License to Kill: Terrorist Group Relationships and Lethality

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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 network analysis in order to assess lethality while accounting for dependence between terrorist groups. I find no evidence that the count of alliances drives lethality. Instead, it is the connectedness of a group's allies and the embeddedness of a group within a clique that leads to increased lethality.

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 as a source of resources, and therefore as a source of increased capacity and increased lethality.

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 rebel 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 reexamine 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 the importance of a group's allies and rather than the number of allies that affects lethality. I find weak 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 hypotheses. 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 the results of the analysis. I conclude by discussing the next steps.

2. Alliances

One of the primary reasons for terrorist group coordination is that these alliances bring increased access to resources, including material resources as well as recruits, skills, and knowledge. Indeed, it is precisely the lack of resources or the desire for further resources that drives militant organizations to seek cooperative associations with one another (Bacon 2018b; Bapat and Bond 2012; Plapinger and Potter 2017). This is because alliances enable access to resources (Acosta 2014; Asal and Rethemeyer 2008; Asal and Shkolnik 2024; Moghadam 2017; Phillips 2014; Price 2012; Topal 2024) or the opportunity to improve operational credibility (Blair and Potter 2022; Plapinger and Potter 2017). This has been found for 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 attractive to other groups, and Phillips (2019) even points out that territory-holding groups are typically 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 survival and capacity, and indeed 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). With expanded access to resources, organizations are also able to turn to attacks against logistically difficult targets. For instance, groups with alliances have turned to focus on more logistically difficult targets such as schools or journalists (Asal, Phillips, and Rethemeyer 2022). In a similar vein, cooperation has 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 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 shared information regarding tactics and efficiency that stems from alliances; 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 this particular 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 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.

This study's focus is on the way that alliances affect organizational lethality. By virtue of increasing resource access, alliances are associated with more deadly groups (Horowitz and Potter 2014; Asal and Shkolnik 2024). There are different ways of

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

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

measuring alliances, from a sheer count of ties to the quality of those ties to an entire network of organizations. Approaching cooperation as a binary concept, Oots (1986) found that transnational attacks from 1968–1977 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 allies (Bonacich 1987). Said another way, being directly 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 three hypotheses stem from the above discussion on resources, alliances, and lethality. In line with Horowitz and Potter (2014); Pearson, Akbulut, and Lounsbery

(2017), I expect that it is the centrality of the allies, or the eigenvector centrality, that matters more so than the count of alliances, or the degree centrality. 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. I further theorize that network embeddedness plays a role, but whereas Asal, Phillips, and Rethemeyer (2022) use a form of closeness centrality that accounts for indirect connections in addition to direct connections, I instead use a measure of transitivity that accounts for how connected local clusters are, which will be explained further in the methods section. Note that below I frame H1 as a hypothesis in order to test a frequently seen hypotheses in extant literature, but I expect that I will not be able to reject the null hypothesis.

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

$H2$: *Organizations with more central allies will be more lethal.*

$H3$: *Organizations that are more embedded in the alliance network will be more lethal.*

3. Rivalries

Whereas militant organizations cooperate to overcome resource scarcity in some cases, 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 groups, such as turning to kidnapping (Welsh 2010) or changing their demands of the government in order to remain distinct from other groups, to 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 outbidding. 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 examine 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 that 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 rivalry[3] leads to higher levels of civilian fatalities.

This discussion on outbidding leads to my fourth hypothesis.

$H4$: *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 their ability to commit attacks and 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) and this would require that terrorist group cooperation or competition with one another is not based on cooper-

[3]Nonviolent rivalry here includes threats and denouncement (Conrad, Greene, and Phillips 2023)

ation or competition with other groups. 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*

I construct original data on terrorist group alliance and rivalry, structured as 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 22 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. 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 the data, and 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 in the MGAR data and I added these organizations to the sample.

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 Clauset and Gleditsch (2012) who use attack frequency. I use the count of attacks as recorded in MGAR, which comes from the 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.

4.1.1. Key Explanatory Variables

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[4] 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.[5] Crucially, my data allow for alliance and rivalry to exist in the same year. 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

[4]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.

[5]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)) 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))”

Future Movement escalated into armed clashes. This constitutes both cooperation and physical violence against one another in the same dyad-year.

After collecting alliance and rivalry dyads, I turn the data into yearly alliance and rivalry networks. The nodes 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.

The models contain three key explanatory variables that use the alliance network and one that uses the rivalry network. Centrality is intended to measure how "central" a node is within a network. I use two measures of centrality. 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. The second centrality measure, eigenvector centrality, measures the number of alliance ties that each group has, but also takes into account the centrality of each group's ties (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 centrality of allies.

