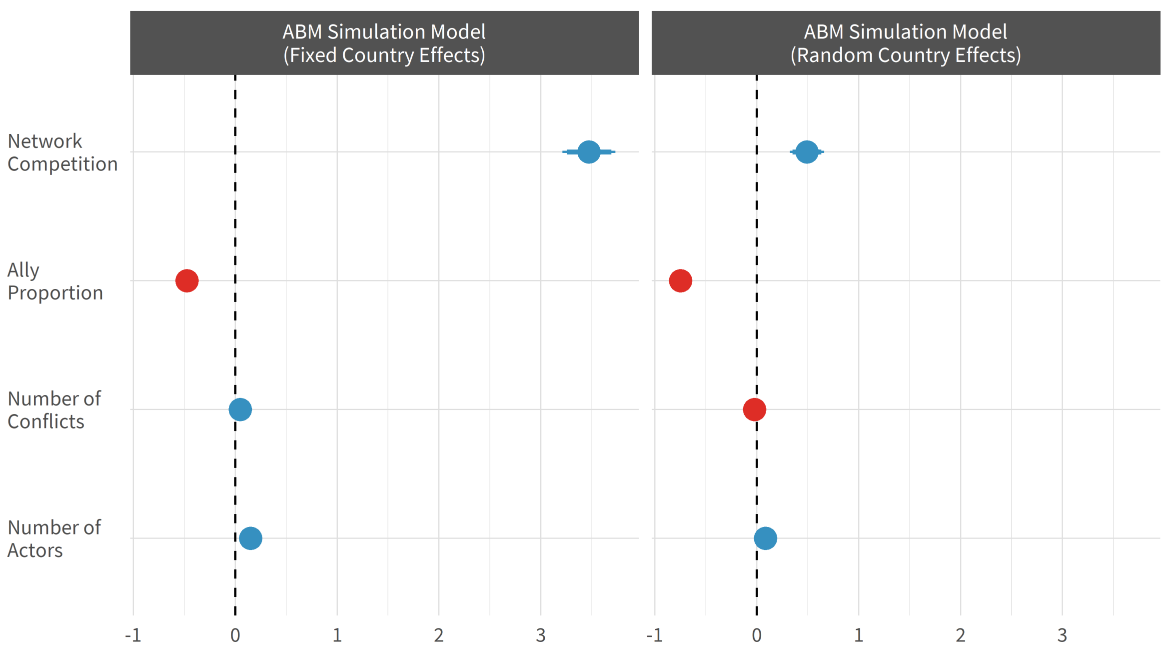


**Figure A9:** Analysis of determinants of victimization in computational model controlling for proportion of allies. The left panel visualizes coefficient estimates when using fixed effects on conflict scenarios and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

Figure A10 and A11 show the results when including this measure in our empirical models, and there as well we find that the network competition measure continues to align with our theoretical expectations.

