License to Kill: Terrorist Group Relationships and Lethality

Kayla Kahn

ABSTRACT

Existing literature in the terrorism field emphasizes the connection between terrorist group alliances, rivalries, and lethality. Building off of the extant literature, this study uses original data on alliances and rivalries in order to assess lethality while accounting for dependence between terrorist groups. I find little evidence that the count of alliances drives lethality. Instead, it is embeddedness of a group within the broader alliance network that leads to increased lethality. I also find support for the outbidding hypothesis.

1. Introduction

What makes some terrorist groups so lethal? Terrorist groups must be able to mobilize resources in order to survive and to commit attacks. These resources include funding, weapons, bases, and even members. There are various ways that organizations acquire resources: state sponsorship (Byman 2005; Carter 2012; San-Akca 2016), diasporas (Byman et al. 2001; Piazza 2018), and crime (Piazza and Piazza 2020), to name a few. This study focuses on alliances between terrorist organizations, adopting the notion that alliances serve as a source of resources and therefore can lead to increased capacity.

Scholarship in the terrorism field and the closely related civil war field has explored the effect of alliances on lethality and survival, but most research thus far does not use social network analysis. Instead, these studies use traditional regression models with the unit of analysis as the dyad-year or group-year (e.g. Acosta 2016; Asal and Rethemeyer 2008; Horowitz and Potter 2014; Phillips 2019; Balcells, Chen, and Pischedda 2022). Work done by Asal and Rethemeyer (2008); Horowitz and Potter (2014); Asal, Phillips, and Rethemeyer (2022) calculate descriptive network statistics, thus coming closer to using network analysis, but these pieces incorporate the network statistics into traditional regression models. This leads to biased results by assuming the independence of groups or dyads.

There are a few notable exceptions in which scholars explore which group-level factors make terrorist groups or insurgent groups more likely to ally (Asal et al. 2016; Gade et al. 2019) or use latent space models to infer actor positions in a network (Metternich et al. 2013). This paper differs because it does not seek to understand what drives alliances. Instead, I use network analysis to explore a group-level behavior: lethality. I use a temporal network autocorrelation model TNAM, which treats the network ties as exogenous and allows me to examine a behavior rather than network structure as the dependent variable while also incorporating dependencies between the groups in the study.

I use this network method to re-examine hypotheses about alliances and lethality that have had ambiguous findings in the terrorism literature. I also incorporate rivalry in order to test the outbidding hypothesis. Using original data on alliances and rivalries among groups that have had a major presence in Lebanon, I find support for the idea that it is network embeddedness rather than the number of allies that affects lethality. I also find support for the outbidding hypothesis. The finding that lethality is affected by the importance of allies is important from a policy perspective. The findings show that when focusing on disrupting alliances, counterterrorism efforts should be on interrupting links that tie groups to very core groups within a network.

The article continues with an overview of alliances among violent subnational groups and the effect that these alliances have had on group tactics, targets, and lethality, which leads to my first two hypotheses. While my analysis is on terrorist groups, I draw widely from literature on militant groups not limited to terrorist groups. Next, I discuss rivalry and competition among these groups, which leads to my last hypothesis. I then discuss the data collection process and the variables to be included in the analysis. This is followed with a discussion of the results. I conclude by discussing the next steps.

2. Alliances

Militant groups need resources — including material resources as well as recruits, skills, and knowledge — in order to survive. One way for militant groups to gain resources is through alliances (Acosta 2014; Asal and Rethemeyer 2008; Asal and Shkolnik 2024; Moghadam 2017; Phillips 2014; Price 2012; Topal 2024). Indeed, it is precisely the lack of resources or the desire for further resources that drives militant organizations to cooperate (Bacon 2018b; Bapat and Bond 2012; Plapinger and Potter 2017). This is applicable to both terrorist groups (Asal and Rethemeyer 2008; Horowitz 2010; Phillips 2019) and larger insurgencies embroiled in civil war (Akcinaroglu 2012; Bapat and Bond 2012). For instance, terrorist groups that hold territory — a valuable resource in that it provides a safe haven and training grounds — are more likely to have an alliance than groups that do not hold territory (Phillips 2019). This suggests that groups that hold territory are seen as useful to other groups, and Phillips (2019) even points out that territory-holding groups tend to be stronger groups that might have the means to provide allies with security or weapons in addition to a safe haven.

The increase in resources that stems from these alliances should lead naturally to a corresponding increase in capacity. This is demonstrated in a number of ways. Militant groups with allies have been found to last longer (e.g. Acosta 2014; Hou, Gaibulloev, and Sandler 2020; Pearson, Akbulut, and Lounsbery 2017; Phillips 2016, 2014; Price 2012) and have also been able to fight civil wars for longer (e.g. Akcinaroglu 2012). Alliances have enabled militant organizations to turn to attacks against logistically difficult targets such as schools or journalists (Asal, Phillips, and Rethemeyer 2022). Cooperation has also led organizations to diversify their tactics. In one of the earliest studies on terrorist groups and alliances, Oots (1986) examined transnational attacks from 1968–1977 and found that when the attacks were joint — meaning that they were committed by at least two groups — they were more likely to be moderately difficult types of attacks, such as armed attacks and hijackings, whereas single-group transnational attacks were more likely to be logistically simple "hit-and-runs," such as bombings. Likewise, organizations embedded within an alliance network have been found to be more likely to pursue the use of CBRNs as opposed to organizations less embedded in the alliance network (Asal, Ackerman, and Rethemeyer 2012).

Several studies have explored alliances and changing tactics by focusing on one of the more lethal types of terrorism: suicide attacks.[1] However, there is some disagreement in the direction of effects when it comes to linking alliances and the spread of suicide attacks. On one hand, Horowitz (2010) finds that suicide attacks diffuse across a network, spreading from particularly strong groups outward as the tactic is picked up by groups linked to the stronger groups. This, Horowitz (2010) argues, is a facet of alliances facilitating shared information about tactics and efficiency; groups learn new tactics from their partners. Jammat-ul-Ahrar[2], for example, greatly increased its amount of suicide attacks after affiliating with Islamic State–Khorasan Jadoon 2022. On the other hand, Acosta (2016) finds that organizations adopt suicide attacks in order to ingratiate themselves to and ally with the stronger organizations already using the tactic. Yet, exploring this relationship with the use of network analysis techniques, Asal et al. (2016) find that terrorist groups that commit suicide attacks do have more allies but that these groups do not seek one another out on the basis of suicide attacks as a tactic. In other words, militant groups attempt to ally with groups that use suicide attacks, but the groups that already use suicide attacks do not necessarily look for use of this tactic as the basis of connection. They find similar results with regard to lethality: highly lethal militant groups have more connections than groups with low lethality, but highly lethal groups are not necessarily connected to one another. One potential implication that stems from this is that many groups seek to ally with more lethal groups because of the resources that these groups have.

In this study, I focus on the way that alliances affect organizational lethality. Because alliances allow expanded access to resources, alliances are associated with more deadly groups (Horowitz and Potter 2014; Asal and Shkolnik 2024). There are different ways of measuring alliances, from a sheer count of ties to the quality of those ties to embeddedness within an entire network of organizations. Approaching cooperation as a binary concept — a group either cooperates with at least one other group or it does not cooperate — Oots (1986) found that transnational attacks from 1968–1977

[1] For source on suicide attacks and lethality, see: Mroszczyk (2019).