The third explanatory variable for the alliance network is the local clustering coefficient, also known as transitivity, which measures the connectedness or density of a local neighborhood of nodes. A group of three nodes is called a triple. When all three nodes in a triple are connected, this forms a triangle. The local clustering coefficient assesses the number of triangles to triples, or in other words, the number of existing triangles out of all possible triangles that can be made for each node. This is used to test H3, which is about network embeddedness. An illustration of the clustering coefficient for a group in the 2012 network can be seen in Figure 2, which shows that Jund al-Sham has alliances with Fatah al-Islam, Abdullah Azzam Brigades, and Asbat al-Ansar. Fatah al-Islam and Abdullah Azzam Brigades are also connected with each other, forming a triangle between the three groups. Meanwhile, Fatah al-Islam and Abdullah Azzam Brigades are not connected to Asbat al-Ansar — another Jund al-Sham ally, leaving these two other triples open. This all factors into the clustering coefficient for Jund al-Sham.

Finally, degree centrality for the rivalry network is a count of how many rivals a group has. This is used to test H4. In the appendix, I include an alternative measure — spatial autocorrelation. This is further discussed in the control variable section.

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.[6]

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 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 cen-

[6]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.

trality 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.

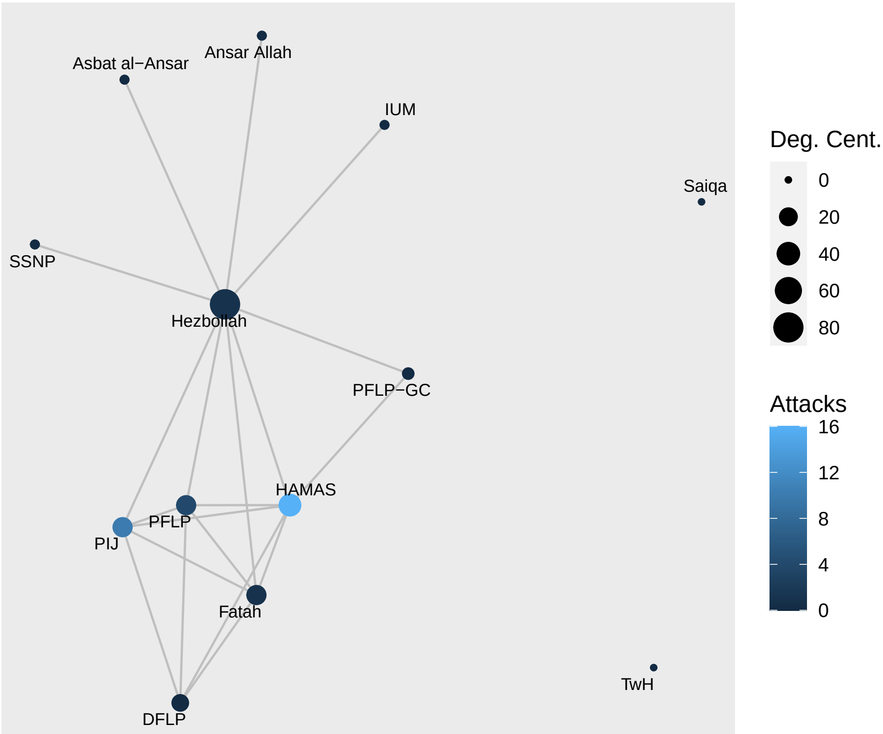
The 2016 graphs show a densely connected cluster of several groups. Within this cluster, DFLP, for example, has a moderate degree centrality with five direct connections. Its eigenvector centrality, however, is one of the highest in the network, likely because of its connections to the highly connected 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.

4.1.2. 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 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 5 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

