An Analysis of Violent Nonstate Actor Organizational Lethality and Network Co-Evolution in the Middle East and North Africa

Multi-Agency, Multi-Method Assessment to Counter-ISIL Messaging by Means of Maneuver and Engagement in Narrative Space

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National Consortium for the Study of Terrorism and Responses to Terrorism
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About This Report

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Contents

Executive Summary

Using new data that spans the years 1998 to 2012 we model the behavior of violent nonstate actors (VNSAs) in the Middle East. Using several statistical techniques, including network modeling, logit analysis, and hazard modeling, we show that governments can use strategies that influence a group's level of lethality, their relationships with other groups, and how long and if these groups become especially lethal.

When modeling why some groups become highly lethal (which we define as having killed more than 100 civilians in terrorist attacks in any year or causing more than 100 battle deaths in any year), we find that:

- VNSAs are more likely to kill many civilians in one year when they control territory and when governments use violence, or what we call a *stick* strategy, against them;
- VNSAs are most likely to kill many civilians in one year when governments use a *mixed* strategy – that is, a combination of violence (*stick*) and negotiation (what we term a *carrot* strategy) as opposed to either stick or carrot alone;
- VNSAs are most likely to inflict more than 100 battle deaths in one year when they control territory, are highly connected to other VNSAs, and are large (though there is a strong relationship between size and controlling territory);
- VNSAs are less likely to inflict more than 100 battle deaths in one year when they have a formal political party.

We also independently modeled the *co-evolution* of network structure and VNSA killing through terrorism. That is, the way in which network structure affects lethality and the way lethality affects alliance choices. This approach unearthed several complementary findings:

- VNSAs that are socially isolated – that is, have no alliance connections – tend to be less lethal and tend to stay relatively less lethal;
- Social isolation is a relatively stable state; however, there are factors that help to drive organization alliance formation like shared location, ideology, and preference for closed relationship – a friend of friend tends also to be a friend;
- Once an organization generates alliance connections, a feedback loop drives lethality up;
- Maintaining organizational isolation appears to be a useful strategy for dampening organizational lethality

Introduction

Previous research focusing on violent nonstate actors (VNSAs) has examined the determinants of terrorist lethality (Asal and Rethemeyer 2008) and terrorist network formation (Asal, Park, Rethemeyer and Ackerman 2015). However, these studies (1) relied on cross-sectional data (2) that covered a compressed period (1998-2005). While there have been numerous studies of terrorist organizations in the Middle East (including one study by two of the co-authors on pursuit and use of CBRN capabilities by organizations in the Middle East (Asal and Rethemeyer 2009)), few of these studies have (1) been both quantitative and longitudinal or (2) examined both insurgent and terrorist organizations (though we note that some organizations can be both).

This study provides an analysis of VNSA lethality as well as the "co-evolution" of VNSA lethality and alliance formation using the Big Allied and Dangerous Version 2 (BAAD2) dataset – a newly created dataset that covers both terrorist and insurgent organizations. We begin this study by presenting an overview of BAAD2 and then present two analyses: one focused just on lethality and another focused on lethality and alliance formation co-evolution.

Data Overview

Dataset: Big Allied and Dangerous Version 2 (BAAD2)

The Big Allied and Dangerous (BAAD) Data Project, directed by Victor H. Asal and R. Karl Rethemeyer through the University at Albany – SUNY's Project on Violent Conflict (PVC), focuses on the creation and maintenance of a comprehensive database of terrorist organizational characteristics that may be linked to prominent event, insurgency, and country-level characteristics datasets. This project was founded in order to fill a major gap in the field's "dataverse." While there are several datasets that record terrorist events (including the International Terrorism Attributes of Terrorist Events (ITERATE) and Global Terrorism Database (GTD) datasets) and one that examines insurgent organizations during periods of conflict (the Non-State Actor Dataset developed by Cunningham, Gleditsch and Salehayan), there is no dataset available to unclassified researchers that comprehensively characterizes the nature of VNSA organizations on a yearly basis. The BAAD project is an effort to provide yearly VNSA data worldwide on insurgent and terrorist organizations.

BAAD Datasets

BAAD Version 1.0 (BAAD1)

BAAD1 contains a single snapshot of 395 terrorist organizations active (meaning they perpetrated at least one attack) between 1998 and 2005. This dataset grew from information that was originally hosted by the Memorial Institute for the Prevention of Terrorism (MIPT) in their Terrorism Knowledge Base (TKB) but greatly expanded and improved upon by PVC. Completed in 2008, the BAAD1 data is publically available for download and includes both organizational and network data.

BAAD Version 2.0 (BAAD2)

BAAD2 improves upon BAAD1 by:

- Providing time series data in yearly slices,
- Expanding the time period – now from 1998 to 2012 (2013-14 will be added by summer 2016)
- Increasing the number and depth of variables collected and coded,
- Expanding the number of entities covered in the dataset to include not only terrorist organizations as identified in the Global Terrorism Database (LaFree and Dugan 2007) but also insurgencies as identified in the Uppsala Conflict Data Program (Themnér and Wallensteen 2010) datasets
- Providing a "cross-walk" that enables researchers to link BAAD2 organizational characteristics data to other data sources

BAAD2 was created through "hand coding" of textual sources. In brief, undergraduate and graduate coders hired by the University at Albany were tasked with finding and reading text sources (including published academic articles, newspaper and magazine accounts, web-based news sources, organizational websites, and other online materials deemed reliable by the coders and coding editors) and then using the coding framework to numerically characterize the nature of terrorist organizations and their network connections to peer organizations and states. Preliminary coding then went through at least four rounds of quality control by "coding editors" and the PIs, including random sampling of "final" coding products that were then subject to re-validation. Coding is continuous and ongoing; updates to completed coding based on emerging information are incorporated into later data releases.

BAAD2 Components and Composition

BAAD2 Inclusion Criteria

An organization is included in BAAD2 for the entirety of its existence from 1998 if it meets one of these three inclusion criteria:

- Commission of at least one terrorist attack during the period 1998-2012 (expanded to 2014 by summer 2016) as recorded in the Global Terrorism Database;
- Inclusion in the Uppsala Conflict Data Program (UCDP) list of insurgent organizations for the period 1998-2012 (expanded to 2014 by summer 2016), as based on recording at least 25 battle deaths in one year;
- Inclusion in the Profiles of Incidents involving CBRN by Non-state actors (POICN).

Slated for completion in summer 2016, the final dataset will include approximately 560 VNSAs and over 5,600 organizational-year entries for the years 1998-2012. For this project, we relied on the body of completed coding, which covers 203 VNSAs that engaged in at least 10 terror attacks between 1998 and 2012 world-wide (GTD) and/or were engaged in battles that resulted in at least 25 battle deaths in one year between 1998 and 2012 (UCDP).

BAAD2 Data Components

Organizational data. The organizational variables include: group name, aliases, homebase country, ideology, size, age, structure, financial and material support, electoral and political involvement, leadership structure, territorial control, provision of social services, and counterterrorism efforts directed at the organization.