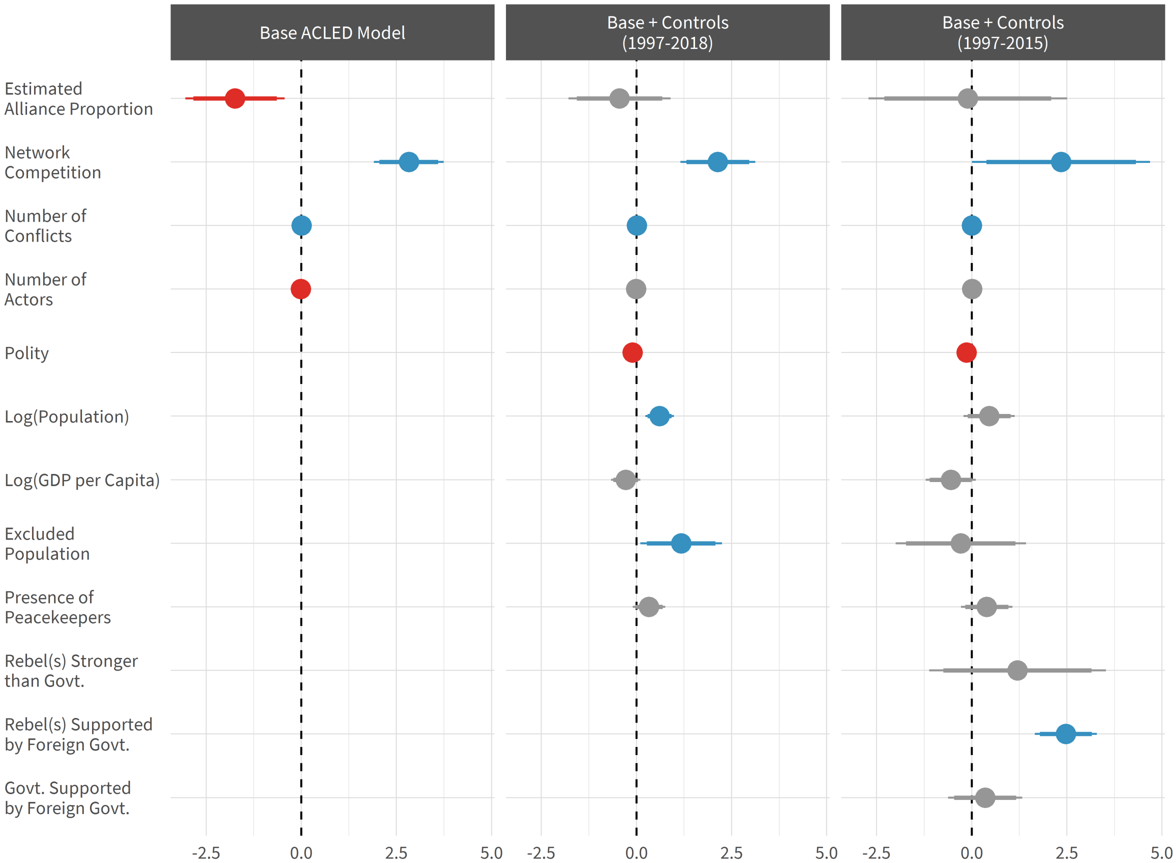


**Figure A10:** Regression results with random effects including a control for the proportion of actors allied in a country-year. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates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

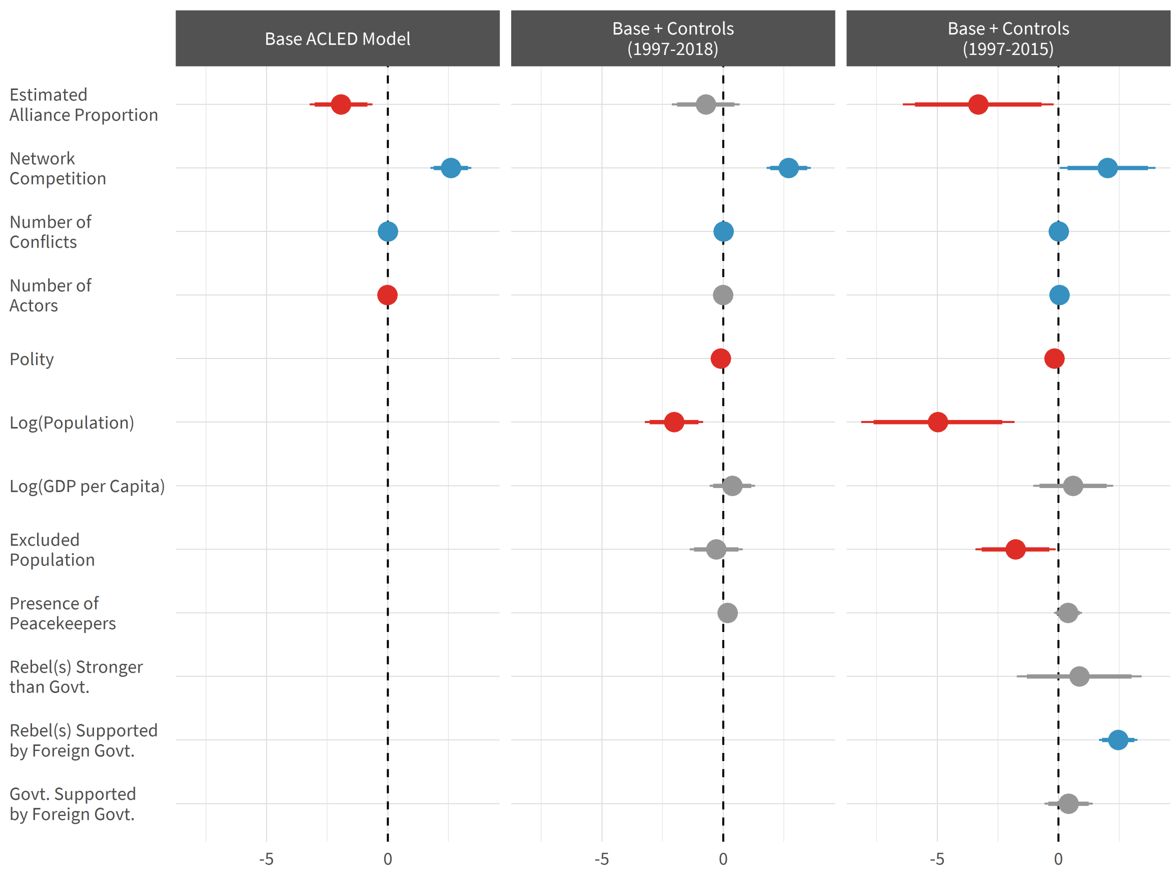


**Figure A11:** Regression results with fixed effects including a control for the proportion of actors allied in a country-year. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

### *A.4.4. Conditional Effect of Government Strength*

Here we examine whether the effect of network competition is conditional on the strength of either the government or the rebel. Within the ABM, we do this by measuring the allocation of territory held by the government relative to rebel groups. Specifically, we create a binary measure, called rebel strength, that has a value of 1 when rebels hold more territory than the government and 0 if less. To test whether or not there is a conditional effect, we add the rebel strength variable to the model specification and also include an interaction between it and the network competition measure. Figure A12 shows predicted levels of victimization for the effect of network competition conditional on rebel strength. In cases where rebels are stronger (government is weaker), the effect of network competition is more muted, whereas in cases where rebels are weaker (government is stronger) the effect of network competition is increasing with network competition. Given, empirically, that the government almost always begins a civil conflict more powerful than various rebel groups, we find it reassuring that our main mechanism holds in the more common circumstance.