Figure 1.: 2005 Network

(a) Degree Centrality



(b) Eigenvector Centrality

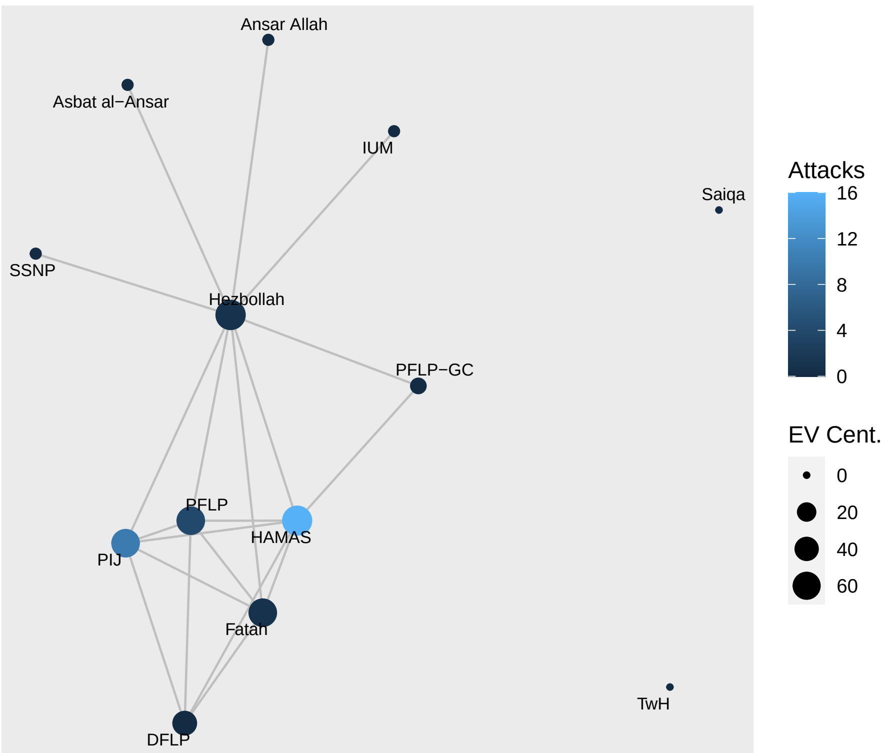
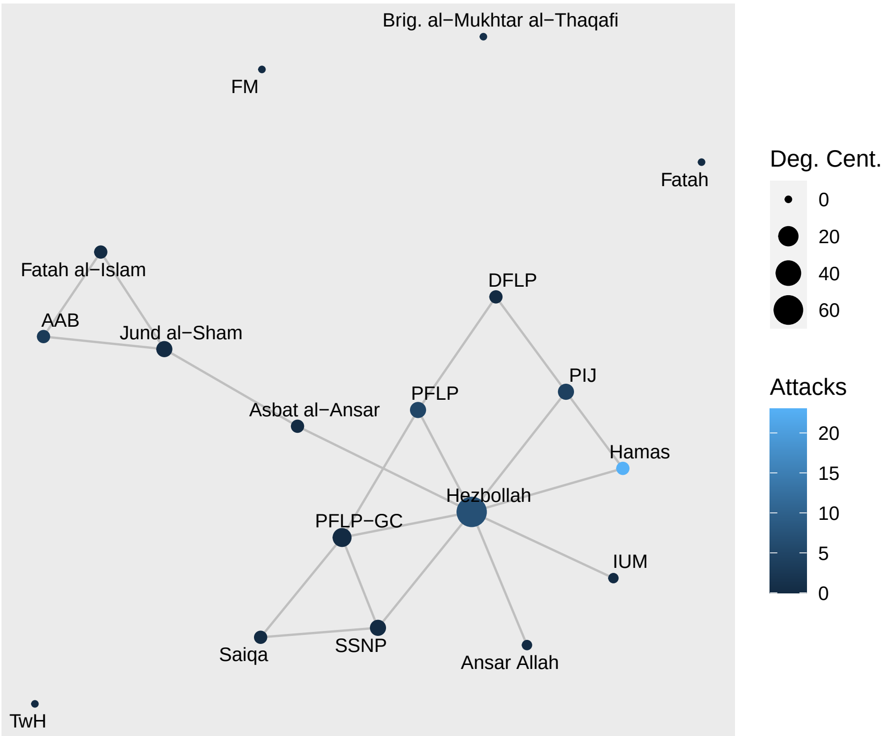