[2] Splinter group of Tehrik-i-Taliban Pakistan

had higher fatalities when they were joint attacks than attacks committed by a single group. Moving beyond a binary measurement of alliances, more recent research has examined the number of alliances, finding that a higher number of allies increases the number of fatalities caused by terrorist organizations (Asal and Rethemeyer 2008). Likewise, among insurgent groups, a higher alliance count has been shown to greatly increase battle deaths and even to make it more likely that a group will cross the 1,000 battle death threshold that indicates a high-intensity conflict (Asal and Shkolnik 2024).

Yet, other studies find that the number of alliances does not play a significant role in terrorist group lethality (Horowitz and Potter 2014; Olzak 2022; Pearson, Akbulut, and Lounsbery 2017). Instead, recent research argues that while alliances do affect lethality, it is not a straightforward count of allies that makes an impact but rather the quality of these alliances. Eigenvector centrality, for example, is a measure of how central each organization is in a network based on the centrality of its direct and indirect allies (Bonacich 1987). Said another way, being connected to an organization with many allies has more of an impact than being directly connected to an organization with few allies. Where the number of alliances has been found to be insignificant, eigenvector centrality — the connectedness of alliance partners — has been found to be associated with an increase in the number of fatalities caused by terrorist groups Horowitz and Potter (2014); Pearson, Akbulut, and Lounsbery (2017) and an increase in the number of attacks committed by terrorist groups (Pearson, Akbulut, and Lounsbery 2017). Similarly, Asal, Phillips, and Rethemeyer (2022) measure network embeddedness using a form of closeness centrality, which is a measure of how many steps a group must take to reach all other actors in a network so that groups that are closer to all other groups are the ones that are most embedded. They find that being further embedded in the alliance network of militant organizations is associated with an increase in both fatalities and frequency of attacks (Asal, Phillips, and Rethemeyer 2022).

My first two hypotheses stem from the above discussion on resources, alliances, and lethality. In line with Asal, Phillips, and Rethemeyer (2022); Horowitz and Potter (2014); Pearson, Akbulut, and Lounsbery (2017), I expect that it is embeddedness in the network that matters more so than the count of alliances. This is because a few strong terrorist organizations with a wealth of resources, such as al-Qaeda or Islamic

State, tend to function as "hubs" at the core of a network (Bacon 2017, 2018a; Blair and Potter 2022). Therefore, allying with one or more of these "core" groups should have a larger impact on capacity than allying with smaller, less resource-wealthy groups. Note that below I frame H1 as a hypothesis in order to test the argument seen frequently in extant literature, but I expect that I will not be able to reject the null hypothesis.

$H1$: *Terrorist organizations with a higher number of alliances will be more lethal.*

$H2$: *Terrorist organizations that are more embedded in the alliance network will be more lethal.*

3. Rivalries

Whereas in some circumstances, militant organizations cooperate to overcome resource scarcity, in other cases, limited resources and political power drive these organizations into violent competition (Chenoweth 2010; Conrad et al. 2021; Fjelde and Nilsson 2012; Christia 2012; Hafez 2020; Gade, Hafez, and Gabbay 2019). This competition frequently leads to outbidding, which is the concept that militant groups engage in more violence as they attempt to convince a target population that only they have the resolve to achieve the goals of the general population (Kydd and Walter 2006). Competing groups turn to more violent tactics like suicide attacks (Bloom 2005), bombings, assassinations, and armed assaults which are meant to kill in higher numbers as opposed to hostage taking, hijacking, or infrastructure attacks (Conrad and Greene 2015) as a form of outbidding that maintains or wins over support from a target population. Rebel groups involved in civil wars also change tactics to set themselves apart from other groupsto outbid other groups for constituent support, or to become more likely to achieve concessions from the government (Tokdemir et al. 2021; Vogt, Gleditsch, and Cederman 2021). Among competing rebels involved in civil wars, ideologically extreme groups turn to infighting with other groups, trying to eliminate them entirely, while the less extreme groups engage in tactics like outbidding in order to gain support (Hafez 2020).

Competition has also led both insurgent groups and terrorist groups to change their targets and to attack more or commit more lethal attacks. This is the most straightforward application of the outbidding theory. Having more active terrorist groups with which to compete has led to increased levels of terrorism (Nemeth 2014), and has led terrorist organizations to turn from attacking infrastructure to civilian targets (Conrad and Greene 2015). The same is true of insurgent groups when faced with other insurgent groups trying to extract from the same pool of resources; these groups turn to coercive forms of support and increase their attacks or the severity of their attacks (Conrad and Spaniel 2021; Gassebner, Schaudt, and Wong 2023; Metelits 2009; Wood and Kathman 2015). Dorff, Gallop, and Minhas (2023) break away from conceptualizing competition as the number of groups in one area. They find that it is not the number of groups but rather how many groups contribute to the violence within a conflict that affects civilian victimization; when more insurgent groups contribute violence to the conflict equally, civilian victimization is higher. Conrad and Spaniel (2021) argue that outbidding attacks increase even more when the state faces high costs in enforcement measures. Farrell (2020) looks beyond groups within the same area and argues that outbidding can occur with transnational terrorism as ideologically similar groups compete even across state lines. She finds support for the argument, with ideologically similar groups increasing the number and severity of attacks as the number of groups sharing the ideology increases. On the other hand, though not necessarily at odds with the findings of Farrell (2020), Belgioioso and Thurber (2024) find that within mass dissident campaigns, including both violent and nonviolent groups, terrorism is more likely when the campaigns are ideologically diverse, because this increases the likelihood of groups seeing interactions as zero-sum.

Other studies consider direct rivalry between groups. That is, rather than examining the number of active terrorist or insurgent groups within an area, ideology, or conflict, they consider the network of fighting groups or whether groups attack each other. With this different conceptualization of competition, findings are similar: Insurgent groups embedded in a network of rivalries commit more attacks and kill in larger numbers (Asal, Phillips, and Rethemeyer 2022; Conrad, Greene, and Phillips 2023). Insurgent groups embroiled in violent rivalries turn to terrorist attacks against the general public as opposed to more specific targets like schools or journalists (Asal, Phillips, and Rethemeyer 2022). Even previously peaceful ethnopolitical organizations have turned to violence when trying to win support over other groups that claim to support the same ethnic group (Asal and Phillips 2018), and Conrad, Greene, and Phillips (2023) find that even nonviolent rivalryleads to higher levels of civilian fatalities.

The discussion on outbidding leads to my fourth hypothesis.

> $H3$: *Terrorist organizations with a higher number of rivalries will be more lethal.*

4. Research Design

This paper uses network analysis instead of traditional hypothesis testing models. First, traditional regression models assume the independence of observations (Desmarais and Cranmer 2018; Schoeneman and Desmarais 2020). From the discussion of alliances and rivalries, we know that terrorist groups are not independent of one another. They can share a variety of resources that affect not only their ability to commit attacks but also the types of attacks they commit, and furthermore, they may commit attacks based on the attack behavior of the groups to which they are connected.

One option to account for cooperative and competitive connections is to conduct traditional regression models at the dyad-year level. However, the independence of dyads cannot be assumed (Cranmer and Desmarais 2016); terrorist group cooperation and competition within dyads is related to the behavior of other dyads. Aside from the non-independence of dyads, other problems arise. At the dyad level, the number of observations is artificially inflated with the number of dyads equal to all possible combinations of terrorist groups in the data, which in turn drives down the standard errors as the number of observations becomes too large (Cranmer, Desmarais, and Menninga 2012). This makes it much more likely to see incorrectly significant results. Related, as pointed out by Cranmer, Desmarais, and Menninga (2012) in the study of state alliances, in dyad-level models, multilateral alliances are treated as several bilateral alliances. Using a dyad-level analysis here would lead to a similar problem, with alliances or rivalries between more than two terrorist organizations being incorrectly treated as several distinct alliances or rivalries between two organizations, creating an incorrect number of these relationships.