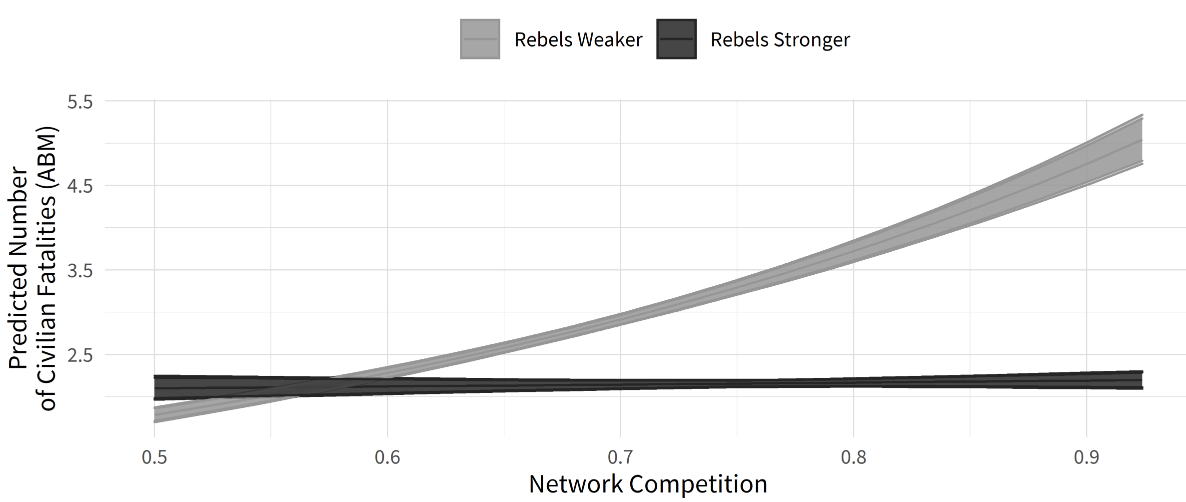


**Figure A12:** Simulation analysis of the ABM results of a random effects model that includes an interaction between government strength and network competition.

For the empirical analysis, we already have a variable measuring whether rebel forces are stronger than the government from the NSA database. We interact the rebel stronger variable from that database with our measure of network competition and conduct a simulation analysis to understand the conditional effect of network competition on victimization. The results of this analysis for the empirical model are shown in Figure A13. Here we see results that are generally in line with what we found in the ABM, though estimated with much less precision. Specifically, the left panel shows predicted levels of victimization by network competition when rebel groups are weaker, and the right for the case in which rebels are stronger. As with the ABM, we can see that higher levels of victimization are predicted as network competition increases when rebel groups are weak, and that there seems to be little effect when rebel groups are relatively stronger. We would caution drawing too much from the interaction analysis using the empirical data, however, given the imprecision of the estimates.

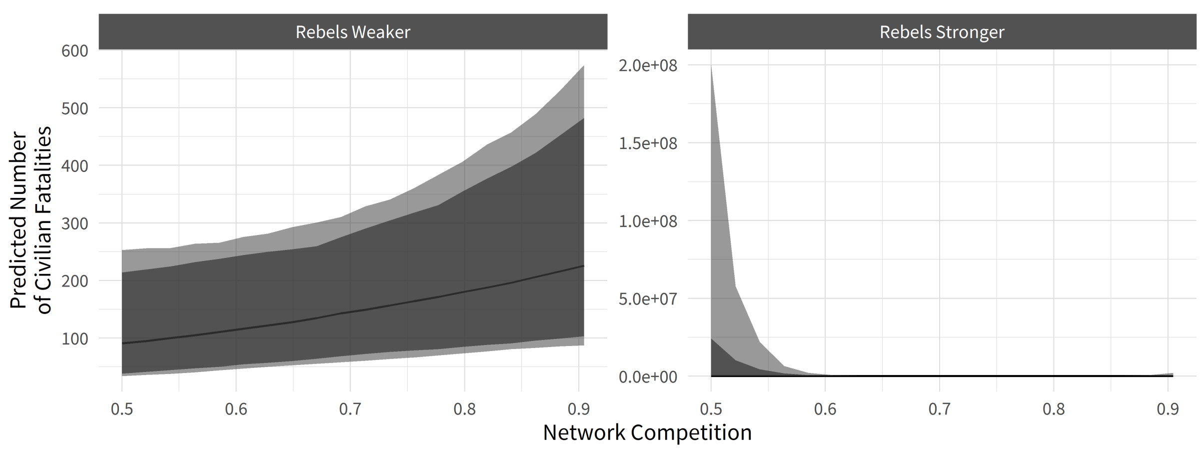


**Figure A13:** Simulation analysis of the empirical results of a random effects model that includes an interaction between an indicator variable for rebels stronger than governmentand network competition.

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

Readers might find that there is a disconnect between our ABM results and the literature, where the number of actors has a positive effect on victimization, and our empirical results, where the number of actors has a negative or insignificant effect on victimization. After further examination of our empirical results, we find that these results can be somewhat explained by our research design. Specifically, two of our modeling choices jointly lead to a negative or insignificant effect of number of actors: (1) the use of fixed effects at the country level and (2) the inclusion of our main independent variable, network competition, into the model. If either modeling choice is made, our results disagree with previous literature. We show the variation in the results for the effect of number of actors below in Figure A14.