Social Network Data. BAAD2's social network data characterizes relationships (1) between VNSAs and (2) between countries and VNSAs. Relationships are coded for categories such as: suspected ally, ally, faction, splinter group, rival, enemy, target and state sponsor.

Terrorist Organization Identification System. The Terrorist Organization (TORG) identification system, which currently contains entries for more than 2,400 primary entities and more than 2,800 aliases, is designed to provide an authoritative list of primary terrorist entities and associated aliases across time. For each primary entity, TORG includes the primary "homebase" country code (both the Correlates of War coding system (CCODE) and the ISO country coding system), age of founding and associated ID numbers from allied datasets, including the Global Terrorism Database (GTD), the Minorities at Risk-Organizational Behavior (MAROB) dataset, the Profiles of Incidents involving CBRN by Non-state Actors (POICN) dataset and the Uppsala Conflict Program (UCDP) datasets. Senior project staff members are responsible for generating and curating the TORG "cross-walk" dataset.

The TORG system is designed to help researchers broaden the range of factors that may be included in models of VNSA organizational behavior and to bring information on terrorism and terrorist organizations into studies of war, insurgency and non-lethal forms of political violence.

A codebook for BAAD2 is available upon request.

Integration of Data from Other Sources with BAAD2

For this project, TORG entries were used to connect BAAD2 organizational data to data in GTD regarding terrorist incidents, including fatality counts by organization-year. Using country codes in the TORG cross-walk, we also linked to the Quality of Governance (QoG) dataset, which is curated by the University of Gothenburg. QoG is a country characteristic datasets that has harmonized information from 70 sources. From QoG we integrated a set of key variables, including GDP, GDP per capita, population size, military expenditures, regime type, etc. Again, each of these measures is yearly to conform to the BAAD2 unit of analysis – the organization-year.

Data Extract for This Project

The data for this analysis was extracted from BAAD2. The extract contains 203 VNSAs that conducted 10 or more attacks or killed 25 or more people in battle between 1998 and 2012. We should note that, on average, the majority of VNSAs do not reach either of these marks, so this data extract is restricted to relatively large and well-organized entities whose organizational features suggest that they pose a substantial threat. As requested, we restricted our analysis to organizations "home based" in the Middle East. To define the Middle East, we relied on the list of 28 countries created by the G8 (see https://en.wikipedia.org/wiki/Greater_Middle_East). Our data included 72 organizations from 15 countries, including Afghanistan, Algeria, Djibouti, Egypt, Iran, Iraq, Lebanon, Pakistan, Palestinian

Territories, Somalia, South Sudan, Sudan, Syria, Turkey, and Yemen. The list of organizations may be found in Appendix A. The data is organized as an unbalanced panel – that is, organizations may enter the sample after the first year and/or depart the sample before the last year. The sample includes 697 organization-years.

Specific Data Used for Logistic Regression

Our unit of analysis is the group-year. In short, each row in our data represents a given group in each year. Our total number of observations is 697. Some of the models include all 697 observations, while others lose a year of data as we lag all independent variables by a year so that last year's actions and structures affect this year's violence.

Dependent Variables

In the models we estimated, we used two dependent variables: *Battle Deaths* and *Terrorism. Battle Deaths* is a variable coded 1 if battle deaths caused by an insurgent group exceed 100 in any year. These deaths are collected by the Uppsala Conflict Data Program (UCDP) and attributed to actions by a specific insurgent organization. *Terrorism* is a measure coded 1 if the organization caused more than 100 deaths in a given year using GTD. Tables 1 and 2 report tabulations of both variables.

Table 1—Battle Deaths < 100 in a year

Battle Deaths > 100	Freq.	Percent
No	567	81.35
Yes	130	18.65
Total	697	100.00

Table 2—Terrorism Deaths < 100 in a year

Terrorism > 100	Freq.	Percent
No	636	91.25
Yes	61	8.75
Total	697	100.00

Independent Variables

Our key independent variables of interest are the strategy of the government regarding each VNSA in the years of our study. We coded four types of counter-terrorism strategies for each government-VNSA pair. Governments can choose:

1) *Do nothing*: Have no observed strategy;
2) *Carrot*: Negotiate, meet with, or make concessions to a VNSA;
3) *Stick*: Use violence, policing, military strikes or other kinetic actions;
4) *Mixed*: Use a combination of violence and negotiation (*carrots* and *sticks*)

Controls

Our model controls for a number of features, including VNSA behavior, number of alliance and/or rivalry connections, regime type of the host state, organizational ideology (specifically, ethnic and/or religious ideological commitments), organizational size, organizational leadership structure, organizational control of territory and/or sponsorship of a political party, and organizational involvement in drug smuggling.

Logistic Regression Methodology

To model the likelihood that an organization in a particular year will break either the 100 terrorism death or 100 battle death threshold we used logistic regression. We used hazard modeling to identify the factors that increase or decrease the time that passes until an actor exceeds the 100 fatality threshold through terrorism or battle.

The coefficients in a logit model are difficult to directly interpret. To ease the interpretations, we used a program called *Clarify* to generate predicted probabilities of how a change in the independent and control variables lead to a change in the probability of that an organization will perpetrate more than 100 deaths through terrorism or battle.

We also did in-sample forecasting as a basis for our reported out-of-sample forecasting. Logit models, unlike ordinary least squares regression, do not produce a meaningful R^2 that can tell us how much of the variation in the dependent variable is explained by the model. Instead Receiver Operating Characteristic (ROC) Curves are a useful way to provide a measure of how well the model predicts positive (here, more than 100 deaths) and negative (less than 100 deaths) outcomes. It is a single score between 0 and 1 with higher numbers meaning better predictions. There is no hard and fast rule, but 90 percent accuracy is regarded as excellent, while ranges in the 80 percent or higher are good. After estimating the models for each, we generated ROC percentages. The model predicts fairly well in-sample. In other words, the model predicts the data that was used to build the model accurately. Our models were 81 percent accurate at predicting highly lethal insurgent groups and 86 percent accurate at predicting highly lethal terrorist organizations. This served as a basis for us to proceed with our out-of-sample forecasting.

To avoid what is termed overfitting – that is, being able to predict the data used to build the model well but not the population at large – we should use the estimated model to predict cases outside of the data we already have. But in our situation – as is often true in the social sciences – we do not have a separate dataset against which to test the data.

