Modeling Inter-Rebel Group Conflict with Network Analysis: The Case of Lebanon's Civil War

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Abstract

The literature on civil war has recently shifted its attention from state-rebel violence to rebel-rebel violence. I build on this work by adopting an empirical, exploratory approach. Namely, I apply tools from Social Network Analysis to visualize, summarize, and model conflict between 22 rebel groups in Lebanon's Civil War, specifically in the period $1980 - 1991$. Using a network graph and node-, dyad-, and network-level statistics, I find a conflict structure in line with historical accounts: a dense pattern of hostilities, high reciprocity and low transitivity in hostilities, infighting within religious sects, and the existence of 3 central groups. Furthermore, using regression models tailored to network data (Exponential Random Graph Models), I find that groups that command support from the ethno-religious sect they belong to, control valuable natural resources and territory, and use terrorist tactics are more likely to attack other rebels, while groups that are able to reach an agreement with the state are less likely to attack other rebels. Finally, using a clustering model (Latent Position Cluster Model), I detect 2 sub-conflicts: a narrow cluster that includes the infighting among Palestinian groups and their Sunni allies and a broader cluster that includes the hostilities between rival Shi'ite groups. My approach is relevant to (inter)national policy-makers deciding which rebel groups to support, particularly in conflicts where opposition to the state is fragmented.

1 Introduction

It is well-established that civil wars are more frequent, longer, more violent, and economically costlier than international wars (Blattman and Miguel, 2010). To end any conflict, we must first understand the complex dynamics between the major actors involved. Aside from the state, this often includes multiple opposition groups with heterogeneous goals, resources, and tactics. However, the literature usually treats civil war as conflict between two *unitary* actors—state and opposition (Collier and Hoeffler, 1998; Fearon and Laitin, 2003). This framework goes a long way towards explaining some conflicts, and it provides a useful starting point for thinking about all conflicts. Yet, as our understanding of civil war grows, data availability and computing power increase, and conflicts become more multidimensional, it becomes both possible and necessary to advance the empirical study of civil war.

One topic that has recently attracted the attention of civil war scholars is that on violence *between* rebel groups. Reflecting the state of the literature, Pearlman and Cunningham (2012) note that "[the] norm in more recent civil conflicts is not coherent antagonists as much as shifting coalitions of groups with malleable allegiances and at times divergent interests, only some of whom actually engage in violence at any given point in time" (p. 4). This evolving research agenda explores two main questions: how is conflict between rebel groups structured, and what explains the presence or absence of hostilities between different rebel groups. Applying this agenda to the ongoing Syrian conflict, one might ask: why is the Islamic State in war with other rebel groups fighting the Syrian government, like the al-Nusra Front? Why, in turn, do both of these groups fight the Free Syrian Army? These questions are important, as anecdotal evidence suggests that the Syrian war is not unique (Kalyvas, 2003). Additionally, as power becomes more balanced within the international system, we might expect internationalized civil wars like the Syrian one to involve more rebel factions and inter-rebel hostilities, reflecting the diverging agendas of each faction's foreign sponsors (Jenne and Popovic, 2016).

Setting-out to uncover the correlates of inter-rebel violence, recent studies sketch the profile of the groups most likely to attack other rebels: they are significantly stronger or weaker than the average group, face greater competition from groups sharing the same ethnic identity, control valuable resources or are in conflict over such resources, are located in territory beyond the state's reach, face a weak state, or are in negotiation with the state (Cunningham, Bakke and Seymour, 2012; Eck, 2010; Fjelde and Nilsson, 2012; Pischedda, 2015). Undoubtedly, these findings advance our understanding of inter-rebel conflict. That said, the research design employed by these studies suffers from a key limitation: it ignores the *relational dependence* in conflict data.