Figure 2.: 2012 Network

(a) Degree Centrality



(b) Eigenvector Centrality

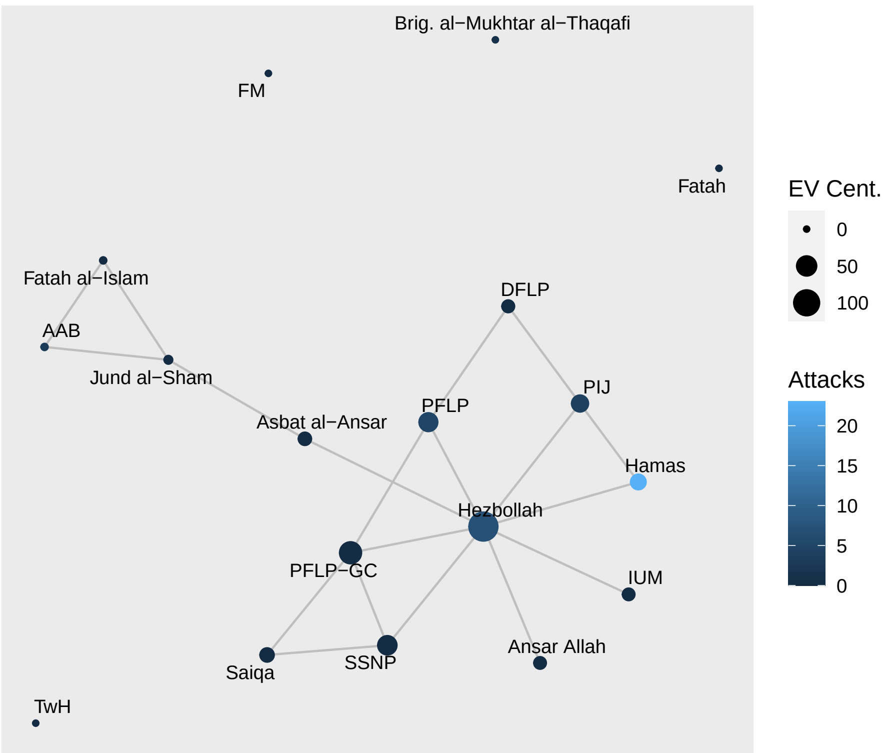
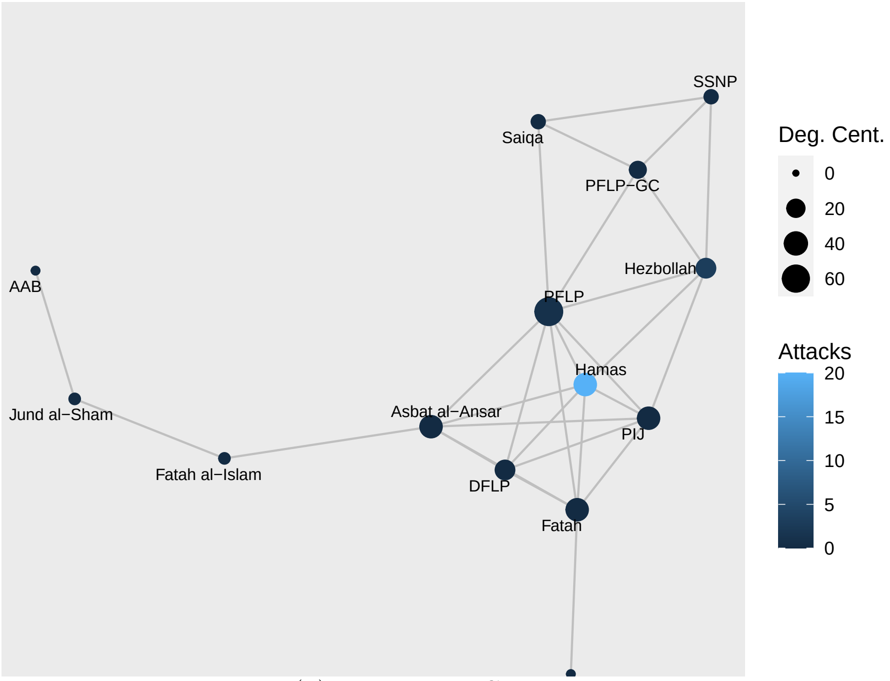
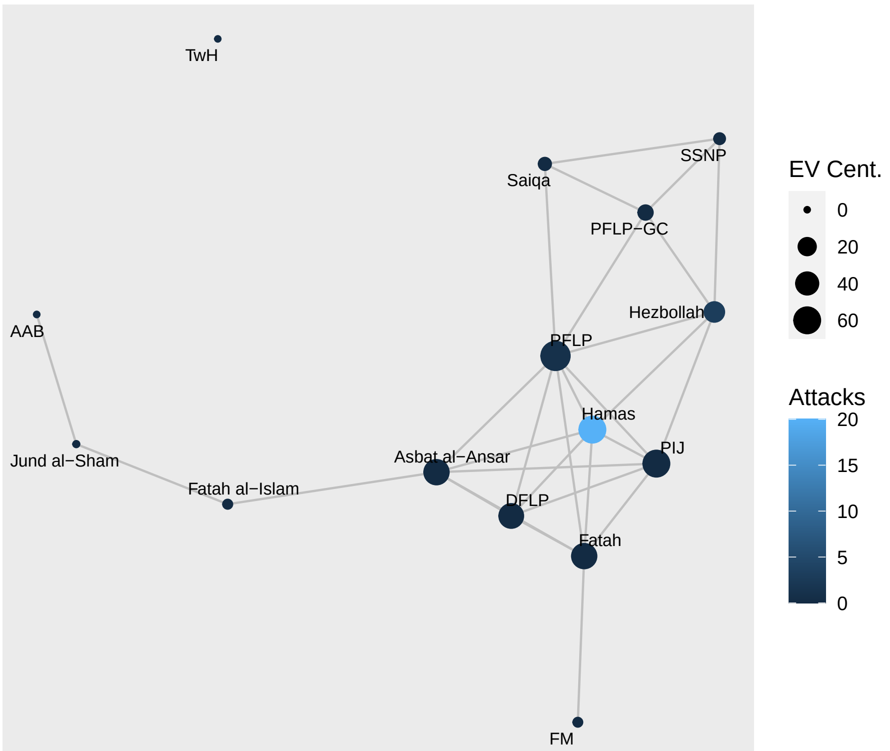


Figure 3.: 2016 Network

(a) Degree Centrality



(b) Eigenvector Centrality



and websites.