A technique called cross-validation allows us to test our model in a way that does not use all the data. There are many ways to do this. We use what is called K(4) cross-validation (Ward, et al. 2010). In short, we cut the data into four pieces. We use three of the pieces to estimate the model. We then test the model on the one piece of data left out of the analysis. We do this four times to ensure that any one piece is not driving the results. We repeat this procedure five times, randomly cutting the pieces differently each time. Thus we estimate the model on data not used to build the model a total of 20 times. ROC curves from each of these pieces then give us an out-of-sample forecast of how well the model predicts killing above 100 fatalities and killing below 100 fatalities. We take an average of the 20 models as a summary of the procedure. For the *Terrorism* models, the model predicts 80 percent of the cases accurately out-of-sample. As we state above, this is good but not perfect. When we have data coded for 2013 and 2014 we can test the model on those periods as well. For the insurgent models, we predict 77 percent of the cases accurately, which does not quite reach the standard for "good." Future data or using new measures could help produce a better prediction.

Hazard Modeling Methodology

Another way to test the effects of CT strategy on violent groups is to examine how it influences *the time* until a group becomes extremely lethal. Up to this point, we have considered the factors that push a group beyond a large fatality threshold. To model the time to a group becoming extremely lethal, we use a technique called hazard modeling.[1] In studies using this technique, the dependent variable is the time to witnessing some outcome or failure. In biostatistics, this tool is used to determine lifespans of patients who do or do not receive some treatment or medicine. In the social sciences, we use it to determine how some variable, like counterterrorism strategy, affects the time to a critical event.

Model Results

Logit model results

In this discussion of our results we should point out that we only discuss the variables that are significant at $p<0.10$ or better. We are uncertain about the effects of variables below this level. In our data, as Tables 1 and 2 shows, there are 61 years where an organization killed more than 100 people in terrorist attacks or 8.75 percent of the total years. The baseline expectation of the statistical model, that is when all variables are set to their means, is that there is a 3.4 percent chance that a group will become highly lethal (killing more than 100 civilians based on GTD data).

The first thing to note is that we cannot include *Carrot* in our model because it perfectly predicts the level of killing. On the one hand, there are no cases where a government uses *Carrot* and a group exceeds 100 terrorism fatalities. On the other, there are 61 cases of a group killing 100 or more in terrorist attacks but no government was using a carrot strategy against those VNSAs in the previous year. The South Asia VNSA, Harkat-ul-Jihad al-Islami, for example, attacks targets in Pakistan, India and Bangladesh. It is moderately sized, does not control territory, but is religious. They negotiated with the Pakistani government in 1999. They have not exceeded the battle death threshold for terror attacks or battle deaths consistent with the predictions of our model. For the *Battle Deaths* model, the baseline probability from our statistical model is much higher: the model predicts that 13.7 percent of organization-years will have more than 100 battle deaths. In 130 (18.65%) of the actual group-years, groups killed at least 100 people in battle. The Taliban and ISIS for example are both larger religious groups that control territory and often exceed these thresholds.

Figures 1 and 2 report the predicted probability from the model that a VNSA exceeds 100 terrorism fatalities (Figure 1) or 100 battle deaths (Figure 2) *in the next year* when a set of variables are manipulated from the minimum to the maximum value *in the present year*. Both graphs show that most VNSAs do not reach the 100 fatalities threshold – the predicted probabilities are all at or below 50 percent. Additionally, the number of VNSAs that can do so declines over time. This is consistent with research that shows VNSA conflict generally leads to a survival of the fittest. One or two powerful groups emerge from a competitive process (Young and Dugan 2014). This is a process we might expect in multi-group conflicts like Syria.

[1] Other terms that are used synonymously include: survival analysis, event history modeling, or duration modeling/analysis.

Figure 1

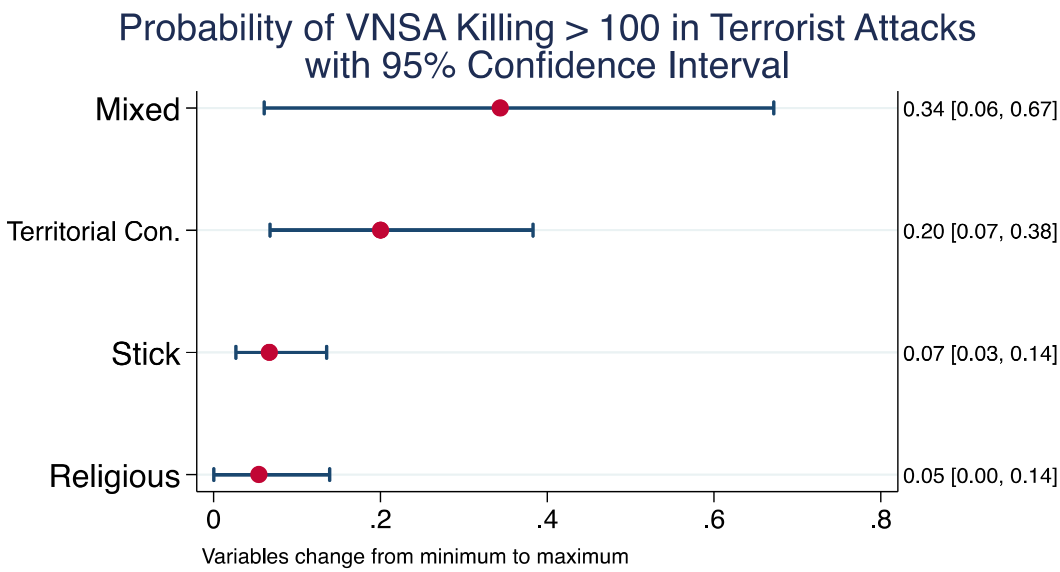
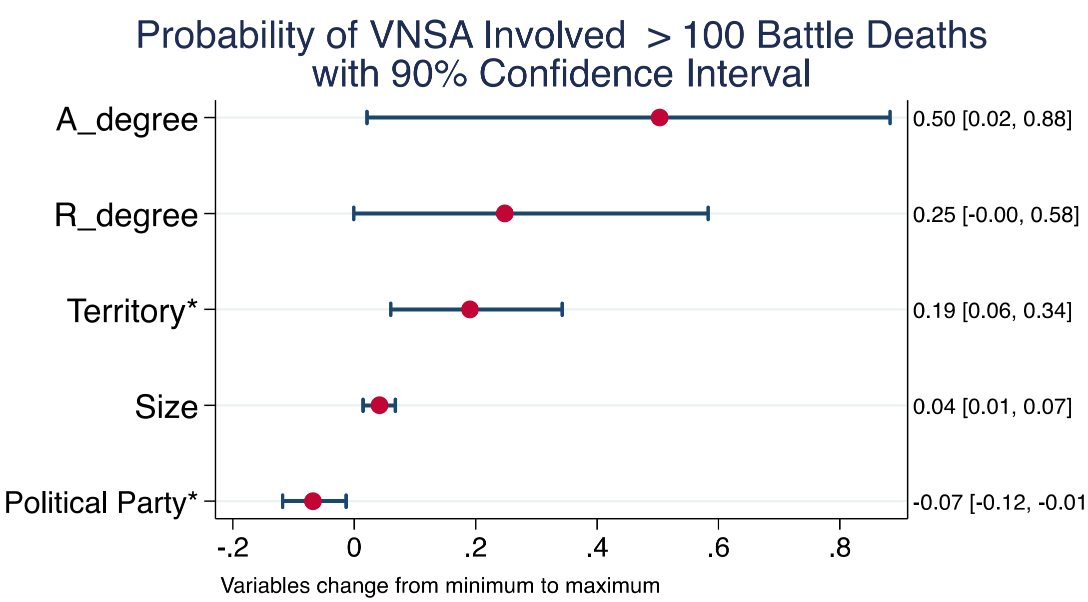


Figure 2



Turning first to the terrorism results, when a *Stick* strategy is used, the probability that a group is highly lethal increases to 7 percent (See Figure 1). This is a 106 percent increase in the probability or a 3.6 percentage point increase over baseline. When a *Mixed* strategy is used the probability that a group is highly lethal increases to 34 percent. **This is a 900 percent increase** in the probability or a 30.6 percentage point increase over baseline.