In this study, I address that limitation. Namely, I treat rebel groups fighting the same civil war as nodes in a network, and model hostilities between rebels as directed edges.[1] A network approach has three advantages over competing approaches. First, it allows us to summarize useful information on the *structure* of inter-rebel group violence, through graphs, and descriptive statistics on edge-level and network-level variables. Though the quantitative information that network graphs and statistics provide are not intended to replace qualitative research on conflict, they provide a more efficient overview of the dynamics between groups. More importantly, it is difficult to provide equal and impartial coverage of opposing factions in a conflict. Indeed, historical accounts are often labeled as biased, a criticism that statistics are less vulnerable to.

The second advantage a network approach enjoys is that it allows us to unbiasedly and consistently estimate the effect of node-, dyad-, and higher-level covariates on hostilities between rebel groups. This is done through the Exponential-Family Random Graph Model (ERGM) (Besag, 1975). Crucially, the standard approach for modeling conflict, regression on dyadic data, with each observation modeling the likelihood of conflict between groups i and j, is problematic. Even if our goal is only to estimate the effect of node-level covariates on the outcome variable (e.g. how do group i's resources affect its likelihood of attacking

[1] Where it does not create confusion, I use the terms node, vertex, rebel group, faction, and militia interchangeably. The same applies to the terms edges, ties, and hostilities, and I also interchange the terms network and graph.

group j), the inability of classical regression models to *include* triad-level effects (e.g. group i more likely to attack group j, all else equal, if group j allied to an enemy of group i) or higher-level effects makes regression estimates biased and their standard errors inconsistent. Moreover, if we are want to *estimate* the effect of triad-level or higher-level terms on the outcome variable, standard regression on dyadic data is inapplicable. The ERGM offers an alternative to the standard approach that overcomes both of its limitations.

The third advantage that a network approach to conflict offers is that it can effectively uncover clusters among groups. Clusters in a conflict network might emerge due to homophily based on observed attributes (e.g. shared political, regional, religious, ethnic, or other identities), transitivity (e.g. the enemy of my enemy is my friend, the enemy of my friend is my enemy), or coordination dynamics (e.g. attack the group most groups are attacking, ally with the group most groups are allying). Overall, we might expect clusters in a network to form around alliances or, alternatively, sub-conflicts within the larger conflict. Though detecting patterns like clusters is often done through visual inspection, that approach is imperfect and misleading, as confirmation bias causes researchers to project clusters onto the network that are consistent with their prior beliefs or theory. A more precise and data-driven alternative is offered by the Latent Position Cluster Model (LPCM). The latter places nodes on a latent "social" space, based on the distance between node- and dyad-level covariates, then it detects the number of clusters and assigns nodes to them.

The conflict I apply these tools to is the Lebanese Civil War; in particular, the years $1980 - 1991$. This choice is made for two reasons, each allowing this study to make a separate contribution. First, though the Lebanese conflict lasted long, claimed many lives, shaped future regional politics, and drew-in many countries, consensus is lacking on many of the conflict's dimensions. Through examining one dimension – hostilities between rebel groups – I aim to shed light on the conflict's complex dynamics. Specifically, I contribute network graphs, descriptive statistics, and a clustering model illuminating the structure of the network of inter-rebel violence. This quantitative information can be used to complement the rich qualitative accounts of the conflict. In addition, I contribute predictive models (ERGMs) of hostilities among rebel groups that are relatively accurate. Although they are based on observational data, in the future these models can be trained for forecasting purposes, in order to yield early warnings of rebel hostilities. In turn, accurate conflict forecasting can allow the international community to intervene – via diplomacy or force – so as to minimize further violence.

The second distinctive feature of the Lebanese Civil War is the number of groups involved, their cross-cutting religious, ethnic, and political identities, and the variation in their capacity, objectives, and strategies. This is convenient from a statistical perspective: the presence of multiple groups enlarges the sample, thereby allowing for consistent and efficient estimates of quantities of interest. Similarly, the frequent hostilities between groups with different features makes for a sufficiently dense network and covariates with common support, thus enabling identification of covariate effects.[2] As such, the Lebanese Civil War is an appropriate testing-ground for introducing network models to *civil* conflict between rebels. This points to the first contribution of this study – as, to the best of the author's knowledge – all previous applications of network analysis are to *international* conflict between states.