Network analysis can account for interdependence that is left unaddressed in traditional models (Cranmer and Desmarais 2016; Wasserman and Faust 1994). It allows for modeling actor-level covariates, dyad-level covariates, and even higher order dependencies (Cranmer, Desmarais, and Menninga 2012). In network analysis, the actors — in this case, terrorist organizations — are called *nodes* and the social relations between the nodes — in this case, alliances or rivalries — are called *ties*. The network is comprised of all nodes in the sample and the ties between them. This study uses time varying networks comprised of terrorist organizations and their alliance and rivalry ties, discussed further below.

Many network models aim to assess how nodel-level or dyad-level covariates affect the overall network structure or the formation of ties between nodes. This research, in contrast, aims to assess how the network of relationships affects actors' behavior. I therefore use a temporal network autocorrelation model (TNAM). TNAM allows modeling an actor-level dependent variable while controlling for the aforementioned network dependencies (Doreian 1992; Duxbury 2023)

4.1. *Data*

4.1.1. Network Data

I construct original data on terrorist group alliance and rivalry, coded initially at the dyad-year level and restructured to be yearly network data. The organizations included in the data are terrorist organizations that have had a major presence in Lebanon at any time since 1970, though I ultimately limit the years of the dataset from 2000 to 2016. The end year is chosen because one of the datasets that is used in establishing the sample of the groups to include, Extended Data on Terrorist Groups (EDTG; Hou, Gaibulloev, and Sandler 2020) goes through 2016. The starting year of the data is chosen because Israel remained in Lebanon after Lebanon's 15-year civil war and eventually pulled out of Lebanon in 2000. The data include 23 groups, though each group is not necessarily present for all years in the time frame.

For the data and the following analysis, terrorism is defined as the premeditated use of violence by a subnational actor targeting an audience beyond the immediate victims in order to achieve a political, social, or religious goal. Accordingly, a terrorist group is any group that uses terrorism. Choosing the scope of the groups to be included posed difficulties because in international conflict literature, terrorism is understood to be committed by subnational groups, while similar types of violence done by the state fall into the category of state repression. However, in Lebanon, some groups that are involved in government also commit acts of terrorism and are by and large considered terrorist organizations and are included in major terrorism datasets, such as the Global Terrorism Database (GTD; START 2020). Hezbollah is a predominant example of this. In 2008, the militias of several political parties — including Future Movement, Hezbollah, and Syrian Social Nationalist Party, among others — were involved in a series of clashes, some of which targeted civilians. These groups are included in my data, so to account for their participation in government, I also include a binary variable indicating whether the groups in the data are political parties involved in the government, discussed further below. The final data include Lebanese militant groups, Lebanese political parties with militant wings, and Palestinian militant groups. A number of Palestinian groups are included because in addition to having played a large role during the 1975–1990 civil war, these groups also are spread among refugee camps.

I use the Militant Group Alliances and Relationships dataset (MGAR; Blair et al. 2021) as the base of groups to be included in the sample, first limiting the dataset to groups based in Lebanon, and then checking groups based in Israel/Palestine or in Syria for whether they had a major presence in Lebanon. MGAR intentionally treats militant wings as distinct from the major groupfootnoteFor example, al-Qassam Brigades is coded as a separate group than Hamas. I carefully cleaned and, where necessary, aggregated the MGAR data so that aliases, misspellings, and armed wings were not counted as separate groups. I then examined EDTG for groups based in Lebanon that may not have ended up in the sample due to having a different base listed in the MGAR data and I added these organizations to the sample.

Alliance is intended to indicate tactical or logistical cooperation, following the conventions of (Acosta 2016; Horowitz and Potter 2014; Phillips 2019). The alliance need not be formal; there must be some evidence of tactical or logistical cooperation even if that cooperation happens without a formally declared alliance. The type of cooperation includes joint attacks or planning, training, funding, providing weapons, or shared members. If there is evidence of this type of cooperation in a dyad-year, then that dyad-year is coded as having an alliance. Although access to a base that functions as a safe haven and/or training grounds is an important type of resource, evidence of a shared base is not grounds for coding an alliance. This is because, for example, groups may be based together in a refugee camp while not cooperating, and even may be fighting while sharing a base, as was the case in the Ain al-Hilweh refugee camp, for example. However, evidence of a group sheltering members of another group is considered to be an alliance. Notably, situations of mere verbal backing or ideological agreement are not included as alliances.

Rivalry is intended to capture violence between groups. A dyad-year is coded as having a rivalry if there is evidence of of violence between groups. This includes one group committing an attack against the other, a clash between the two, or intentional attacks against civilians that have a group as the intended broader target. Rivalry is also coded when a dyad is on opposite sides of a civil war and it can be reasonably assumed that the groups experienced a violent confrontation. For instance, during the civil war in Syria, as-Saiqa was allied with the regime, while Hamas broke ties with the regime and sided with the anti-Assad rebels in 2012. Because of the ongoing fighting between the two sides, it can be reasonably assumed that Hamas and as-Saiqa engaged in violence against each other. Situations of verbal opposition, denouncement of another group, or differing goals are not coded as rivalry if there is no evidence of violence.

To code alliances and rivalries, I first collect data at the dyad-year level. I used existing datasets[3] and news sources. For dyad-years that lacked information about either alliances or rivalry after consulting various datasets, I searched for the dyad on NexisUni, making sure to incorporate aliases, alternative spellings, and militant wings.[4] Crucially, my data allow for alliance and rivalry to exist in the same year.

[3]Blair et al. (2021), Balcells, Chen, and Pischedda (2022), BAAD2, and UCDP/PRIO. MGAR has four possible positive relationship types for militant groups. I code an alliance in my data if the same MGAR dyad-year is coded as "allies," "associates," or "supporters." These three relationship types indicate a level of cooperation that rises above rhetorical support. I code a negative relationship if the MGAR data is coded as "competition," which indicates a rivalry that has gone beyond rhetoric and risen to violence.

[4]I used a Boolean search in order to search pairs of groups. An example is: "((popular pre/1 Front pre/3 Liberation pre/2 Palestine) w/3 ((general or gen) pre/1 (command or cmd))) or (pflp pre/1 gc) or pflpgc or (jibril* w/2 (army or force or unit or battalion or brigade or group or faction or squad or unit or militia))

This was very prevalent during the 1975–1990 civil war in Lebanon, for example, with frequently changing alliances and rivalries. It is less prevalent throughout the scope of my 2000–2016 data, but does still happen. For instance, in 2015, Hezbollah and Future Movement, along with a number of other groups, coordinated in Northeast Lebanon against ISIS and ISIS-affiliated groups. Also in 2015, tensions between Hezbollah and Future Movement escalated into armed clashes. This constitutes both cooperation and physical violence against one another in the same dyad-year.

After collecting dyad-year alliance and rivalry data, I turn the data into yearly alliance and rivalry networks. The groups are the same between the alliance and rivalry networks; it is only the ties between them that differ between the two networks. Another way to conceptualize the data is as one time-varying network with two distinct types of relationships. While networks in network analysis can contain weighted ties, such as by giving more importance to a link when interactions happen more often, the ties in this data are unweighted, thus only accounting for the the existence or lack of alliance or rivalry ties. The ties are also undirected, meaning that they are not coded separately based on sender or receiver. If a group does not exist in a certain year, then it is not included in the network for that year. For example, Abdullah Azzam Brigades begins in 2009, so it joins the network data in 2009 but is not included in the data before that. If groups do exist but have no ties in a particular year, they do still exist in the network for that year. In network analysis, nodes with no ties are called isolates.