Territorial Control also has a large effect on the probability that a group will kill prolifically through terrorism. When a VNSA controls territory, the probability that a group is highly deadly increases to 20 percent. This is a 488 percent increase in the probability or a 16.6 percentage point increase over baseline. By contrast, religious ideology has a smaller effect. Religiously-inspired organizations have a 5 percent probability of reaching 100 terrorism kills, which is a 47 percent increase in the probability over baseline.

Turning next to the battle death results, *Alliance and Rivalry connections* increase the number of battle deaths that the group produces. When a group has many alliance connections (A_degree in the Figure 1), this leads to a 36.3 percentage point increase in the probably that a VNSA will cross the 100 battle death threshold. That is a 265 percent expected increase over baseline. When a group has many rivals (R_degree in Figure 2), this leads to an 11.3 percentage point increase in the probably that a VNSA will cross the 100 battle death threshold. That is an 82 percent expected increase over baseline. *Size* has a small positive effect, while having a political party reduces the expected insurgent violence.

Hazard model results

The hazard models use the same variables as the logit models to predict when groups produce high lethality. In general, the results are consistent with the previous models. *Carrot* perfectly predicts the time until a group exceeds 100 terrorism fatalities and thus is dropped from the model.[2] *Mixed* and *Stick* decrease the time until a group will be highly lethal. Similarly, holding territory decreases the time until a group is highly lethal. One important difference is *Religion* decreases the time until a group is lethal but is not related to whether a group becomes highly lethal or not. In other words, among the VNSAs who become lethal, religion seems to speed up their use of violence but not whether or not they actually become excessively deadly. Connectedness, like in the previous models, speeds up the time to becoming highly lethal among both terrorists and insurgents.

[2] A positive coefficient here means that the variable increases the likelihood of failure (exceeding 100 battle deaths and 100 terrorism fatalities). Another way to say it is that a positive coefficient decreases the time to failure.

Figure 3--Probability a Group Produces 100 Battle Deaths Over Time

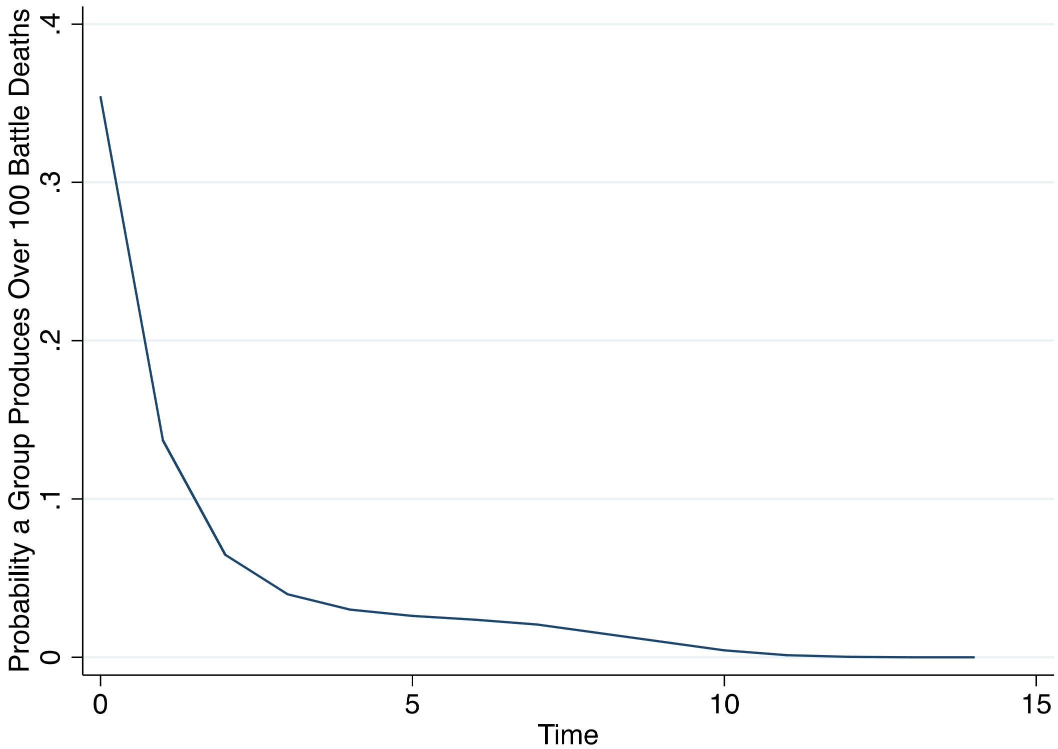
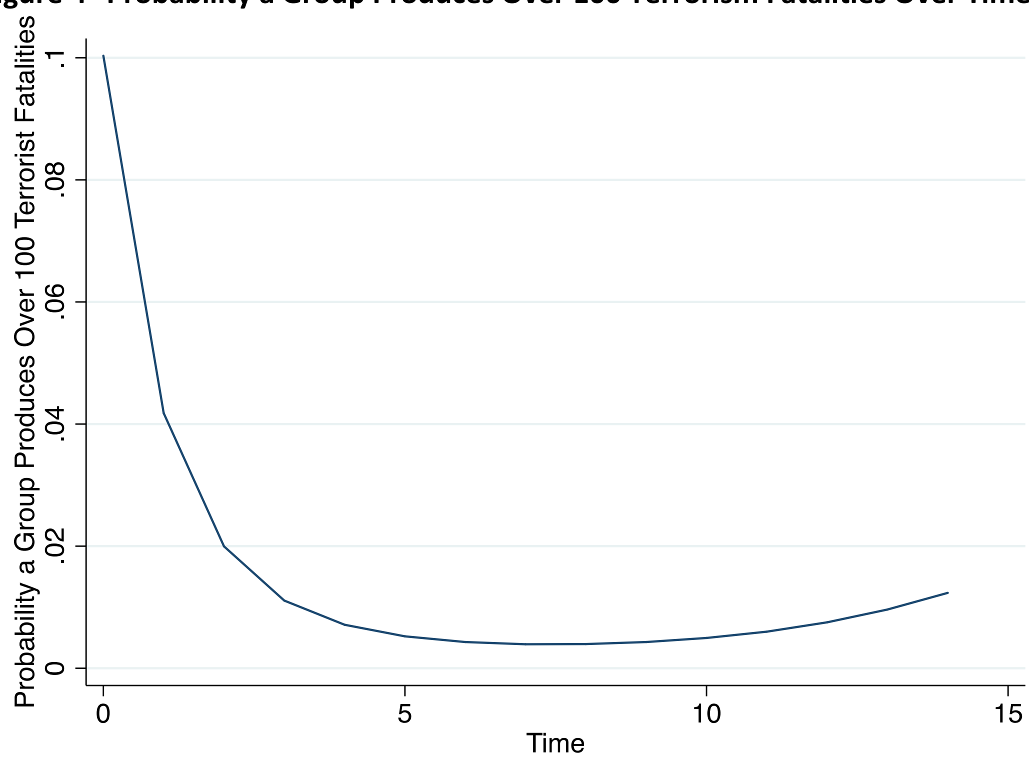