Using data on a network of 22 rebel groups and their hostilities during the $1980 - 1991$ period of the Lebanese Civil War, I showcase the strengths of the network approach to studying inter-rebel conflict. I begin by graphing the network and displaying descriptive statistics at the node-, dyad-, and network-level. These reveal patterns in line with historical accounts of the conflict: a relatively dense network of hostilities, high reciprocity and low transitivity in hostilities (i.e. the enemy of my enemy is my friend), significant infighting within sects, and the presence of 3 central groups (Amal, Fatah/PLO, South Lebanon Army) belonging to the three largest sects (Shia, Palestinians, Maronites). Then, I estimate a series of ERGMs, uncovering several correlations that speak to the literature. Like previous

[2] If hostilities are rare, thereby producing a sparse conflict network, it becomes more likely that hostile groups exhibit different covariate values from non-hostile groups, particularly for binary covartiates (no overlap). This makes the coefficients on these covariates non-identified or, at best, noisily estimated.

research, I find that groups that command support from the ethnic community they belong to, as well as groups that control valuable natural resources and/or territory, are, all else equal, more likely to initiate hostilities against other rebels. On the other hand, and contrary to some of the literature, I find that groups that are able to strike an agreement with the state are less likely to attack other groups. Furthermore, I make two novel findings: groups that use terrorist tactics attack other groups with a higher probability, while the opposite holds for groups using ethnic cleansing tactics. Finally, I estimate an LPCM, which uncovers 2 sub-conflicts in the network: a narrow cluster that includes the infighting among Palestinian groups and their Sunni allies and a broader cluster that also includes the hostilities between the two rival Shi'ite groups (Amal and Hezbollah).

The rest of this study is structured as follows. Section 2.1 introduces the data, graphs the network, and presents descriptive statistics at the node, dyad, triad, and network level. Section 2.2 displays the results of the ERGMs predicting inter-rebel group hostilities. Section 2.3 presents the output of the LPCM. Section 3 discusses the significance of my results vis-á-vis the literature and the history of the Lebanese Civil War. Section 4 summarizes and offers policy implications and directions for future research.

2 Analysis

This section introduces the data and presents the network graph, descriptive statistics, output from ERGMs, and output from the LPCM.

2.1 Data & Descriptive Statistics

The network I analyze is constructed using the Minorities at Risk Organizational Behavior (MAROB) dataset (Asal, Pate and Wilkenfeld, 2008). MAROB restricts its attention to the Middle East and North Africa in the period $1980 - 2004$, and codes "the characteristics of those ethnopolitical organizations most likely to employ violence and terrorism in the pursuit of their perceived grievances" (Asal, Pate and Wilkenfeld, 2008, p. 1). Subsetting the observations for Lebanon from 1980 to 1991, I am able to capture all but 5 years of the Lebanese Civil War (1975 – 1979).

Because the non-state (rebel) actors involved are groups representing different ethnic, religious and political goals, they are all observed in MAROB. These 22 groups constitute the nodes in my network. The (directed) edges in the network are indicators of hostilities between groups, coded using MAROB variables on "inter-organization conflict" (Asal, Pate and Wilkenfeld, 2008, p. 30).[3] Note that my edges are *binary* indicators of hostility by group i towards group j, not counts of hostilities. Similarly, there is no temporal dimension to the edges; they merely capture whether *at least one* hostility by group i towards group j took place between 1980 – 1991, not whether a hostility was observed each year.

The network is graphed in Figure 1.[4] Four features are worth noting. First, the network is neither overly sparse, nor dense. This is confirmed by the network's density score: for two randomly chosen rebel groups i and j, there is an 8% chance that i attacked j sometime during the period in question.[5] Though this figure might seem low, for a conflict network it is relatively dense—compare it, for example, to that of international conflict in the period 1990 – 2000. One factor reducing the network's density is that 4/22 nodes are isolates, i.e. they have no edges. Interestingly, 3/4 of isolates are Palestinian – the ethno-religious group with the largest number of factions in the conflict – but non-isolate Palestinian groups are relatively hostile (e.g. Fatah/PLO). This is consistent with perceptions of Palestinians as the most strategically diverse ethno-religious group in the War. Indeed, it will not surprise Lebanon scholars that Palestinians' wide range of preferences and tactics maps into significant within-Palestinian variation in hostilities.