The theory in this article is one of resources, and state sponsorship is a 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 a state, Fatah and Hamas do administer the West Bank and Gaza, respectively. 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). 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, I also include network measures as covariates. Clustering coefficient, which measures the connectedness or density of a local neighborhood of nodes, is included for the rivalry ties. While I hypothesize about clustering coefficient for alliance ties, I do not hypothesize about this measure for rivalry ties. It is included as a potential counfounding variable because there is a possibility that within a cluster of groups all connected to each other via physical rivalry, they may expend so much effort fighting one another that it reduces their ability to launch terrorist attacks.

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 important to capture these network dependencies rather than treating groups as independent. I include this for both the alliances and rivalries. Furthermore, because the logic behind H4 is outbidding, I include in the appendix models that use this spatial autocorrelation for rivalry instead of using degree centrality. The idea is that a group might be influenced by its rivals' behaviors, as opposed to only being influenced by how many organizations a group is in competition with.

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). Tables 1 and 2 report exponentiated coefficients so that they may be interpreted as incidence rate ratios (IRRs). The reported standard errors have been correspondingly transformed. Model 1 of Table 1 incorporates all covariates and can be thought of as a pooled panel model that accounts for network dependencies. Model 2 adds random effects to account for unobserved variability among years. Different events such as the Second Intifada or the fighting of the Lebanese government and Fatah al-Islam in the Nahr al-Bared refugee camp may lead to time heterogeneity. Model 3 uses random effects to account for unobserved variability among terrorist organizations. 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, BIC, and log likelihood suggest that Model 3 with node-level random effects is the best fitting model.

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. Table 1 shows that degree centrality for the alliance network is insignificant in all three models. Additionally, the IRRs are very close to 1, suggesting that an increase in allies has very little effect on a terrorist organization's attack frequency. This 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 being connected to well-connected allies. Eigenvector centrality of the alliance network is used to test this hypothesis. This variable is positive and significant in all three models, suggesting that the more well-connected a terrorist organization's allies, the more frequently a terrorist organization commits attacks. Eigenvector cen-

Table 1.: Full Models

	(1)	(2)	(3)
(Intercept)	0.053***	0.056***	0.038**
	(0.036)	(0.040)	(0.038)
Ally Eigenvector Cent.	3.114**	3.020**	2.098*
	(1.079)	(1.214)	(0.786)
Ally Degree Cent.	0.912	0.948	0.854
	(0.115)	(0.133)	(0.106)
Ally Clustering	1.070	1.224	1.751
	(0.513)	(0.662)	(0.852)
Ally Spatial Lag 1	1.021**	1.016	1.020**
	(0.007)	(0.010)	(0.007)
Ally Spatial Lag 2	0.982	0.972	0.994
	(0.018)	(0.022)	(0.019)
Rival Degree Cent.	1.261*	1.243	1.326*
	(0.140)	(0.144)	(0.167)
Rival Spatial Lag 1	0.989	0.993	1.011
	(0.013)	(0.014)	(0.013)
Rival Clustering	0.663	0.692	0.465
	(0.310)	(0.340)	(0.219)
Religious	2.892**	2.703**	4.920*
	(0.996)	(1.013)	(3.665)
State Sponsor	4.033***	3.853***	6.200**
	(1.405)	(1.451)	(4.134)
Multiple Bases	4.447***	3.934**	2.269
	(1.845)	(1.768)	(1.709)
Political Party	1.603	1.474	1.021
	(0.600)	(0.582)	(0.497)
Duration	0.349***	0.359***	0.545*
	(0.064)	(0.070)	(0.157)
Num.Obs.	268	268	268
AIC	753.3	754.9	736.8
BIC	807.1	768.3	755.0
Log.Lik.	−361.640	-361.469	-352.413
ICC		0.1	0.4

trality 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

Table 2.: Alliance Network

	(4)	(5)	(6)
(Intercept)	0.060***	0.065***	0.043**
	(0.040)	(0.046)	(0.041)
Ally EV Cent.	3.191***	3.102**	2.472*
	(1.099)	(1.229)	(0.906)
Ally Degree Cent.	0.909	0.953	0.823
	(0.114)	(0.134)	(0.102)
Ally Clustering	1.246	1.469	1.595
	(0.597)	(0.779)	(0.771)
Ally Spatial Lag 1	1.019**	1.014	1.024***
	(0.006)	(0.009)	(0.007)
Ally Spatial Lag 2	0.981	0.969	0.993
	(0.017)	(0.022)	(0.019)
Religious	2.786**	2.538*	5.060*
	(0.948)	(0.930)	(3.580)
State Sponsor	3.492***	3.260***	4.894*
	(1.165)	(1.157)	(3.101)
Multiple Bases	4.681***	4.099***	3.366
	(1.752)	(1.712)	(2.343)
Political Party	2.511**	2.165*	1.896
	(0.800)	(0.724)	(0.798)
Duration	0.333***	0.338***	0.482**
	(0.055)	(0.057)	(0.133)
Num.Obs.	268	268	268
AIC	751.7	752.7	739.0
BIC	794.8	763.5	753.7
Log.Lik.	−363.840	-363.354	-356.487
ICC		0.2	0.3