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

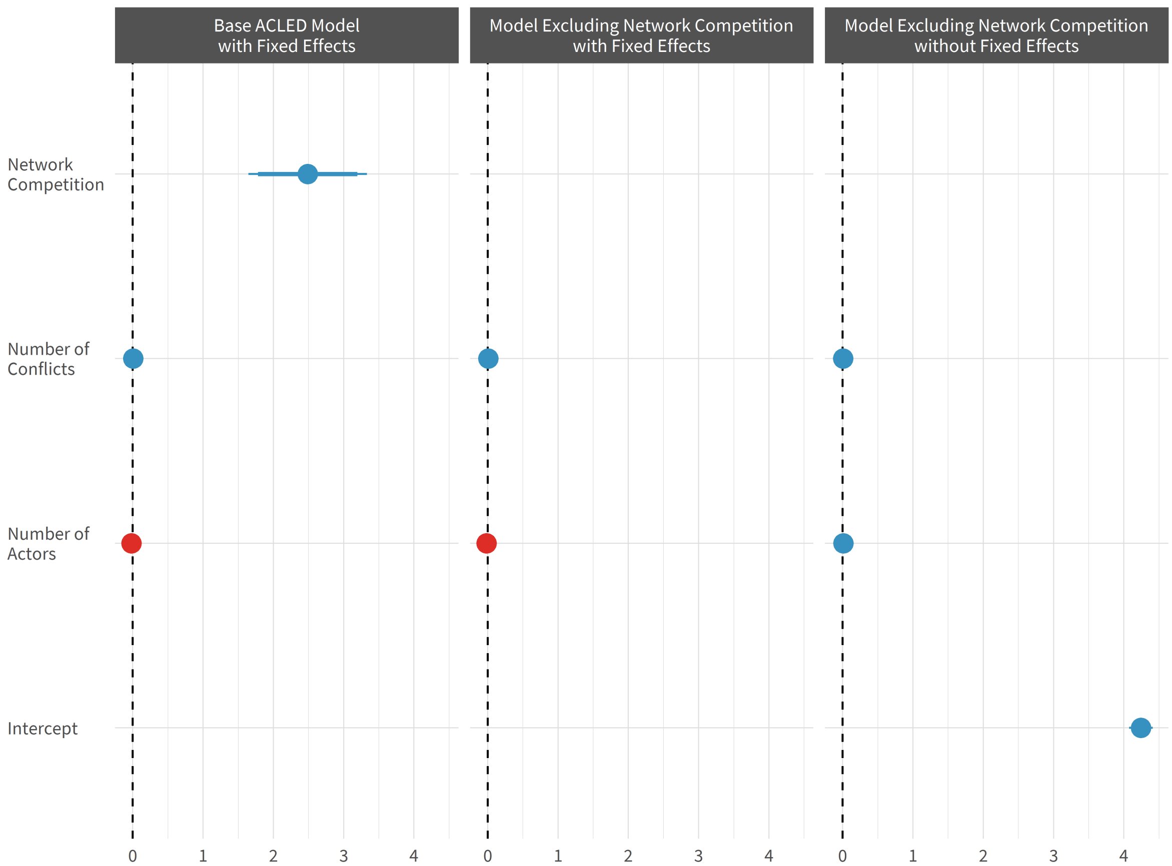


**Figure A14:** Regression results exploring the effect of Number of Actors: in the first column we show the results in our paper, in the second we exclude our measure of network competition, and in the third we exclude our measure of network competition and run the model without fixed effects for countries. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

## A.5. Robustness to Sample Changes

### *A.5.1. Results using Various Thresholds to Include Countries*

In the Base results presented in Figure **??** of the manuscript, the underlying sample had a requirement that a country must have at least three years of observations to be included in our analysis. This led to a sample of 42 countries from 1997 to 2020. Here we modify this three year minimum to test the robustness of our results. The first row in Figure A15 depicts our results when we employ no minimum and the second row when we employ a five year minimum per country. The former criterion leads to a sample of 45 countries and the latter 39. Our results in terms of network competition are robust to any of these minimum country year requirements.