4.1.2. Dependent Variable

The dependent variable is lethality, which I measure as a count of attacks committed by a group in a year. This is similar to Gaibulloev and Sandler (2013), who measure terrorist campaign intensity with the number of transnational attacks per million people and Carter (2012); Clauset and Gleditsch (2012); Hao (2022) who use a count of attacks. I use the count of attacks as recorded in MGAR, which comes from the

AND (abd*llah pre/1 azzam pre/1 (brigade or battalion or group or unit or force or army)) or (qa*da* pre/1 in pre/1 (lebanon or syria)) or (qa*da* pre/4 levant pre/1 and pre/1 egypt) or (land pre/1 of pre/2 sham) or (of pre/1 the pre/1 martyr pre/1 abd*llah pre/1 azzam) or (tanzim pre/2 qa*da* pre/1 fi pre/1 balad pre/2 SHAM pre/4 k*nana*) or ((ziad or ziyad) pre/2 jarrah pre/1 (battalion or brigade)) or (yusuf pre/2 u*ayri pre/1 (brigade or battalion)) or (marwan pre/1 had*id pre/1 (brigade or battalion))”

GTD. Where attacks are missing, I use the count from EDTG, which also comes from the GTD but has been cleaned to exclude attacks that are of the GTD's category "doubt terrorism proper," so there is a discrepancy between these two sources of data even though they use the same underlying source, but overall, only two groups from EDTG and not MGAR are included in the data, so the discrepancy is minor. In cases in which attack data is missing from both EDTG and MGAR, I use news articles to determine the number of attacks committed per year. Because the dependent variable is a count model, the model that I use within the temporal network autocorrelation models is a negative binomial model.

4.1.3. Explanatory Variables

I measure alliances in two ways. First, degree centrality is a measure of alliance ties for each organization in each year (Borgatti and Everett 2006). This can be thought of as a count of alliances and is used to test H1, which is about the number of allies. Second, I use eigenvector centrality, which measures the number of alliance ties that each group has, but also takes into account the number of alliances of each group's allies and so on across the network (Bonacich 1987; Borgatti and Everett 2006). With eigenvector centrality, a node connected to well-connected nodes is considered more important to the network than a node connected to the same number of nodes that are less connected. This is because being connected to well-connected nodes gives a node more influence within the network. Eigenvector centrality is used to test H2, which is about the embeddedness of a group in the network. For rivalry, I use degree centrality, which is a count of how many rivals a group has. This is used to test H3.

Figures 1, 2, and 3 present the alliance networks for 2005, 2012, and 2016. For each year, the nodes of the network are scaled according to either the degree centrality or eigenvector centrality and are colored based on attack count.[5]

In the 2005 network, the differences between degree centrality and eigenvector centrality are clearest with the cluster toward the bottom. With degree centrality, we see that PIJ, Hamas, PFLP, and Fatah are much less central than Hezbollah. This

[5]Eigenvector centrality is between 0 and 1. For the graphs, it is doubled and squared in order to view differences more clearly. Degree centrality is a count. For the graphs it is squared in order to view differences more clearly. The scales and node sizes for the two should not be directly compared. Instead, the size of each node should be compared to the rest of the nodes in the network.

is because they have fewer allies than Hezbollah. However, the graph for eigenvector centrality shows the four aforementioned groups being as central or almost as central as Hezbollah. This is because they are all connected to highly connected groups, while several of Hezbollah's connections have only one connection.

In 2012, Jund al-Sham has three allies, giving it a low — but not the lowest — degree centrality compared to the rest of the network. Its degree centrality is even higher than that of Hamas, which has two allies. Yet, the eigenvector centrality graph shows that Jund al-Sham's eigenvector centrality is one of the lowest in the network because the group's allies are not highly connected. Meanwhile, the eigenvector centrality of Hamas, relative to the rest of the network, increases in comparison to its degree centrality (relative to the rest of the network) and by virtue of connections to the highly connected Hezbollah. PFLP's eigenvector centrality is also higher than its degree centrality, relative to the rest of the network, because it is connected to both Hezbollah and PFLP-GC.

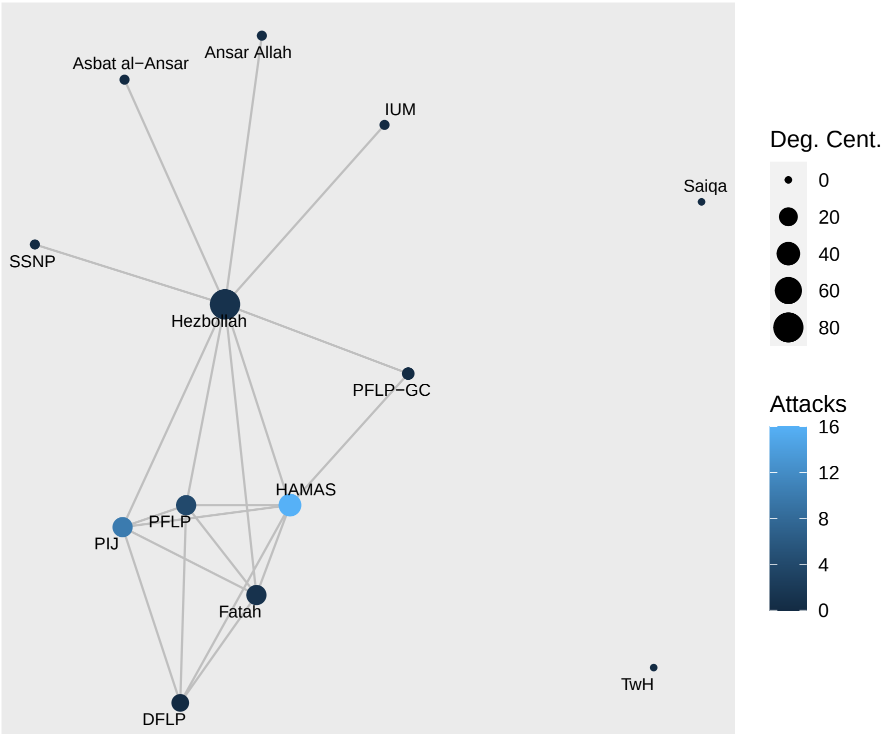
The 2016 graphs show a densely connected cluster of several groups. Within this cluster, DFLP, for example, has a moderate degree centrality with five direct connections. Its eigenvector centrality, however, is one of the highest in the network, likely because of its connections to the highly connected Hamas, PFLP, PIJ, Fatah, and the moderately connected Asbat al-Ansar. The graphs show PIJ's change in importance in much the same way. Meanwhile, PFLP-GC is moderately central with four direct connections, but less central when considering eigenvector centrality. The group has two highly connected allies — PFLP and Hezbollah — but also has two scarcely connected allies, whereas groups like Hamas and PIJ are connected to several highly connected groups.