Figure 4--Probability a Group Produces Over 100 Terrorism Fatalities Over Time



Modeling Using Network Analysis

An Introduction to a Network Perspective

Social network analysts have long realized that network formation and behavior are deeply intertwined with one another. However, most analysts have attacked only one side of this feedback loop at a time. Quantitative models of VNSA (primarily terrorist organizations) behavior sometimes include summary measures of network structure – for instance, measures of network centrality – but usually examine only the "influence" channel. That is, these models assume that network position influences behavior. Another group of analysts have sought to understand formation of terrorist networks, their structure, and their evolution. This modeling attacks the "selection" channel, seeking to explain how behavior helps to structure partner selection in networks. Both literatures have created important insights into the behavior of terrorist organizations. However, it is also possible that a simultaneous model may reveal new insights. Additionally, stochastic co-evolution models provide a more rigorous methodological foundation for studying these questions (assuming, of course, that both influence and selection operate) as the well-known issues of simultaneity and observational dependence that may bias other methods are explicitly modeled in this approach.

In Figure 5 we have sketched out a basic co-evolutionary model for VNSA organizational alliance formation and VNSA lethality (in this analysis we focus on terrorist fatalities). Co-evolution models allow one to include exogenous factors that affect only network or the behavior as well as influence and selection effects. Our model is greatly influenced by our previous work on lethality (Asal and Rethemeyer 2008), network formation (Asal, Park, Rethemeyer and Ackerman 2015), and our longitudinal regression analysis done with BAAD2 for this report. Starting with the networks, our previous research found that terrorist networks tend to be:

- Sparse: there is a preference against making connections because connections are costly and dangerous (as the new contact could be a counterterrorism operative);
- Closed: there is a preference to make alliances such that a friend of a friend is also a friend; closed networks improves partner monitoring and makes infiltration harder;
- Ideologically homophilous: Birds of an ideology tend to flock together – and avoid those with differing ideological persuasions;
- Local: Organizations make connections close to home when they can;
- Safety-seeking: Organizations prefer to ally with peers that control territory;
- Capability-seeking: Organizations want friends that have financial, material, or knowledge resources

However, behavior also seems to drive connections:

- Capability seeking: Organizations that kill more may connect more in order to gather resources to maintain operational tempo;
- Success = popularity: Operationally active organizations become more visible and "popular" because they have demonstrated knowledge and capability.

Thus we expected a “selection” effect from lethality to alliance structure.

With respect to the lethality side of the wheel, our previous research and our concurrent modeling for this project found that VNSAs tend to kill when:

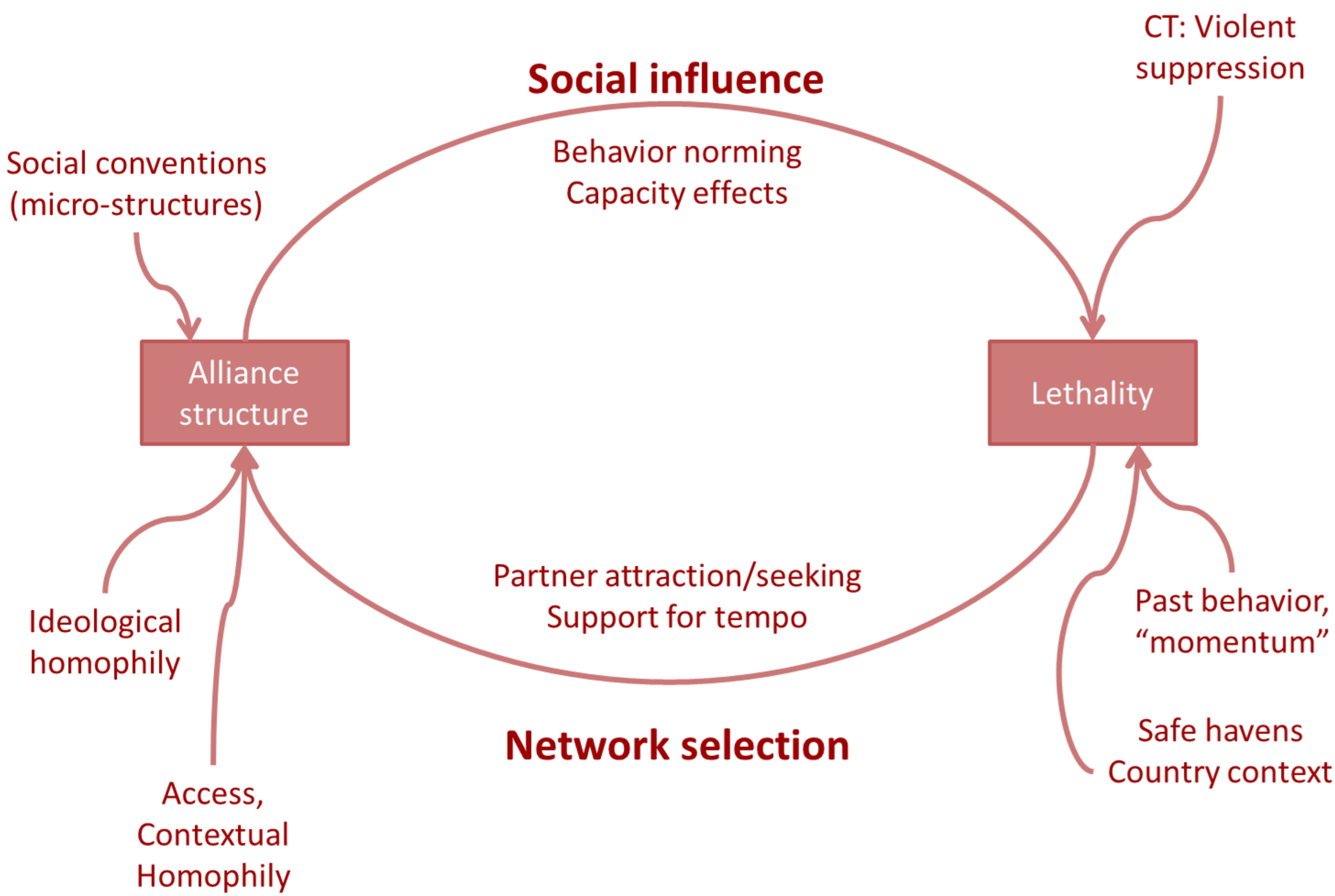
- Momentum builds: Killing today helps to explain killing tomorrow;
- Context allows: (a) Controlling territory makes it easier to safely organize attacks and (b) democracies may make it easier to organize killing because they are committed to more open, unfettered movement and information exchange;
- COIN choices are violent: Using *Stick* may goad VNSAs into violent response.