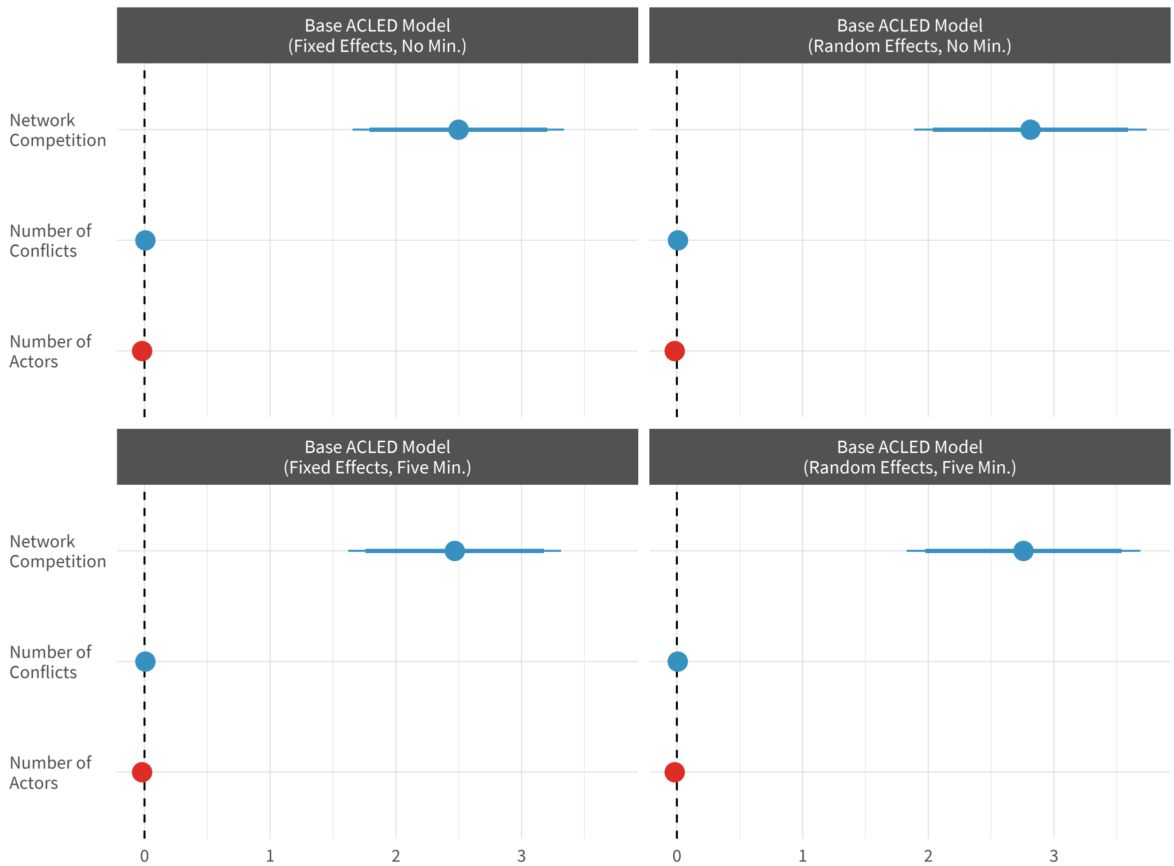


**Figure A15:** Regression results from unimputed data on Base specification when using various thresholds to include countries and estimations via fixed or random effects. Specification in the left panel includes 38 countries from 1997 to 2018 and the right includes 19 countries from 1997 to 2015. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

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

COVID-19 may impact not only our results but even the reporting of conflict data in a number of ways. To insure that our results are not being affected by this type of exogenous dynamic, we limit our sample to 1997 and 2019. Figure A16 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.