4.1.4. Control Variables

I include five group level control variables. Religious is a binary variable indicating whether a group has a religious orientation, which, for the groups in the sample, is a Sunni, Shia, or Salafi orientation. Many scholars show the importance of group orientation — usually presented as left wing, right wing, religious, or nationalist-separatist (e.g. Horowitz and Potter 2014; Hou, Gaibulloev, and Sandler 2020; Asal

Figure 1.: 2005 Network

(a) Degree Centrality



(b) Eigenvector Centrality

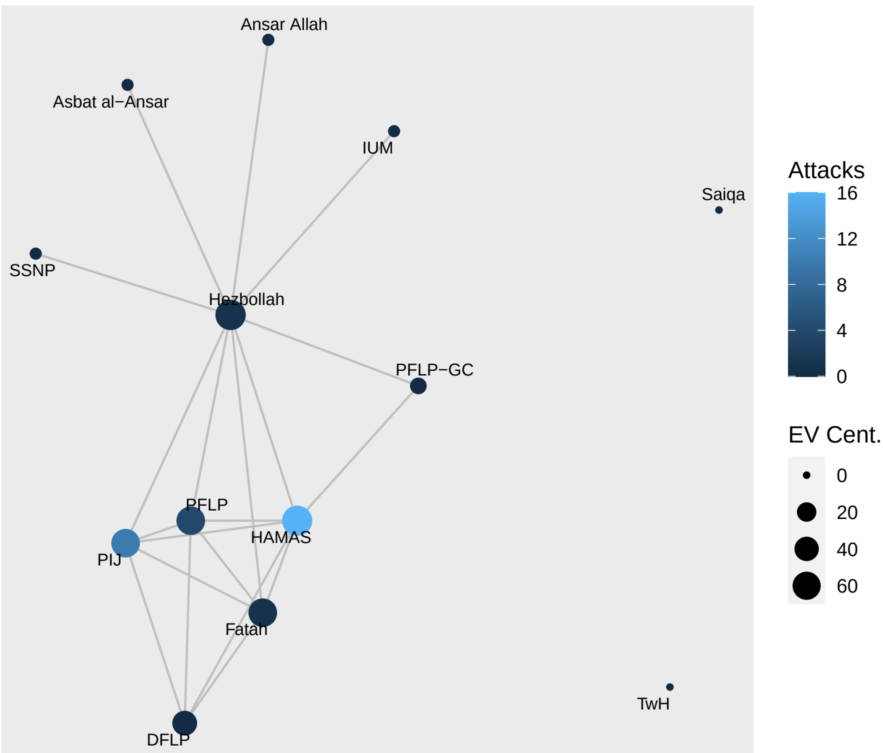
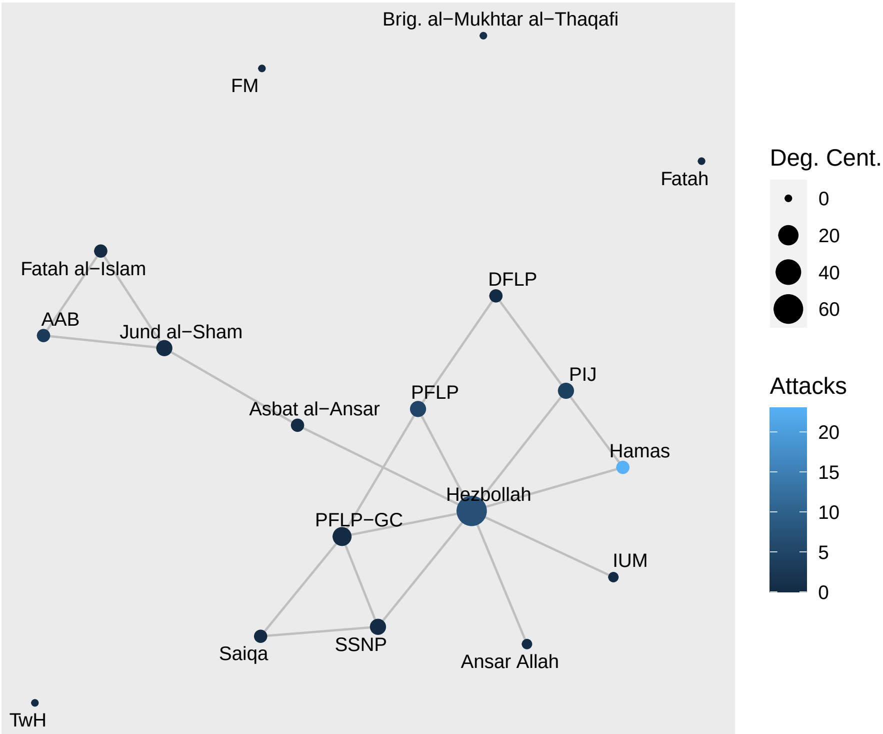


Figure 2.: 2012 Network

(a) Degree Centrality



(b) Eigenvector Centrality

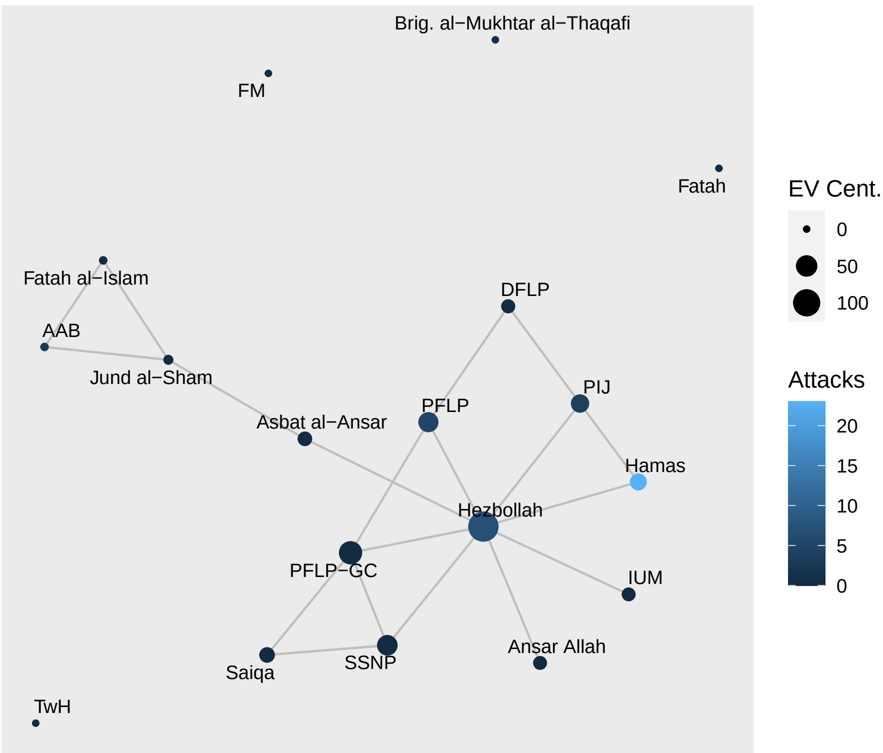
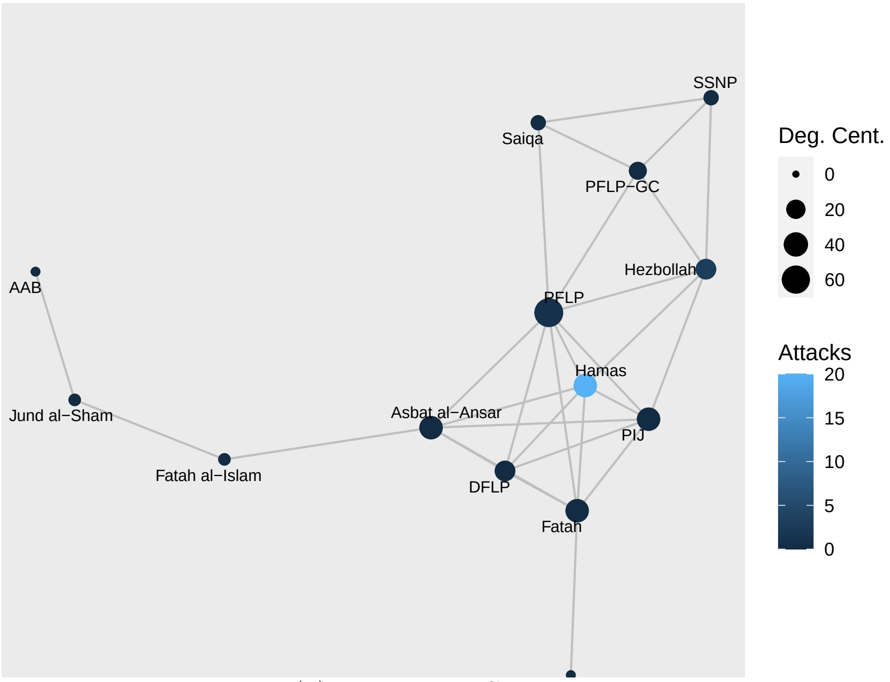
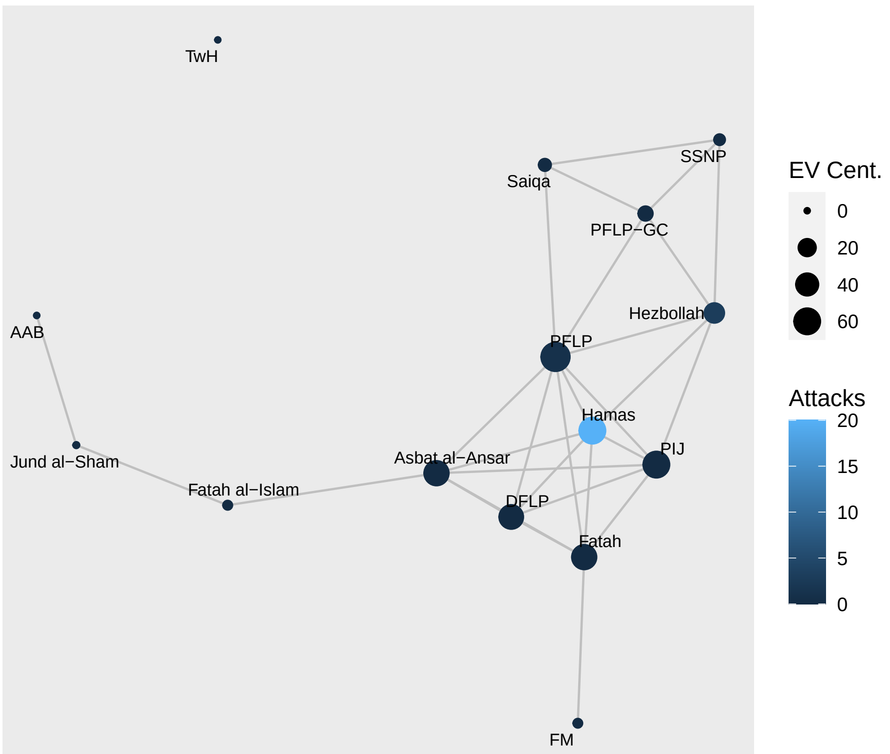