[3] These variables are `INTERSEV1DES`, `INTERSEV2DES` and `INTERSEV3DES`, which record the "organization with [the] highest level of inter-organizational conflict" (Asal, Pate and Wilkenfeld, 2008, p. 30-31).

[4] I cross-check the MAROB data with the UCDP Non-State Actors Dataset (NSA) (Sundberg, Eck and Kreutz, 2012) and the historical accounts in O'Ballance (1998). I find general agreement across the different sources regarding the pattern of hostilities. However, note that the NSA data only covers the last 3 years of the period I study, and thus a complete cross-check is unfeasible.

[5] The density score can be derived simply by dividing the number of edges (37) by the number of dyads (462); the latter is also the maximum feasible number of edges.

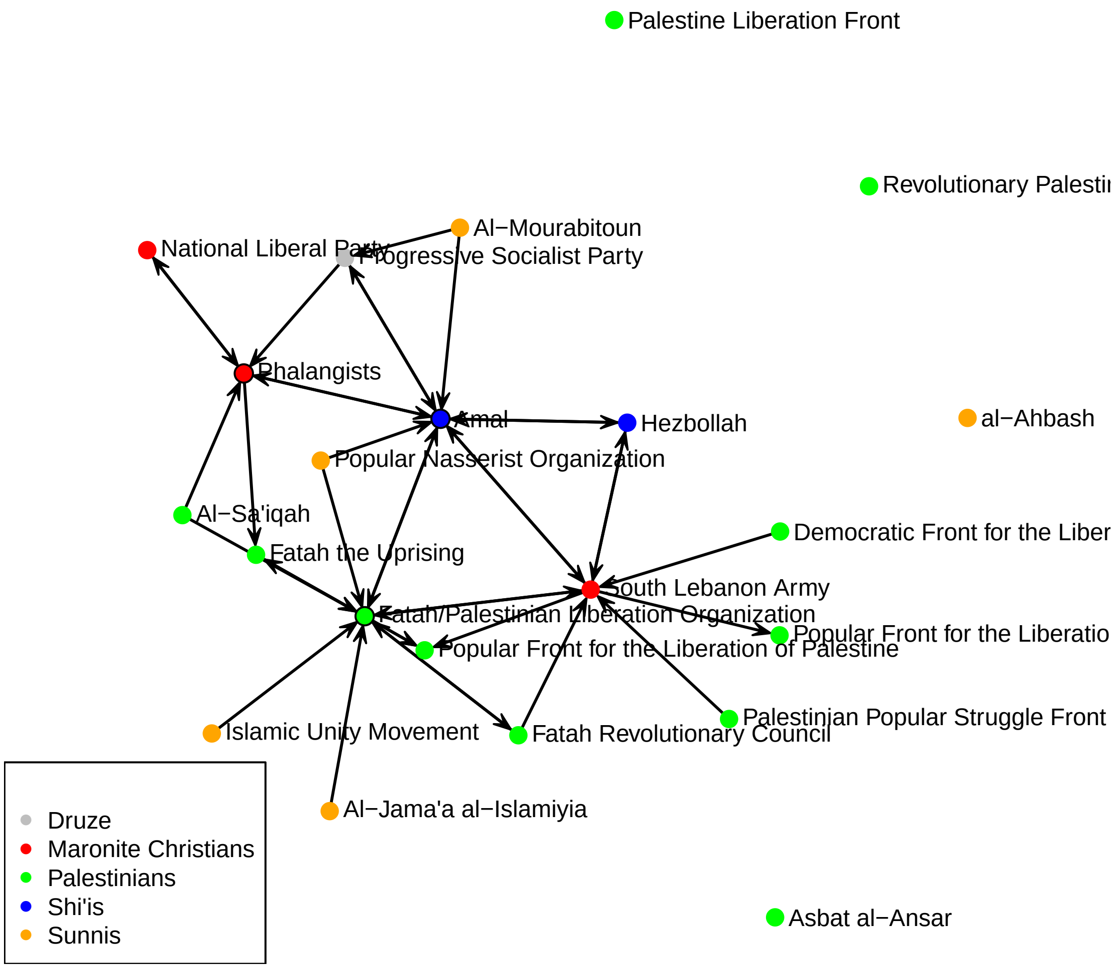

Figure 1: Inter-Rebel Hostilities in Lebanon's Civil War, 1980 – 1991

Notes: An edge from i to j represents at least one hostility directed by i to j during the period in question. Groups are labeled as in the MAROB data and might be labeled differently in other sources.

A second feature to note in Figure 1 is the high degree of mutuality in ties (if i attacks j, most likely j attacks i, and vice-versa). This is also confirmed by the network's relatively high edgewise reciprocity score (fraction of ties that are mutual): 0.54.[6] High mutuality/reciprocity is intuitive for a civil conflict network. With few constraints on rebels' strategies other than resources, we should expect violence to be met with violence. This stands in contrast to international conflict, where domestic political constraints (laws, elections) and international political constraints (treaties, sanctions) limit states' abilities to attack each other.