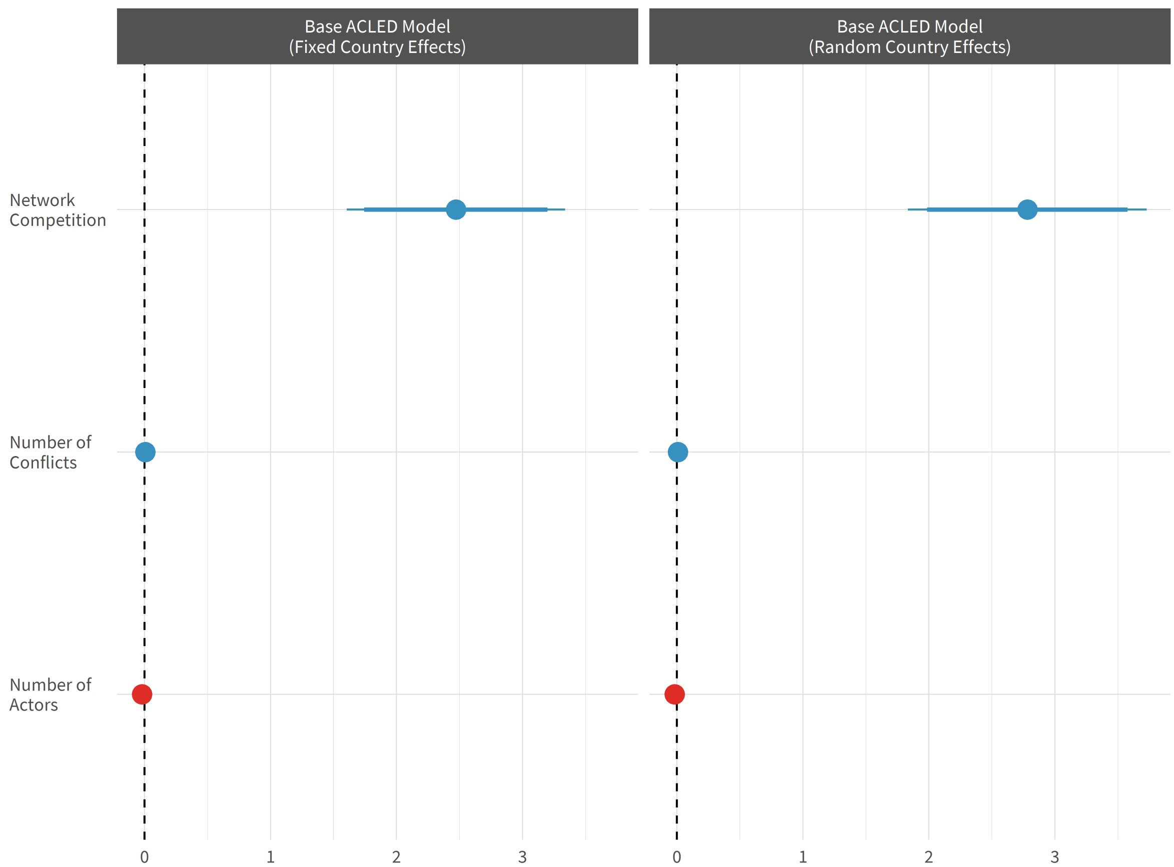


**Figure A16:** Regression results using Base specification that includes 42 countries from 1997 to 2019. The left panel visualizes coefficient estimates when using fixed effects on countries and the right random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

### *A.5.3. Model Estimates with UCDP*

Given that the information in various event datasets can vary widely across countries (Eck, 2012), we also run our analysis using information from UCDP. Ideally, we would like to integrate information from both data sources (Donnay et al., 2018), but such a task would require building a dictionary that can bridge actor level information between UCDP and ACLED. Figures A17 and A18 show the results when using data from UCDP instead of ACLED. Results for our network competition measure remain positive and significant when using information from UCDP. For the manuscript, we choose to focus on results using ACLED. UCDP data records information only on groups that commit a specific threshold of violence during a battle, whereas ACLED data contains information about all groups relevant to all battles, regardless of the number of deaths incurred. Due to our focus on measuring network competition based on how groups are interacting with one another we focus on results with ACLED.

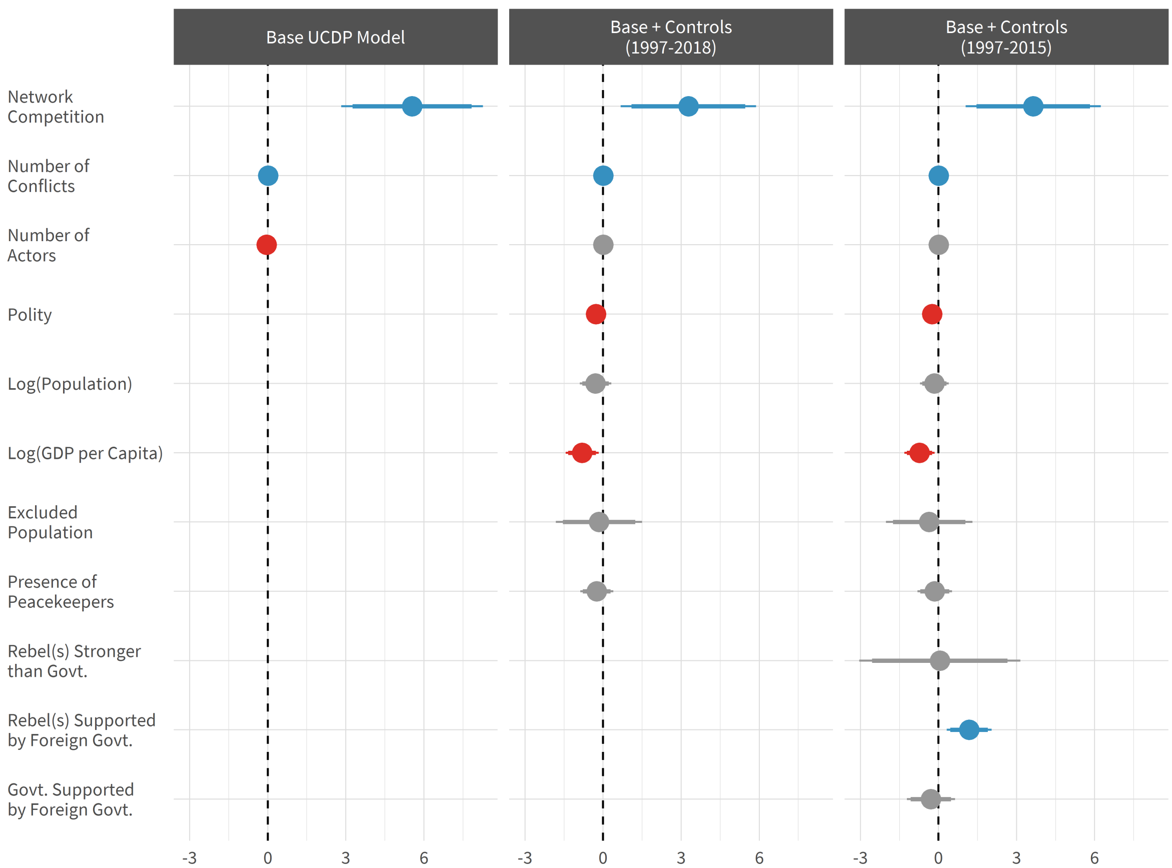


**Figure A17:** Regression results with random effects using UCDP data. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