Figure 3.: 2016 Network

(a) Degree Centrality



(b) Eigenvector Centrality



et al. 2016; Jones and Libicki 2008). Other studies consider Islamist terrorism as a distinct category rather than considering all religious terrorism as one category (LaFree and and 2022; Piazza and LaFree 2019; Piazza 2008). In this study, this variable falls in line with the latter way of defining orientation/religion. I also include an alternate measure of group orientation, replacing the variable for religious orientation with a binary variable indicating whether a group is jihadist. This can be seen in Table 3 in the appendix. Farrell (2020), for example, examines outbidding between jihadist groups, and Moghadam (2017) looks at cooperation between jihadist groups. The data for the group-level variables come from MGAR and from various news articles and websites.

In this paper, I theorize that one major benefit of alliances is the increased access to resources. State sponsorship is another major source of resources for terrorist groups, for those that manage to acquire sponsorship (Byman 2005; Carter 2012; Conrad 2011). Therefore, I account for this form of resources with a binary variable labeled 1 for state sponsorship and 0 for no sponsorship. The data come from Hou, Gaibulloev, and Sandler (2020); San-Akca (2016); Berkowitz (2018) and various US State Department reports and news articles.

Closely related to state sponsorship is that many terrorist groups in Lebanon play a role in Lebanon's government. Additionally, while Palestine is not considered a state in studies of international conflict, Fatah administers the West Bank and Hamas began administering Gaza in 2007. I therefore include a binary variable indicating whether a group is involved in governance in a given year.

Multiple bases is a dichotomous variable indicating whether a group is based in more than one country. This is a loose measure of organizational strength (Avdan, Piazza, and Soules 2023; Gaibulloev and Sandler 2013). Finally, duration is included because organizational age has been shown to be an important factor when studying group lethality (Hou, Gaibulloev, and Sandler 2020; Horowitz and Potter 2014).

In addition to group level variables, a number of network measures are included. I include a measure of cliques, which is a way of measuring a group's exposure to groupings of three terrorist groups or more that are completely connected. Colloquially, it can be thought of as local embeddedness. I include this for both the alliance network and the rivalry network.

Spatial network lag is included to account for spatial autocorrelation. A terrorist organization may be influenced by the behavior of its allies or rivals. It is essential to capture these network dependencies rather than treating groups as independent. I include this for both the alliances and rivalries. I include measures for both the alliance and rivalry networks. *Spatial lag* is the attack behavior of either direct allies or direct rivalries. *Spatial & Temporal Lag* is the attack behavior of either direct allies or direct rivalries in the previous year. In Table 4 of the appendix, I include *Spatial Lag Order 2* for the ally network, which is the attack behavior of groups two "hops" away, or allies' allies. The behavior of these indirect connections has a decay so that the behavior of indirect connections is treated as less important than the behavior of direct connections.

5. Analysis

Because the dependent variable attacks is a count variable with overdispersion, the TNAM is used with a negative binomial distribution function. Results can be interpreted as they would be when using a negative binomial model (Duxbury 2023). Table 1 reports exponentiated coefficients so that they may be interpreted as incidence rate ratios (IRRs). The reported standard errors have been correspondingly transformed. P-values are calculated from the untransformed coefficients and standard errors.

Models 1 and 2 of Table 1 incorporates all covariates and can be thought of as a pooled panel model that accounts for network dependencies. Models 3 and 4 add random effects to account for unobserved variability between the terrorist groups. The clandestine nature of terrorist organization makes data collection inherently difficult. Aspects like group size or overall funds can lead to variability that is not accounted for. The AIC and BIC that the models with node-level random effects are better fitting models than the pooled models, and the ICC suggests variability is indeed coming from the nodes.

H1 is about the count of alliances leading to higher lethality, but I expected that I would not be able to reject the null hypothesis. Degree centrality — or the number of alliances — is significant in model 1 but loses significance in model 3 when random effects are included. Additionally, once random effects are included, the IRR becomes very close to 1, suggesting that an increase in allies has very little effect on a terrorist organization's attack frequency. The insignificance of the result means that there is no evidence that having more alliances increases a group's lethality, and the null hypothesis cannot be rejected. Because past studies have found this variable to be significant, this highlights the importance of accounting for network dependence.