The third interesting feature of the network relates to hostilities within triads; in particular, whether hostilities are transitive (i.e. if i attacks j and j attacks k, how likely is it that i also attacks j). Transitivity is often recorded when edges denote cooperative behavior or positive preferences, as in business or friendship networks (Wasserman and Faust, 1994). However, in conflict networks we should expect edges to be intransitive, since i might gain from coalescing with k to defeat j—per the proverb "the enemy of my enemy is my friend". Alternatively, i might have no incentive to attack k, as i can free-ride on j's hostilities towards k. In any case, all else equal, the strategic logic behind i attacking k just because j attacks k is weak. Perhaps for this reason, the Lebanese network has a transitivity score of just 0.23 (fraction of triads with transitive edges).

The fourth noteworthy feature in Figure 1 is the significant number of edges between nodes of the same color, representing infighting within ethno-religious groups. In particular, we see hostilities between several Palestinian groups, the only 2 Shi'ites groups, and 2/3 Maronite groups. Sectarian infighting is a well-established feature of the Lebanese Civil War, thus it is reassuring that the network graph depicts it. This feature also differentiates the Lebanese Civil War from current conflicts in the region, where alliances and hostilities follow sectarian lines. For example, in Iraq and Syria there is no infighting among Kurdish

[6] Note that edgewise reciprocity is probably suppressed by the fact that some rebel groups in the network were actually eliminated during this period (e.g. National Liberal Party). If they were eliminated by a group attacking them for the first time and, thus, were unable to reciprocate, then the respective edge will necessarily be non-reciprocal.

or Shi'ite groups, while there is limited infighting among Sunni groups in Syria (e.g. IS vs al-Nusra) and non-violent competition between Palestinian groups in the Palestinian territories (Hamas vs. Fatah) (Christian and Druze militias are no longer active in the region).

Table 1: Degree Summary Statistics

Degree	Minimum	Mean	Median	Maximum	σ	ρ (Id, Od)
Indegree	0	1.68	0.5	8	2.46	0.84
Outdegree	0	1.68	1.5	5	1.61	