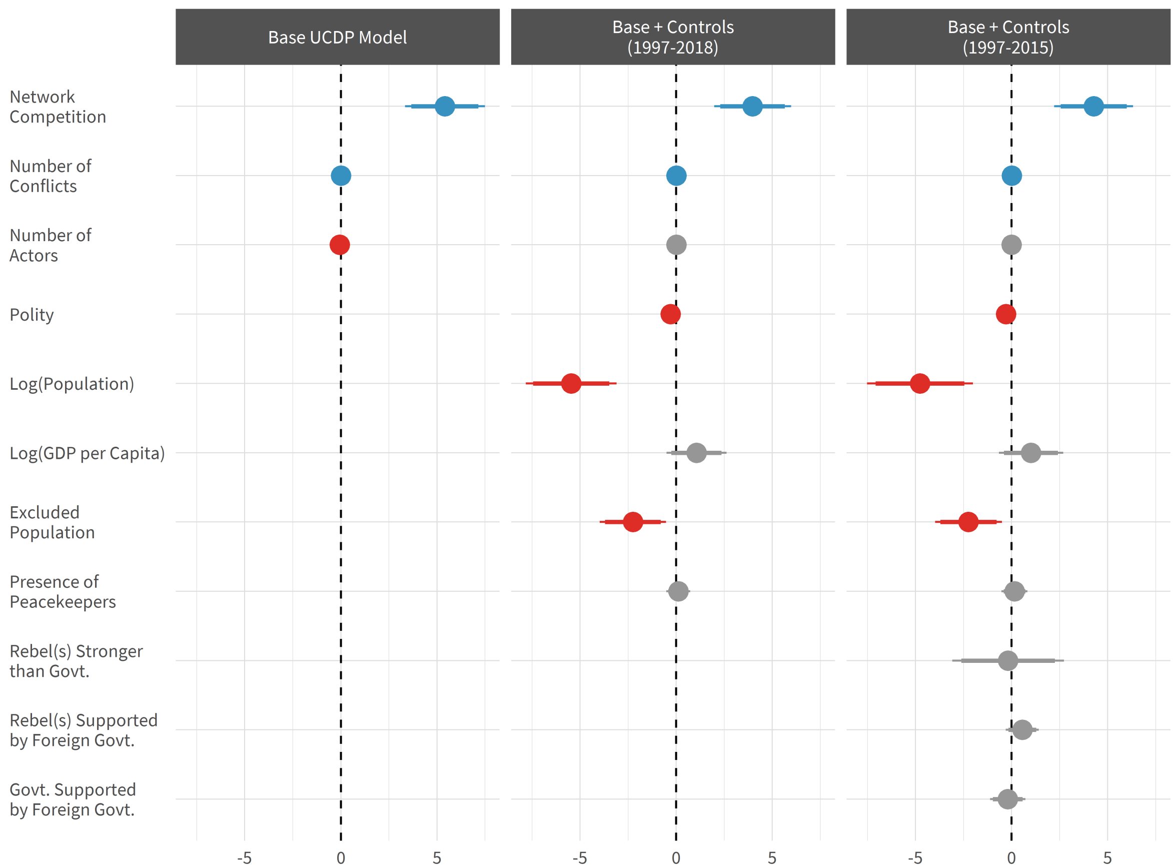


**Figure A18:** Regression results with fixed effects using UCDP data. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

## A.6. Alternative Dependent Variable

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

Because there are difficulties in accurately measuring fatality counts from conflict (Dawkins, 2021), we also reestimate our model using a count of one-sided violent events in a country-year as the dependent variable. The results are presented below in Figures A19 and A20. With this alternative dependent variable we find that our network competition measure has a positive and significant effect on the number of civilian victimization events in a given year using either a random or fixed effects framework.