unit increase because it means moving further away from the average. In this case, looking at Model 3, the IRR suggests that on average for each group, a one standard deviation increase in the positive direction doubles the incidence rate of attacks. Put another way, as eigenvector centrality grows further from the mean in the positive direction, the incidence rate of attacks increases. In Models 1 and 2, a one standard deviation increase in the positive direction triples the incidence of attacks. There is strong support for H2, which is that organizations with more connected allies will be more lethal.

H3 is about network embeddedness. For this, I turn to the clustering coefficient of the alliance network, listed in the table as Ally Clustering. In Model 1, the IRR is very close 1, indicating that clustering or transitivity has very little effect on the incidence of attacks. It is slightly higher in Model 2, but only in Model 3 does it appear to have a substantial effect on the incidence of attacks. However, the IRRs are insignificant, meaning that the null hypothesis for H3 cannot be rejected. Taken together with the results for H2, this suggests that it is network influence rather than embeddedness that affects resources and therefore lethality.

Turning to the network of rivalries, H4 is that organizations with a higher number of rivalries will be more lethal. Degree centrality for the rival network has IRRs above 1 for all three models and these are significant in Models 1 and 3. Model 1 indicates that the addition one one rival increases the incidence rate of attacks by 1.36. Model 3 indicates that, on average for each group, the addition one one rival increases the incidence rate of attacks by 1.326. This provides support for H4. H4 follows the from the logic of outbidding, which is the idea that terrorist organizations try to outperform each other. Degree centrality or number of rivals, is used to account for the idea that the more rivals a group has, the more it must work to outperform them. However, I also examine the spatial lag in addition to the number of rivals because this variable captures a organization basing its behavior on the behavior of its direct ties, which is also in line with outbidding logic. In this case, the idea is that if a node's direct ties commit a higher number of attacks, then the node itself will commit a higher number of attacks. I only account for direct connections. Rival spatial lag is insignificant in the main three models. Table 4 in the appendix shows rival spatial lag used to test H4 without the addition of degree centrality. Rival spatial lag remains insignificant, as well as having IRRs of 1, meaning that there is no evidence that the attack behavior of direct rivals affects the number of attacks a group commits. It is possible that it is the fatalities of attacks rather than the number of attacks that has an effect.

Table 5 in the appendix shows the results of using jihadist instead of religious. This leaves the results of ally clustering coefficient and ally degree centrality unchanged. The ally eigenvector centrality loses significance in Model 3, but the un-exponentiated coefficient of 0.728 with an un-transformed standard error of 0.376 and p-value of 0.053 suggest that this loss in significance is extremely minor, and the effect — a doubling of the incidence rate of attacks — is still quite substantial, so it can reasonably be concluded that there is indeed still a substantial effect of a group's eigenvector centrality on its incidence rate of attacks. Rival degree centrality, meanwhile, loses significance in Model 1, weakening the support for the outbidding hypothesis.

Turning to control variables, I include two spatial lags for the alliance network in the main models. These variables capture the idea that a terrorist group's attack behavior is influenced by the attack behavior of its allies or rivals. Table 3 in the appendix shows the effects of spatial lags alone and the appendix includes a brief discussion on the effects that this autocorrelation has on group attacks. Ally Spatial Lag 1 in Table 1 accounts for direct connections. Ally Spatial Lag 2 accounts for connections that are two paths away. An example of this can be seen in Figure 3, where Fatah al-Islam is two paths away from Abdullah Azzam Brigades, or Future Movement (FM) is two paths from DFLP, PFLP, Hamas, and PIJ. Ally Spatial Lag 2 has a decay so that attack behavior of groups two paths away matters half as much as the attack behavior of direct connections, but this variable is insignificant across all three models. Ally Spatial Lag 1, however, is significant in Model 1 and Model 3, but not in Model 2 which has random effects for time. It is possible that the non-independence — or the groups' dependence on each other — is happening in specific time periods, and that random effects for time accounts for this. This demonstrates the importance of accounting for network dependence.

The clustering coefficient for the rival network is insignificant. The IRRs are close to 0.7 for both Models 1 and 2. This rate suggests that as a terrorist group's local neighborhood gains another triangle, the incidence rate decreases by a factor of 0.3. The factor by which the incidence rate decreases is even larger in Model 3, though not significant. The IRR below one may be because being so strongly connected within a rivalry clique means that these groups are all engaged in fighting one another, using up more resources on attacks against each other and having fewer resources to commit terrorist attacks.