H2 is about network embeddedness. Eigenvector centrality of the alliance network is used to test this hypothesis. Eigenvector centrality is positive and significant in model 2, and once random effects are added as seen in model 4, it remains marginally significant. This suggests that the more embedded a terrorist organization is in the alliance network, the more frequently a terrorist organization commits attacks. Eigenvector centrality scores are usually between 0 and 1, so it is unclear what is meant by a "one unit increase." This is in contrast to degree centrality, for example, in which a one unit increase means one more ally. Therefore, the eigenvector centrality variable has been standardized to have a mean of 0 and standard deviation of 1, so the interpretation is that of a one standard deviation increase, which is less obscure than a one unit increase because it means moving further away from the average. In model 2, the exponentiated coefficient of 2.337 suggests that a one standard deviation increase in the positive direction more than doubles the incidence rate of attacks. In model 4, which includes random effects, the effect is still substantively large; the exponentiated coefficient of 1.547 suggests that on average across groups, a one standard deviation increase in the positive direction increases incidence rate of attacks by over 50%. Put another way, as eigenvector centrality grows further from the mean in the positive direction, the incidence rate of attacks increases. There is strong support for H2, which is that organizations that are more embedded in the alliance network will be more lethal.

H3 is that organizations with a higher number of rivalries will be more lethal. Degree centrality for the rival network has IRRs that are above 1 and significant for all four models. Models 3 and 4 show that one additional rival increases the incidence rate of attacks by about 1.4. This provides support for H4. Results for the main explanatory

Table 1.: TNAM Models

	Degree No RE (1)	Eigenvector No RE (2)	Degree RE (3)	Eigenvector RE (4)
(Intercept)	0.039***	0.134**	0.009***	0.016**
	(0.025)	(0.093)	(0.012)	(0.021)
Alliance Network Terms				
Degree Centrality	1.258**		1.066	
	(0.102)		(0.102)	
Eigenvector Centrality		2.337***		1.547+
		(0.503)		(0.407)
Cliques	1.007	1.005	1.007+	1.007
	(0.004)	(0.004)	(0.004)	(0.004)
Spatial Lag	1.017*	1.018*	1.017*	1.017*
	(0.008)	(0.008)	(0.007)	(0.007)
Spatial & Temporal Lag	1.012+	1.010	1.011+	1.010+
	(0.007)	(0.006)	(0.006)	(0.006)
Rival Network Terms				
Degree Centrality	1.412**	1.347**	1.439**	1.400**
	(0.158)	(0.149)	(0.190)	(0.182)
Cliques	0.979	0.976+	0.987	0.984
	(0.013)	(0.013)	(0.014)	(0.014)
Spatial Lag	0.983	0.988	0.997	0.998
	(0.013)	(0.013)	(0.015)	(0.015)
Spatial & Temporal Lag	0.990	0.988	1.005	1.003
	(0.012)	(0.012)	(0.013)	(0.013)
Group Covariates				
Religious	3.118**	3.290***	6.800*	6.838*
	(1.083)	(1.113)	(5.844)	(5.588)
State Sponsorship	5.494***	3.818***	7.555**	5.746*
	(1.941)	(1.423)	(5.497)	(4.056)
Multiple Bases	10.476***	9.267***	5.347+	5.678*
	(4.496)	(3.930)	(4.589)	(4.636)
Government	1.819+	1.924+	1.093	1.203
	(0.658)	(0.687)	(0.547)	(0.595)
Duration	0.935***	0.925***	0.983	0.974
	(0.013)	(0.013)	(0.025)	(0.025)
SD (Intercept node)			3.127	2.875
SD (Observations)			5.316	5.300
Num.Obs.	245	245	245	245
AIC	689.0	683.2	671.2	668.9
BIC	741.5	735.7	727.2	724.9
ICC			0.7	0.6

Note: $^{+}$p<0.1; *p<0.05; **p<0.01, ***p<0.001

variables are robust to different model specifications as seen in the appendix.

Turning to network effects and control variables, in the main models, I include two spatial lags for the alliance and rivalry networks each. These variables capture the idea that a terrorist group's attack behavior is influenced by the attack behavior of its allies or rivals. The alliance spatial lag is above 1 significant in all four models, suggesting that more frequent attack behavior of direct allies increases a group's attack frequency. In other words, a group's attack frequency increases when its direct allies commit more attacks. The substantive effect is small, however. Additionally, the spatial lag that has been lagged temporally is also above 1 and significant in models 1, 3, and 4, which suggests that direct allies' attack behavior in the previous year increases groups' attacks in the current year. However, the substantive effect is even smaller than with the spatial lag without the temporal lag.

The rivalry spatial lag effects are insignificant across all four models, which means that there is no evidence that rival attack behavior in the current or previous year affects groups' current attack behavior. One possibility is that this is because the rivalry network is very sparse — more so than the alliance network. A second possibility is that rivalry alliances are already accounting for the idea that rival attack behavior affects group attack behavior, or in other words, that the spatial lag is attempting to capture a concept already captured by degree centrality of the rival network. Table 4 in the appendix includes a spatial lag of order 2 for the alliance network. This is intended to capture how a group's attack behavior is affected by the allies of a group's direct allies, or indirect allies that are two "hops" away. The results of these models show no evidence that attack behavior is influenced by the attack behavior of indirect allies, and the main results are robust with this model specification.

The effect of cliques is close to 1 and insignificant for both the alliance network and the rivalry networks. The effect of rivalry cliques is marginally significant in model 2 and the effect of alliance cliques is marginally significant in model 3, but the effect is very small and insignificant in the other models. This means that there is very little evidence that being in a densely connected clique of three or more terrorist groups has an effect on terrorist group lethality.

The other control variables are group-level characteristics. The IRR for being a religious group, which for the groups in the sample is Sunni, Shia, or Salafi, is above 1 and significant for all three models. In the sample, groups that are not religious are coded as nationalist or as leftist. For Models 1 and 2, the IRR suggests that being a religious group as opposed to not being a religious group more than triples incidence rate of attacks. When random effects are included, the effect of being a religious group is even higher. The models presented in table 3 use a dichotomous variable indicating whether a group is jihadist or not. The main effects for allies and rivalries are very similar and the effect of the jihad variable is in the same direction as the effect of the religious variable but substantively much larger.

The IRRs for state sponsorship are well above 1 and significant for all three models. The large effect that state sponsorship has on attacks is likely due to the resources provided by state sponsorship that increase a group's ability to commit an attack. The results for being a political party/government group, which is a variable meant to be a counterpart to state sponsorship, are ambiguous, with significant effects in models 1 and 2 but insignificant effects when random effects are included. The results for having multiple bases and for duration are also ambiguous.

6. Conclusion

This article assessed prominent hypothesis about terrorist groups and their alliances and rivalries. I used original data that, importantly, allows for terrorist groups to be involved in alliances and rivalries with the same groups in the same year. It is important to note that attacks come from the GTD, though many of the groups were embroiled in civil wars, and additionally, groups often fought each other or the government in refugee camps. This article is strictly about terrorist attacks and does not include the capacity of groups to do violence to each other.

I presented the hypothesis that a higher count of alliances leads to higher lethality, but I did not expect to find support for this hypothesis and indeed I was unable to reject the null hypothesis. This contradicts the findings of other research in the field and shows the importance of treating groups as interdependent instead of independent. Instead, I found support for the importance of being more deeply embedded in the larger network of alliances, which I measure with eigenvector centrality. I theorize that this is because being further embedded in the network facilitates access to resources. I further found support for the outbidding hypothesis. Rather than much of the work in the field that treats competition as the number of groups in an area, I examine the actual network of rivalries.

This article contributes to the terrorism literature by using network analysis to explore the effects of alliances and rivalries on lethality and shows that including spatial dependence in the models can account for some of the ambiguity seen in the current literature, especially where number of allies is concerned. Future research can work on expanding the data to including more groups or more years. The current data focuses narrowly on groups that had a major presence in Lebanon. Future work can build from this by broadening the sample of groups. Many of the groups in the data are Palestinian groups. They are in the sample because of the large role that they have in Lebanon. However, several Palestinian groups have not had a major presence in Lebanon and therefore are not included in the sample, but these groups could have been embroiled in outbidding wars or alliances with several groups in the sample. Additionally, some groups in the data were dragged into the Syrian civil war or were involved in spillover violence from this civil war, but the groups involved in Syria are not included in the sample unless they had a major presence in Lebanon.