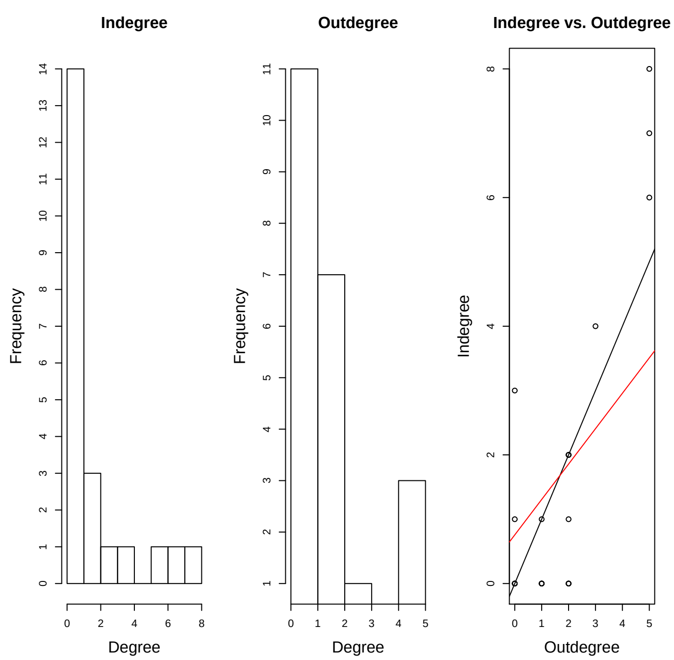

Figure 2: Degree Histograms & Scatterplot

Notes: Black line in scatterplot is 45 degree line.

Moving on to a more thorough analysis of the network's structure, we turn to the distribution of hostilities across groups. Figure 2 shows that both indegree (number of groups attacked by) and outdegree (number of groups attacked) follow a right-skewed distribution, with some nodes (e.g. the 4 isolates) attaining the minimum of 0, and others attaining the maxima of 8 and 5, respectively. This skew is also reflected in Table 1, where the mean of both degree distributions is greater than the respective median and their standard deviations are relatively high. Taken together, this information suggests that there are few, central rebel groups in the network, a pattern that is also visible in the network graph. An interesting feature of the network that is not easily discernible in the graph is that there is more variation in the targets vs. initiators of hostilities (since $\sigma_{Id} > \sigma_{Od}$). Finally, it is worth noting that, owing to the aforementioned mutuality of hostilities, there is a strong positive correlation between indegree and outdegree (0.84), also mirrored in the steep slope of the scatterplot in Figure 2.

At this stage, we can focus on the node level. Table 2 displays four different centrality scores for each rebel group. Across most measures, three groups stand out: Amal, Fatah/PLO, and the South Lebanon Army (SLA). Unsurprisingly, these are three groups that are included in virtually every historical account of the conflict. Moreover, they are the biggest factions from the three ethno-religious groups most active in the conflict—Amal from the Shi'ites (though later surpassed by Hezbollah), Fatah from the Palestinians, and SLA from the Maronite Christians. Clearly, these groups' centrality scores bode well with popular facts about the conflict, but what do the different measures reflect?

Betweenness centrality, a metric more complicated than the intuitive indegree and outdegree scores, measures a node's propensity to act as a bridge between other nodes. In social networks, it is intended to measure the control that a node controls on communication between other nodes (Freeman, 1979). In the case of civil conflict, groups with high betweenness centrality stand in the way of smaller groups attacking other groups—for example, SLA attacks Amal and is attacked by 5 Palestinian groups, but none of *those* groups attacks Amal. Eigen centrality, in turn, measures a node's ties to *central* nodes—a node's ties with central nodes make that node eigen central (Bonacich, 1972). A good illustration of this concept is the Popular Nasserist Organization (PNO), which ranks fourth in eigen centrality, but only has 2 ties. This is because these ties are Amal and Fatah, the two most central groups by most measures. Returning to Amal, Fath, and SLA, their high eigen centrality is owed to the fact that all they attack each other, and all are attacked by several other groups. A final centrality measure that is binary, and hence omitted from the table, is whether a node acts as a cutpoint. Cutpoints are nodes whose removal disconnects the network, dividing it into smaller networks. Again, 3 cutpoints are detected, corresponding to Amal, Fath, and SLA. In short, Table 2 shows how using multiple and complementary measures of actor centrality reenforces our understanding of the complex dynamics in the Lebanese conflict.