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 doubles — indeed almost triples — the incidence rate of attacks. For Model 2, this is on average for each year. For model three, the IRR suggests that, on average for each group, being religious as opposed to not increases the incidence rate of attacks by almost 5. Models 1, 2, and 3 of Table 5 in the appendix report results when jihadist is used instead of religion. The incidence rate ratio for jihad is above 1 and significant for the first two models, but not the third, which is the best fitting model. Taken together, the models suggest strongly that being religious as opposed to not being religious increases attacks, but are less conclusive on the effect that being a jihadist group has on attacks.

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 insignificant.

The dichotomous variable multiple bases has an IRR near 4 and is significant in both Models 1 and 2, suggesting that groups that have more than one base commit attacks four times as often as groups that do not have more than one base, further supporting the idea of multiple bases as a proxy for group strength. The significance disappears and the IRR loses magnitude in Model 3, which includes random effects for organization. There may be overlap in the variability among groups and variability in which groups have multiple bases, and it is plausible that stronger groups have multiple bases but at the same time other unobserved sources of strength such as size and funding are being controlled for with the random effects, rendering multiple bases insignificant. Interestingly, duration appears to decrease the incidence of attacks. This may have to do with the number of groups that were heavily involved in militant and terrorist activity during the 15 year civil war but committed fewer attacks after becoming involved in government.

The yearly networks in the data are unimodal; they include terrorist groups but not other entities such as states. However, one or more states may be the primary rivalry of these groups more so than each other, as is the case with Palestinian groups and Israel. I therefore present models that include only the alliance network effects in Table 2. The results remain unsupportive of H1 (as expected), supportive of H2, and unsupportive of H3. The model with node-level random effects remains the best fitting model. Models 4, 5, and 6 of Table 5 in the appendix exclude the network rivalry effects and show little change.

6. Conclusion

This article assessed prominent hypothesis about terrorist groups and their alliances and rivalries. I used an 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 the *connectedness* of one's allies, which I theorize is because of the capacity gained by having allies that are strong and have a wealth of resources. I did not find support for the hypothesis about network embeddedness, but I measure this with local transitivity, or embeddedness among cliques, and future work could explore alternate methods of incorporating network embeddedness, such as closeness centrality, which would speak to influence in the network.

I found weak support for the outbidding hypothesis. The limitations of the sample cast doubts on the weakness of these results. Many of the groups in the sample 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 with several groups in the sample. Additionally, some groups in the data were dragged into the Syrian civil war or were involved spillover effects from this civil war, but the groups involved in Syria are not included in the sample unless they had a major presence in Lebanon. This affects both alliances and rivalries networks, but especially the rivalries when considering outbidding and spatial effects.

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 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 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 3 shows the effect that spatial autocorrelation that is inherent in networks has on group attacks. The models include direct connections for both the alliance and rivalry networks. The models show statistically significant incidence rate ratios above 1 for autocorrelation with direct neighbors in all models. This can be interpreted as a group's attack frequency increasing when its direct allies commit more attacks. The models also include alliances that are two “hops” away, or nodes that are indirectly connected to each other via an intermediate note that to which both are directly connected. This second statistic is included only for the ally network. At two hops, the IRRs remain significant but are below one, suggesting that a group's attack frequency decreases when when its indirect connections commit more attacks, but the significance disappears in Models 5 and 6, which include node level random effects and are the best fitting models. However, for spatial autocorrelation for both direct and indirect allies, the IRRs are very close to 1, suggesting that the magnitude of any effect is very small. Models 2, 4, and 6 add in direct connections with a temporal lag for both the ally and rivalry networks. This accounts for direct connections at the previous point in time. There is no evidence that attack behavior of allies or rivals in the previous time point has an effect on a group's attack behavior in the current time point, so these effects were left out of the primary models. Though spatial lag for direct rivalries is insignificant, it is included in the main models as an important network effect and as an alternative form of outbidding.

Table 3.: Spatial Autocorrelation

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.987	0.901	0.985	0.872	0.340**	0.202**
	(0.191)	(0.204)	(0.225)	(0.238)	(0.137)	(0.103)
Ally Spatial Lag 1	1.044***	1.036***	1.044***	1.034**	1.025***	1.023***
	(0.007)	(0.008)	(0.011)	(0.013)	(0.007)	(0.007)
Ally Spatial Lag 2	0.933***	0.929**	0.932***	0.927**	0.989	0.992
	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)	(0.020)
Rival Spatial Lag 1	1.024	1.023	1.025	1.026	1.018	1.017
	(0.013)	(0.014)	(0.018)	(0.021)	(0.012)	(0.012)
Ally Spatial & Time Lag		1.010		1.012		1.009
		(0.008)		(0.010)		(0.006)
Rival Spatial & Time Lag		1.009		1.009		1.010
		(0.013)		(0.020)		(0.013)
Num.Obs.	268	245	268	245	268	245
AIC	833.6	769.2	836.1	771.5	742.6	676.0
BIC	851.6	793.7	841.1	777.7	749.4	684.0
Log.Lik.	−411.813	−377.610	-412.066	-377.739	-365.298	-330.000
ICC			0.0	0.1	0.6	0.6