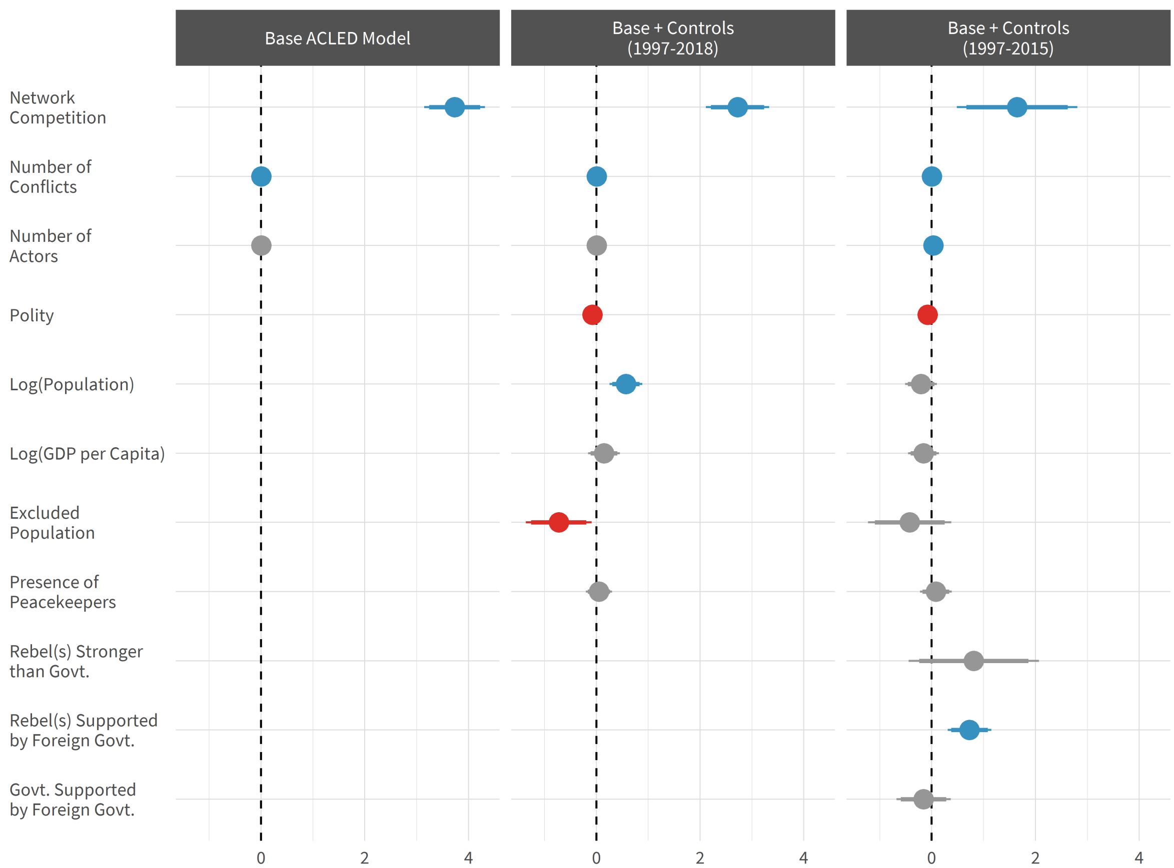


**Figure A19:** Regression results on count of OSV events with random effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

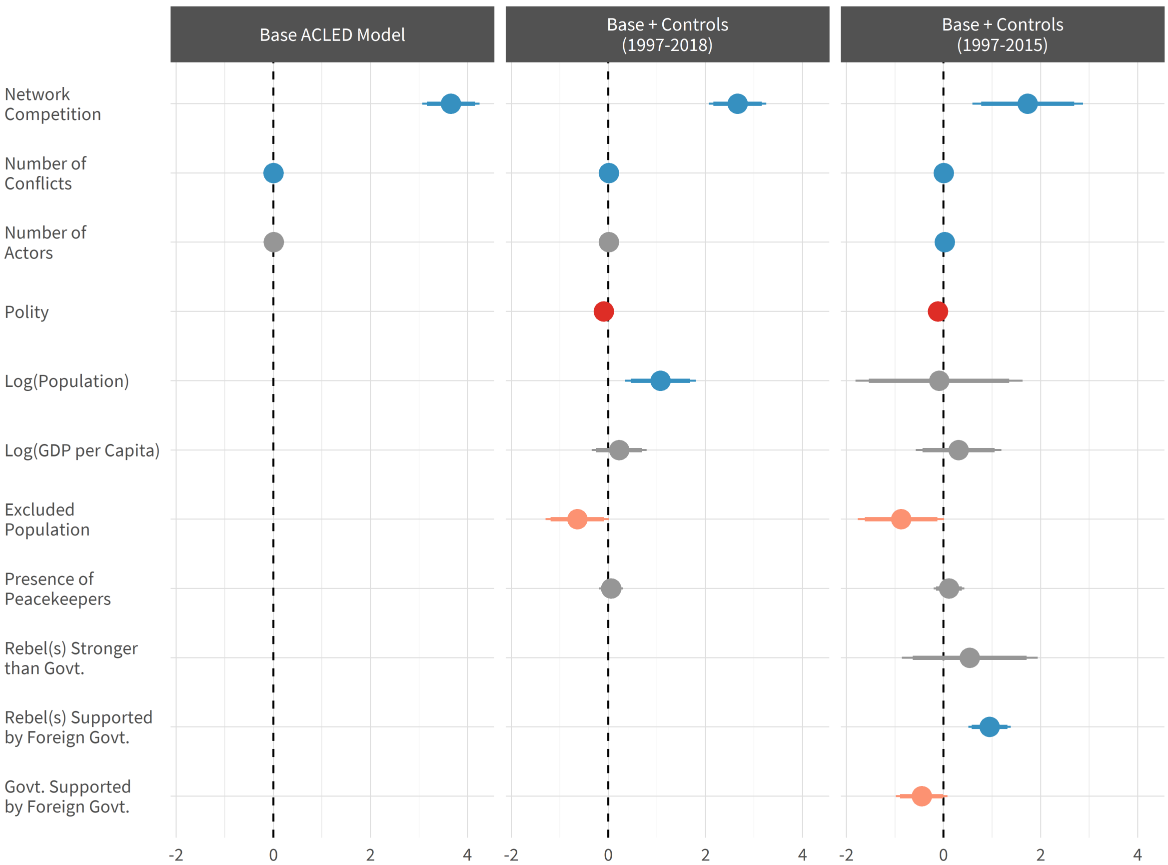


**Figure A20:** Regression results on count of OSV events with fixed effects. Points represent average values of parameters. Thicker lines represent the 90% confidence interval and thinner lines the 95% interval. Darker shade of red (blue) indicates significant positive (negative) values.

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