Table 2: Centrality Scores by Group

Group	Indegree	Outdegree	Betweenness	Eigen
al-Ahbash	0	0	0	0
aJaI	0	1	0	0.13
al-Mourabitoun	0	2	0	0.23
al-Saíqah	0	2	0	0.20
Amal	**7**	**5**	**60.67**	**0.48**
Asbat al-Ansar	0	0	0	0
DFLP	0	1	0	0.12
FRC	1	2	0	0.25
Fatah Uprising	2	2	4.33	0.13
Fatah/PLO	**8**	**5**	**56.50**	**0.39**
Hezbollah	2	2	0	0.27
IUM	0	1	0	0.13
NLP	1	1	0	0.07
PLF	0	0	0	0
PPSF	0	1	0	0.12
Phalangists	4	3	27.67	0.22
PFLP	3	0	0	0
PFLP-GC	1	0	0	0
PNO	0	2	0	0.28
PSP	2	2	1.33	0.22
RPCP	0	0	0	0
SLA	**6**	**5**	**42.50**	**0.37**

Notes: Bold numbers denote the 3 highest values in each score. Groups are labeled as in the MAROB data and might be labeled differently in other sources.

2.2 Predicting Inter-Rebel Hostilities

In this section, I predict hostilities in the conflict network by fitting an array of regression models, aiming to maximize fit and predictive power. In choosing terms to include in my models, I look to the emerging literature on inter-rebel violence. However, I also contribute to the literature by including novel node-level covariates from the MAROB data, as well as dyad-level covariates.

For this purpose, I employ the state-of-the-art model for predicting edges in networks, the ERGM. Crucially, this model treats the observed network – as a whole – as a draw from a (multivariate) distribution, and thus does not require nodes and edges to be independently distributed in order to estimate the effects of covariates on the network's structure (Cranmer and Desmarais, 2011). In other words, because the unit of observation – from the model's standpoint – is the whole network and not its nodes and edges, the ERGM does not require the independence assumption for unbiased and consistent estimation. On the contrary, the classical regression model does require (conditionally) independent observations to deliver statistically sound estimates—whether from a frequentist or Bayesian perspective.

I begin by attempting to exploit another advantage of the ERGM over the classical regression model: it can incorporate edge-, dyad-, and triad-level terms in the regression. However, adding terms for transitivity, cyclicality, or other triadic features causes the model to not converge. Similarly, the diagnostics for edgewise and dyadwise shared partners terms suggest they should not be included in the model. The only exception is the term for mutual ties, which improves model fit drastically. Recalling the network's relatively large reciprocity score (0.54), based on the fact that hostilities are reciprocated in conflict, the significant effect of the Mutual term is not surprising.

Moving on, I use the ERGM to estimate the effect of node-level covariates on hostilities, something which the literature attempts through ill-applied standard regressions. I search through the MAROB dataset for node-level covariates that appear in the literature as predictors of inter-rebel hostilities. I start by setting a baseline: a naive model that only includes the number of edges each node has as a predictor. After supplementing this model with a term for mutual ties – as noted above, the only higher-level covariate that improves model fit – I progressively add node-level covariates in an effort to minimize Residual Deviance. The latter is the most popular goodness-of-fit statistic for models estimated through Maximum Likelihood and nested within each other. Note that all of my nodal covariates terms are estimated effects for *out*-edges. This is because the literature on inter-rebel violence forms hypotheses about the effect of *group* i *having feature* x_i on its likelihood of attacking other groups. Table 3 shows the results of this search, through a series of Analysis of Variance (ANOVA) comparisons. Every model from the third one onwards adds a nodal covariate, and all models aside from the penultimate one make a statistically significant improvement in fit. Overall, at the cost of only 8 degrees of freedom (residual dof = 454), residual deviance drops by more than 75% between the baseline and final model (from 640 to 157).