Table 4.: Full Models - H4 Rival Spatial Lag

	(1)	(2)	(3)
(Intercept)	0.060***	0.065***	0.046**
	(0.040)	(0.046)	(0.046)
Ally Eigenvector Cent.	3.241***	3.118**	2.422*
	(1.125)	(1.250)	(0.891)
Ally Degree Cent.	0.911	0.954	0.817
	(0.115)	(0.134)	(0.100)
Ally Spatial Lag 1	1.020**	1.014	1.019**
	(0.007)	(0.010)	(0.007)
Ally Spatial Lag 2	0.982	0.969	0.992
	(0.018)	(0.022)	(0.019)
Ally Clustering	1.248	1.478	1.796
	(0.600)	(0.788)	(0.876)
Rival Spatial Lag 1	0.998	1.000	1.020
	(0.012)	(0.013)	(0.013)
Rival Clustering	0.913	0.954	0.580
	(0.407)	(0.450)	(0.272)
Religious	2.758**	2.525*	5.157*
	(0.950)	(0.939)	(3.852)
State Sponsor	3.416***	3.250**	5.481*
	(1.159)	(1.186)	(3.644)
Multiple Bases	4.848***	4.118**	2.794
	(1.968)	(1.844)	(2.090)
Political Party	2.541**	2.161*	1.727
	(0.849)	(0.738)	(0.739)
Duration	0.325***	0.335***	0.515*
	(0.058)	(0.064)	(0.152)
Num.Obs.	268	268	268
AIC	755.6	756.7	740.0
BIC	805.9	769.2	757.1
Log.Lik.	−363.802	-363.348	-355.020
ICC		0.2	0.4

Table 5.: Full Models - Jihad instead of Religious

	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.070***	0.074***	0.103**	0.078***	0.084***	0.115*
	(0.049)	(0.053)	(0.091)	(0.054)	(0.059)	(0.099)
Ally Eigenvector Cent.	3.539***	3.441**	2.071	3.487***	3.413**	2.450*
	(1.276)	(1.415)	(0.779)	(1.253)	(1.379)	(0.902)
Ally Degree Cent.	0.937	0.962	0.864	0.934	0.964	0.827
	(0.118)	(0.131)	(0.107)	(0.118)	(0.133)	(0.102)
Ally Spatial Lag 1	1.022**	1.018	1.020**	1.024***	1.019*	1.024***
	(0.007)	(0.010)	(0.007)	(0.006)	(0.009)	(0.007)
Ally Spatial Lag 2	0.976	0.968	0.995	0.975	0.965	0.993
	(0.018)	(0.022)	(0.019)	(0.017)	(0.021)	(0.019)
Ally Clustering	0.855	0.949	1.626	0.912	1.050	1.444
	(0.407)	(0.502)	(0.792)	(0.433)	(0.547)	(0.697)
Rival Degree Cent.	1.217	1.207	1.326*			
	(0.138)	(0.141)	(0.172)			
Rival Spatial Lag 1	1.002	1.004	1.012			
	(0.013)	(0.014)	(0.013)			
Rival Clustering	0.496	0.532	0.430			
	(0.232)	(0.264)	(0.201)			
Jihad	4.078*	3.694*	2.623	3.831*	3.333*	2.968
	(2.406)	(2.222)	(2.197)	(2.125)	(1.923)	(2.386)
State Sponsor	6.152***	5.766***	5.582*	5.057***	4.576***	4.731*
	(2.803)	(2.712)	(4.209)	(2.149)	(1.999)	(3.445)
Multiple Bases	2.751*	2.529*	1.251	3.054**	2.832**	1.815
	(1.084)	(1.046)	(0.978)	(1.082)	(1.064)	(1.326)
Political Party	1.486	1.380	0.876	2.218*	1.977*	1.607
	(0.549)	(0.557)	(0.429)	(0.700)	(0.657)	(0.682)
Duration	0.350***	0.358***	0.543*	0.339***	0.340***	0.489*
	(0.065)	(0.072)	(0.163)	(0.057)	(0.060)	(0.142)
Num.Obs.	268	268	268	268	268	268
AIC	755.5	757.4	739.7	753.4	755.0	742.0
BIC	809.3	770.7	757.9	796.5	765.8	756.8
Log.Lik.	−362.738	-362.690	-353.853	−364.725	-364.479	-358.003
ICC		0.1	0.4		0.1	0.4