However, network factors may also help to explain how lethal an organization can or chooses to be:

- Norming: Organizations may choose to norm their level of killing to the level of killing among their alliance connections.
- Resource gathering: The number of alliance connections may indicate the level of resources from secondary sources that are available to invest in lethal attacks.

So we also expect a social influence effect.

Figure 5: Co-Evolution Model of VNSA Alliance Formation and Lethality



Social Network Modeling Approach Used

In order to estimate the model in Figure 5 we used the R-based Simulation Investigation for Empirical Network Analysis (RSIENA) package (Ripley, Snijders, Boda, Voros and Preciado 2015; Snijders 2001; Snijders 2005; Snijders and Duijn 2002; Snijders, Steglich and Schweinberger 2007). RSIENA implements a Stochastic Actor-oriented Model (SAOM) of network and behavior change that is estimated through a Markov Chair Monte Carlo (MCMC) simulation process. For an introduction to RSIENA and the technical aspects of co-evolution modeling, see Ripley, Snijders, Boda, Voros, and Preciado (2015).

As is the case for co-evolution models, our estimations take the 15 yearly alliance networks and the 15 yearly reports of terrorist fatalities as the network and behavior dependent variables, respectively. The other independent variables include:

- A country co-location matrix that takes a one if two VNSAs are operating from the same country;
- Three ideology variables that are mutually exclusive:
  - Religious ideology,
  - Ethnonationalist ideology,
  - Both religious and ethnonationalist ideology;
- An indicator whether an organization controls territory in a given year;
- An indicator whether an organization was subject to a violent counterterrorism strategy or a mixed violent/nonviolent strategy in a given year;
- A count of terrorist fatalities each year for each organization;
- The Freedom House imputed POLITY2 regime type variables, which ranges from 0 (authoritarian) to 10 (democratic).

For the ideology variables, each is general and does not distinguish between types or subtypes. For instance, the religious variables is set to "1" for organizations that are inspired by Islam, Judaism, Christianity, or other major religions. Also, the variable does not distinguish between sub-sects, like Sunni and Shia. The "religious-ethno-nationalist category would include, for instance, organizations that are inspired by, for instance, Islam and Palestinian grievances. Finally, other ideological commitments – leftist, rightist, etc. – were not modeled in this analysis and thus serve as the basis for comparison. Similarly, the ethno-nationalist variable is set to "1" regardless of whether the group is inspired by grievances by the Palestinians, Kurds, etc. This extract is dominated by Islam-inspired organizations.

Additionally, the program itself calculated variables to indicate:

- Social isolates: The group had no connections with other VNSAs in the Middle East that year;
- Closed triads: The number of times an actor was involved in a social arrangement where an ally of ally is also an ally.

The network data for this is "undirected." There was no sense of "direction" where Organization A was coded to be allied with Organization B but Organization B was not coded to be allied with Organization A. Relationships were present or absent. Organizations were also allowed to "enter" and "exit" the data. Some organizations did not form until after the beginning of our time frame; some dissolved during our time frame. RSIENA includes specific procedures to properly cope with "joiners and leavers." We used the method of "joiners and leavers" (Ripley, Snijders, Boda, Voros and Preciado 2015, 33-34).

Per the conventions with this analysis, the model reported in the next section is considered to have "converged" because the estimated parameters are able to reproduce the observed data over several thousand simulations with high fidelity. Convergence is assessed by the difference between the actual network and behavior statistics and the average across the simulations. The program calculates a t-statistic that measures the difference between the observed and measured given the standard deviation of the simulated values. Convergence occurs when the t-statistic is very small (no difference). The convention is that all t-statistics should be below 0.10. For the model reported next, 42 of 43 parameters are below 0.10; one is reported at 0.1066.

Network Analysis Results

Findings

The model results are reported in Table D1 and D2 in Appendix D. Tables D1 and D2 report "standard" t-statistics. That is, the t-statistics are used to determine if the coefficients are statistically significant. Values greater than 1.96 are significant at the 5 percent level and above 1.645 at the 10 percent level. Turning first to the network structure dynamics (see Table D1), as expected, there is a strong tendency for organizations to *avoid* making connections (see *Propensity to form connections* in Table D1), presumably because it is costly and dangerous as noted above. Additionally, there is strong tendency, all else being equal, for organizations that choose to be isolates to stay so over time (see *Network isolates* in Table D1). Again, this points to the strong need for trust and affinity to form connections.

However, the modeling does find three strong bases for connections: shared ethnonationalist ideology, shared religious ideology, and shared "home base" country (see, respectively, *Same ethnonationalist ideology, Same religious ideology,* and *Same country* in Table D1), though organizations that espouse the compound ideology "ethnonationalist-religious" were no more likely to connect than those with other ideological commitments (leftist, rightist, etc.). Also as expected, territorial control is an important factor, though the t-statistic falls just below the 2.00 cutoff. Because our data are not directional we cannot say whether those that control territory become more popular and thus garner more connection, or that territory holders become more outgoing (possibly because they can more securely make connections knowing their main base of operations is safe even if the connection proves to be hostile).

As expected, we also found a clear behavioral dynamic in network formation: the count of fatalities from terrorist attacks is a highly significant predictor of network activity. Like with territorial control, we cannot say for certain whether this is due to popularity (killing attracts peers that seek a partner, trainer, mentor, or supplier) or "outgoingness" (killing requires more supplies and help that may be secured from peers).

Turning now to the behavioral dynamics (see Table D2), the behavioral component of co-evolution models are similar to multinomial logit models where changes from one level to another are modeled. For this reason the dependent variable, fatalities, was divided into nine categories ranging from 0 fatalities to 500 or more.

Our findings indicate that, on average, most organizations do not kill very much (see *Change over time, linear term* in Table D2, which is negative). Indeed, many terrorist organizations never kill. However, the significant quadratic term (see *Change over time, quadratic term* in Table D2) suggests that once organizations start killing, they tend to move to higher and higher levels of killing. In co-evolutionary models a positive coefficient on the quadratic term is usually indicative of an "addictive" behavior that feeds on itself. Our analysis of *Territory control* and *Regime type, home base country* (see Table D2) confirms our previous findings that organizations that control territory and operate from more democratic countries tend to kill more. The *CT strategy: violent or violent & nonviolent* variable in Table D2 also confirms a finding from other work in this study: "mixed" counter-terrorism strategies elicit increased violence.