The additional data will also allow for the use of fatalities as an alternate measure of lethality, which, with missingness, was not possible with such a small sample of groups. Perhaps more importantly, an expanded sample will allow researchers to see how generalizable these findings are. Lebanon in 2000–2016 provides an interesting case because it is set against a background of a recently ended 15-year civil war, instability, militant groups like Hezbollah that also function as part of the government, and refugee camps that host many militant groups. Finally, while militant groups do exist in Israel, the primary rival of Palestinian groups is the government, so it will be important for future work to consider both state and sub-national actors together, something that is currently lacking in the conflict field.

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7. Appendix

Table 2.: TNAM Models — Ally Network Only

	Degree No RE (1)	Eigenvector No RE (2)	Degree RE (3)	Eigenvector RE (4)
(Intercept)	0.061***	0.211*	0.010***	0.021**
	(0.037)	(0.141)	(0.014)	(0.028)
Degree Centrality	1.304***		1.043	
	(0.102)		(0.103)	
Eigenvector Centrality		2.550***		1.638+
		(0.526)		(0.426)
Cliques	1.003	1.001	1.006	1.005
	(0.004)	(0.004)	(0.004)	(0.004)
Spatial Lag	1.015+	1.016*	1.017*	1.017*
	(0.008)	(0.008)	(0.007)	(0.007)
Spatial Lag with Temporal Lag	1.010	1.007	1.011*	1.009+
	(0.006)	(0.006)	(0.006)	(0.006)
Religious	2.661**	2.915**	7.755*	7.230*
	(0.927)	(0.981)	(7.166)	(6.011)
State Sponsorship	5.694***	3.975***	7.356**	5.284*
	(1.886)	(1.355)	(5.576)	(3.665)
Multiple Bases	10.364***	8.907***	7.524*	7.671*
	(4.129)	(3.509)	(6.760)	(6.195)
Government	3.282***	3.067***	1.995	2.172+
	(1.090)	(1.001)	(0.968)	(1.009)
Duration	0.929***	0.920***	0.981	0.969
	(0.012)	(0.012)	(0.027)	(0.026)
SD (Intercept node)			3.492	2.933
SD (Observations)			5.301	5.278
Num.Obs.	245	245	245	245
AIC	690.9	683.6	672.2	668.7
BIC	729.4	722.1	714.2	710.8
ICC			0.7	0.6

Note: $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$, $^{***}p<0.001$

Table 3.: TNAM Models — Jihad Covariate instead of Religious

	Degree No RE (1)	Eigenvector No RE (2)	Degree RE (3)	Eigenvector RE (4)
(Intercept)	0.012***	0.047**	0.008**	0.015**
	(0.012)	(0.046)	(0.012)	(0.021)
Alliance Network Terms				
Degree Centrality	1.330***		1.079	
	(0.106)		(0.105)	
Eigenvector Centrality		2.699***		1.627+
		(0.586)		(0.441)
Cliques	1.007	1.005	1.007+	1.007
	(0.004)	(0.004)	(0.004)	(0.004)
Spatial Lag	1.019*	1.021**	1.018*	1.018*
	(0.008)	(0.008)	(0.007)	(0.007)
Spatial Lag with Temporal Lag	1.011	1.009	1.011+	1.010+
	(0.007)	(0.006)	(0.006)	(0.006)
Rival Network Terms				
Degree Centrality	1.305*	1.237+	1.420**	1.371*
	(0.150)	(0.140)	(0.191)	(0.182)
Cliques	0.979	0.977+	0.988	0.985
	(0.013)	(0.013)	(0.014)	(0.014)
Spatial Lag	0.995	1.002	0.998	1.000
	(0.013)	(0.013)	(0.015)	(0.015)
Spatial Lag with Temporal Lag	1.000	0.997	1.007	1.005
	(0.012)	(0.012)	(0.013)	(0.013)
Group Covariates				
Jihad	11.585**	14.119***	10.435+	11.907*
	(9.260)	(11.099)	(12.839)	(13.997)
State Sponsorship	15.965***	12.087***	14.150**	12.251**
	(9.519)	(7.126)	(14.361)	(11.873)
Multiple Bases	6.949***	5.777***	3.396	3.617
	(2.826)	(2.276)	(3.013)	(2.974)
Government	2.362*	2.533*	1.050	1.218
	(0.952)	(0.984)	(0.539)	(0.624)
Duration	0.949***	0.937***	0.990	0.979
	(0.014)	(0.014)	(0.027)	(0.026)
SD (Intercept node)			3.573	3.130
SD (Observations)			5.321	5.303
Num.Obs.	245	245	245	245
AIC	689.6	683.0	671.9	669.4
BIC	742.1	735.6	728.0	725.4
ICC			0.7	0.7

Note: $^{+}$p<0.1; *p<0.05; **p<0.01, ***p<0.001

Table 4.: TNAM Models — With Spatial Lag Order 2

	Degree No RE (1)	Eigenvector No RE (2)	Degree RE (3)	Eigenvector RE (4)
(Intercept)	0.046***	0.160*	0.009***	0.017**
	(0.030)	(0.115)	(0.012)	(0.022)
Alliance Network Terms				
Degree Centrality	1.254**		1.066	
	(0.101)		(0.102)	
Eigenvector Centrality		2.330***		1.552+
		(0.501)		(0.409)
Cliques	1.007	1.005	1.007+	1.006
	(0.004)	(0.004)	(0.004)	(0.004)
Spatial Lag	1.017*	1.017*	1.017*	1.017*
	(0.008)	(0.008)	(0.007)	(0.007)
Spatial Lag with Temporal Lag	1.012+	1.011+	1.011+	1.010+
	(0.006)	(0.006)	(0.006)	(0.006)
Spatial Lag Order 2	0.989	0.987	1.000	0.999
	(0.019)	(0.019)	(0.020)	(0.020)
Rival Network Terms				
Degree Centrality	1.415**	1.350**	1.440**	1.398*
	(0.159)	(0.150)	(0.190)	(0.182)
Cliques	0.977+	0.974+	0.987	0.984
	(0.014)	(0.013)	(0.014)	(0.014)
Spatial Lag	0.985	0.991	0.997	0.998
	(0.014)	(0.014)	(0.016)	(0.016)
Spatial Lag with Temporal Lag	0.990	0.988	1.005	1.003
	(0.012)	(0.012)	(0.013)	(0.013)
Group Covariates				
Religious	2.965**	3.109***	6.780*	6.711*
	(1.037)	(1.060)	(5.846)	(5.486)
State Sponsorship	5.269***	3.622***	7.541**	5.814*
	(1.868)	(1.353)	(5.512)	(4.135)
Multiple Bases	9.538***	8.240***	5.341+	5.753*
	(4.296)	(3.670)	(4.625)	(4.731)
Government	1.737	1.819	1.092	1.217
	(0.650)	(0.673)	(0.547)	(0.602)
Duration	0.936***	0.926***	0.983	0.972
	(0.013)	(0.013)	(0.025)	(0.025)
SD (Intercept node)			3.123	2.860
SD (Observations)			5.336	5.320
Num.Obs.	245	245	245	245
AIC	690.7	684.7	673.2	670.9
BIC	746.7	740.7	732.7	730.4
ICC			0.7	0.6

Note: $^{+}$p<0.1; *p<0.05; **p<0.01, ***p<0.001