The last two variables in Table D2 seek evidence of the network effect on behavior. The first variable, *Behavior norming to triadic member*, measures the extent to which killing is normed to others in a closed triad. The effect is not significant. For what it is worth, the sign is negative, suggesting that organizations kill *less* when they have two connected allies that kill *more,* which is counter to our expectations. The second modeled effect, *Behavior effect from being an isolate*, is significant. This finding suggests that isolates are significantly less likely to kill. If isolates do kill, they tend to ratchet down their killing over time.

The "isolate" effect is interesting because it closes a causal loop. We know from the network dynamics that isolates tend to stay isolates over time. The behavior dynamics suggest that isolates usually do not kill prolifically; if they do kill they usually ratchet down their killing. Over time, this mutual feedback suggests, all else being equal, that in the Middle East there is a relatively stable state: isolated groups tend to stay isolated, tend not to kill much, tend not to start killing if they are not currently killing, and tend to kill less over time if they start. This is not to say that these groups will not engage in other forms of violence, just that killing is largely off the table.

The key phrase in the above discussion is "all else being equal." The analysis suggests that there are some factors that can nudge an organization away from being an isolate – for instance, ideological affinity. Also, the model is stochastic, so random and unmodeled factors could move organizations away from isolation. It does suggest, however, that any observed movement from organizational isolate status toward broader engagement with terrorist "peers" may initiate a process that ratchets up killing. We also know that once killing commences, all else being equal, there appears to be a dynamic toward escalation. The model suggests that this transition – from isolate to engaged – should be considered a predictor of future violence.

Conclusions

Our analysis of VNSAs in the MENA region from 1998 to 2012 has some important implications for strategies to deal with successful violent organizations. We found using a variety of methodologies that several factors enable us to identify which organizations are likely to be more deadly as well as COIN/CT factors that make organizations more or less likely to be deadly.

- When it comes to organizational lethality, a stick or a mixed approach to counter-terrorism/counter-insurgency makes organizations more likely to be violent while carrot approaches may make the use of violence less likely.
- Our findings also underline the importance of the following factors when it comes to identifying which organizations are likely to be much more deadly:
    - Territorial control
    - Organizational size
    - Alliance and rivalry connections.

When it comes to being less likely to be deadly, our social network analysis provides an additional nuance: isolated organizations are less likely to be extremely lethal.

Our social network analysis modeling efforts also hint at other dynamics that we plan to explore in the future, including:

- The possibility that more connected organizations move to higher levels of killing faster,
- That social norming of killing may occur based on network structures other than closed triads,
- That the network of rivalrous connections – that is, connections of enmity, distrust, hostility, and outright conflict – may also affect both network and behavioral dynamics.

We should note, though, that this is a first cut at this analysis that focuses specifically on the MENA region. We are not modeling smaller organizations, nor do we model connections outside of MENA. In the future we also plan to examine how government strategies over the long run may impact the termination or survival of such organizations and the end of conflicts.

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Appendix A: Organization List

Organizations
Al-Aqsa Martyrs Brigade
Al-Fatah
Al-Gama'at Al-Islamiyya (IG)
Al-Ittihaad Al-Islami (AIAI)
Al-Qa'ida
Al-Qa'ida in the Arabian Peninsula (AQAP)
Ansar Al-Islam
Armed Islamic Group (GIA)
Baloch Liberation Army (BLA)
Democratic Front for the Liberation of Palestine (Dflp)
Eastern Turkistan Islamic Movement (ETIM)
Hamas (Islamic Resistance Movement)
Harkatul Jihad-E-Islami
Hizballah
Hizb-I-Islami
Hizbul Mujahideen (Hm)
Islamic Army in Iraq (al-Jaish al-Islami Fi al-Iraq)
Great Eastern Islamic Raiders Front (Ibda-C)
Islamic Jihad Group (IJG)
Islamic Movement of Uzbekistan (IMU)
Jaish-E-Mohammad (Jem)
Jamiat Ul-Mujahedin (Jum)
Kurdistan Freedom Hawks (Tak)
Kurdistan Workers' Party (PKK)
Lashkar-e-Jhangvi
Lashkar-E-Taiba (Let)
Lord's Resistance Army (LRA)
Mahdi Army
Mujahedin-e Khalq (MEK)
Islamic State of Iraq and al Sham (ISIS)
Abdullah Azzam Brigades
Palestinian Islamic Jihad (PIJ)
Popular Front for the Liberation of Palestine (PFLP)
Popular Resistance Committees
Salafist Group for Preaching and Fighting (GSPC)
Sudan People's Liberation Army (SPLA)
Taliban
Devrimici Halk Kurtulus Cephesi (Dhkp/C)
Eritrean Islamic Jihad Movement (EIJM)
Jundallah

Asa'Ib Ahl Al-Haqq
Baloch Liberation Front (Blf)
Al-Qa'ida in the Lands of the Islamic Maghreb (AQLIM)
Free Syrian Army
Kurdistan Free Life Party
South Sudan Liberation Army (SSLA)
United Baloch Army (Uba)
Lashkar-E-Islam (Pakistan)
Islamic Courts Union (ICU)
Sindhu Desh Liberation Army (Sdla)
Tehrik-i-Taliban Pakistan (TTP)
Al-Shabaab
Haqqani Network
Tehreek-e-Nafaz-e-Shariat-e-Mohammadi (TNSM)
Justice and Equality Movement (JEM)
Front for the Restoration of Unity and Democracy - Ahmed Dini Faction
Al-Qa'ida In Yemen
Baloch Republican Army (BRA)
Somali Reconciliation and Restoration Council (SRRC)
Sudan Liberation Movement/Army-Unity
Hizbul Al Islam (Somalia)
National Redemption Front
The Northern Alliance (or United Islamic Front for Salvation of Afghanistan - UIFSA)
Sudan Liberation Movement
Southern Mobility Movement (Yemen)
Sudan Liberation Movement/Army - Minni Minawi Faction
Harakat Ras Kamboni
Union of Forces for the Resistance (UFR)
South Sudan Defence Movement/Army
Sudan People's Liberation Movement-North
Al-Nusrah Front
Sudan Revolutionary Front

Appendix B: Models Predicting Which Groups Become Highly Lethal

The models reported here are estimated using the same independent variables, and the same estimator (logit). Next to variable names are the reported coefficients and standard errors in parentheses followed by the p values. The coefficients are not directly interpretable but the direction matters. A positive coefficient increases the likelihood of a group passing the battle death or terrorism fatality threshold, whereas a negative coefficient decreases this probability.

	Terrorism			Battle Deaths		
Variable	coef	(se)	pval	coef	(se)	pval
Carrot	--	--	--	-0.772	(0.972)	0.427
Stick	0.478***	(0.731)	0.000704	0.500	(0.582)	0.390
Mixed	0.142***	(0.802)	0.00757	0.255	(0.654)	0.696
Social Services	0.626	(0.686)	0.362	-0.101	(0.716)	0.888
Ethnic	0.477	(0.560)	0.394	0.572	(0.549)	0.297
Religious	1.442*	(0.767)	0.0601	-0.0715	(0.549)	0.896
Size	0.394	(0.324)	0.225	0.622**	(0.299)	0.0378
Leadership	0.306	(0.372)	0.411	0.0255	(0.272)	0.925
Political Party	1.343	(0.842)	0.111	-1.319*	(0.718)	0.0663
Territorial Control	.560***	(0.482)	0.00122	1.257***	(0.465)	0.00690
State Sponsor	0.315	(0.510)	0.537	-0.180	(0.503)	0.720
Drug Trafficking	0.113	(0.619)	0.856	1.089	(0.801)	0.174
Count, Rivals	0.311	(0.256)	0.224	0.560*	(0.327)	0.0867
Count, alliances	0.0629	(0.0487)	0.196	0.117*	(0.066)	0.0754
Democracy	20.351	(0.425)	0.410	-0.302	(0.427)	0.479
Constant	6.383***	(1.324)	1.43e-06	-3.881***	(0.926)	2.77e-05
N	607			625		

Robust standard errors in parentheses clustered on group
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: Hazard Models Predicting Time to Becoming Highly Lethal

In this appendix, the two models reported are the same with only the dependent variable changing. This model is estimated using a set of independent and control variables and three variables to model the time to an event: time, $time^2$, and $time^3$. While we are using a discrete time model with a logit estimation, using these three time variables to model temporal dependence is analogous to a cox proportional hazards model. We estimated several other kinds of hazard models with different parametric assumptions. The results are consistent across these changes. Positive coefficients suggest the variable decreases the time until a group crosses this threshold. Negative coefficients suggest that the variable increases the time until a group would become highly lethal.

	Terrorism Fatalities			Battle Deaths		
Variables	coef	se	pval	coef	se	pval
Carrot	--	--	--	2.142**	(1.029)	0.037
Mixed	2.906**	(1.472)	0.048	2.394***	(0.725)	0.001
Stick	3.755**	(1.704)	0.028	2.606***	(0.737)	0.000
Social Services	0.474	(0.485)	0.328	-0.369	(0.443)	0.405
Ethnic	0.403	(0.458)	0.378	0.164	(0.362)	0.652
Religious	1.421***	(0.529)	0.00721	-0.154	(0.351)	0.661
Size	0.591*	(0.315)	0.0608	0.668***	(0.243)	0.006
Leadership	0.177	(0.475)	0.710	-0.001	(0.201)	0.996
Political Party	1.015	(0.867)	0.242	-0.757	(0.564)	0.180
Territorial Control	1.171***	(0.390)	0.00271	1.438***	(0.384)	0.000
State Sponsor	0.150	(0.521)	0.773	-0.078	(0.337)	0.817
Drug Trafficking	0.074	(0.573)	0.897	0.774	(0.523)	0.139
Count, Rivals	0.568**	(0.261)	0.0292	0.525**	(0.220)	0.017
Count, alliances	0.078	(0.051)	0.128	0.109***	(0.030)	0.000
Democracy	20.135	(0.400)	0.736	-0.319	(0.347)	0.359
Time	1.026***	(0.308)	0.001	-1.472***	(0.287)	0.000
$Time^2$	20.0965	(0.068)	0.156	0.249***	(0.083)	0.003
$Time^3$	0.002	(0.004)	0.508	-0.015***	(0.006)	0.007
Constant	6.889***	(2.368)	0.004	-4.103***	(0.929)	0.000
Obs.	676			697		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Co-Evolution of Alliances and Lethality – Network Dynamics

The Table A below contains the model results for both network and behavior dynamics. The rate parameters in both sections are necessary controls but not interpretable (so-called "nuisance parameters") in the context of this study. The other parameter estimates are similar to logit coefficients: the magnitude is not directly interpretable, but the sign and statistical significance are. The t-statistics reported here are *not* convergence statistics but traditional t-statistics that indicate statistical significance. A value of 2 or higher is strongly significant; values between 2.00 and 1.66 are weakly significant; values below 1.66 are insignificant.

Table D1: Co-Evolution of Alliances and Lethality – Network Dynamics

Effect	par.	(s.e.)	t stat.
Rate, period 1	0.18	-0.126	.
Rate, period 2	0.276	-0.119	.
Rate, period 3	0.476	-0.174	.
Rate, period 4	0.414	-0.152	.
Rate, period 5	0.701	-0.24	.
Rate, period 6	0.401	-0.157	.
Rate, period 7	0.371	-0.136	.
Rate, period 8	0.352	-0.124	.
Rate, period 9	0.499	-0.15	.
Rate, period 10	0.441	-0.13	.
Rate, period 11	0.623	-0.137	.
Rate, period 12	0.235	-0.084	.
Rate, period 13	0.532	-0.171	.
Rate, period 14	0.269	-0.093	.
Propensity to form connections	-4.344	-0.445	9.759
Network closure (transitive triads)	0.678	-0.161	4.208
Network isolates	3.528	-0.688	5.13
Same country	1.587	-0.229	6.942
Same ethnonationalist ideology (1=yes)	0.728	-0.324	2.248
Same religious ideology (1=yes)	0.95	-0.267	3.563
Count, fatalities from terrorist attacks	0.255	-0.057	4.471
Territory control (1=yes)	0.662	-0.345	1.92

Table D2: Co-Evolution of Alliances and Lethality – Behavior Dynamics

Effect	par.	(s.e.)	t stat.
Rate, period 1	6.666	-6.29	.
Rate, period 2	2.222	-1.084	.
Rate, period 3	31.355	-20.161	.
Rate, period 4	5.453	-2.32	.
Rate, period 5	14.115	-8.8	.
Rate, period 6	13.733	-7.084	.
Rate, period 7	5.075	-2.137	.
Rate, period 8	17.993	-6.179	.
Rate, period 9	75.976	-19.773	.
Rate, period 10	4.979	-1.761	.
Rate, period 11	16.857	-4.114	.
Rate, period 12	2.284	-0.684	.
Rate, period 13	5.429	-3.833	.
Rate, period 14	14.785	-8.285	.
Change over time, linear term	-0.883	-0.075	11.824
Change over time, quadratic term	0.064	-0.007	8.602
Territory control (1=yes)	0.226	-0.057	3.961
Regime type, home base country (1-10)	0.02	-0.009	2.071
CT strategy: violent or violent & nonviolent	0.599	-0.105	5.695
Behavior norming to triadic members	-0.008	-0.006	1.278
Behavior effect from being an isolate	-0.280	-0.097	2.875