Table 3: ANOVA of ERGMs

Model	Deviance	Resid. DoF	Resid. Dev	Pr(>|Chisq|)
Edges	640.47	461	640.47	0^{***}
+ Mutual	414.70	460	225.77	0^{***}
+ Terrorist Tactics	24.53	459	201.24	0^{***}
+ Popular (=BIC-min.)	30.48	458	170.77	0^{***}
+ Ethnic Cleansing	3.49	457	167.28	$0.06^{\cdot}$
+ Control Resources	5.03	456	162.24	0.02^{*}
+ Control Territory	0.95	455	161.30	0.33
+ Agreement w/ State	4.36	454	156.93	0.04^{*}

Notes: BIC-min denotes the BIC-minimizing model. The Residual Deviance- and AIC-minimizing model is the last one. The p-value is with respect to the reduction in Residual Deviance being statistically significant. $^{**}p < .05$; $^{***}p < .01$

Nevertheless, Residual Deviance is only one of many criteria for model selection. I supplement my search for the best-fitting model by using the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). Though the difference between the criteria is small, the former is better-suited to small samples and penalizes additional parameters more heavily (i.e. rewards parsimony). Table 4 shows output from the BIC- and AIC-minimizing

ERGMs. Incidentally, the latter model is the same as the model minimizing Residual Deviance. However, the BIC-minimizing ERGM has four fewer nodal covariates. Substantively, this is an important difference, because the excluded covariates – Ethnic Cleansing, Control Resources, Control Territory, Agreement with State – are presented as determinants of inter-rebel violence in previous studies. I return to this point in Section 3. All of the terms in the models, including the nodal covariates, are statistically significant at the 5% or 1% level. Moreover, all of the diagnostics for both models indicate that the ERGMs converged.[7] Interestingly, the coefficient for Popular is larger in the AIC-minimizing model, despite the model controlling for more covariates. In contrast, the other coefficients (aside from the Edges term) decrease in size, as would be expected if they were confounded with the additional covariates.

Table 4: Best-Fit Models

	BIC-Min	AIC-Min
Edges	-11.2^{***}	-14.4^{***}
	(1.7)	(2.5)
Mutual	2.0^{***}	1.6^{**}
	(0.7)	(0.7)
Terrorist Tactics	1.7^{***}	1.3^{**}
	(0.3)	(0.6)
Popular	1.6^{***}	2.3^{***}
	(0.3)	(0.5)
Ethnic Cleansing		-6.9^{**}
		(3.4)
Control Territory		1.6^{**}
		(0.7)
Control Resources		8.3^{***}
		(3.0)
Agreeement with State		-3.8^{**}
		(1.9)
BIC	195.3	206.2
AIC	178.8	173.2
Residual Deviance	170.8	156.9

$^{**}p < .05$; $^{***}p < .01$

[7] I surpress diagnostics tables and plots to conserve space.

2.3 Clustering

The last aspect of network structure I explore is clustering. To do this, I employ the Latent Position Cluster Model (LPCM), which has the ability to identify clusters in the network and assign nodes to them. This is done by first placing nodes on a latent "social" space, based on the Euclidean distance between nodes' and dyads' covariates, as well as higher-order terms like transitivity (Hoff, Raftery and Handcock, 2002). Moreover, the LPCM can account for clustering based on "unobserved attributes or on endogenous attributes such as position in the network, 'self-organization' into groups or a preference for popular actors" (Handcock, Raftery and Tantrum, 2007, p. 302).

I fit an LPCM using all of the nodal covariates identified in Table 4 as significant predictors of hostilities. According to various diagnostics, the model converges.[8] Figure 3 shows (posterior mean) estimates of the latent positions of rebel groups, projected onto 2-dimensional space. Two clusters are identified by the model: they are almost co-centric, with one subsuming the other, and are centered around 0 on both latent dimensions. The narrower cluster contains all but one of the Palestinian and Sunni groups, and it places them relatively close to each other. (It also contains 2/3 Maronite groups, also positioned adjacently, though far from the cluster's center.) In turn, the broader cluster contains the only two Shi'ite groups in the network, though they are far from each other as well as the cluster's center. Note that the broader cluster subsumes the narrower one—all groups in the latter cluster also belong to the former, but not the vice-versa. Finally, the only groups outside both clusters are the third Maronite group (SLA) and the only Druze group (PSP), but they are placed at maximal distance from each other.

[8] I use the `latnet` package in `R` to fit these models (Krivitsky and Handcock, 2008). Again, I supress these diagnostics to conserve space.

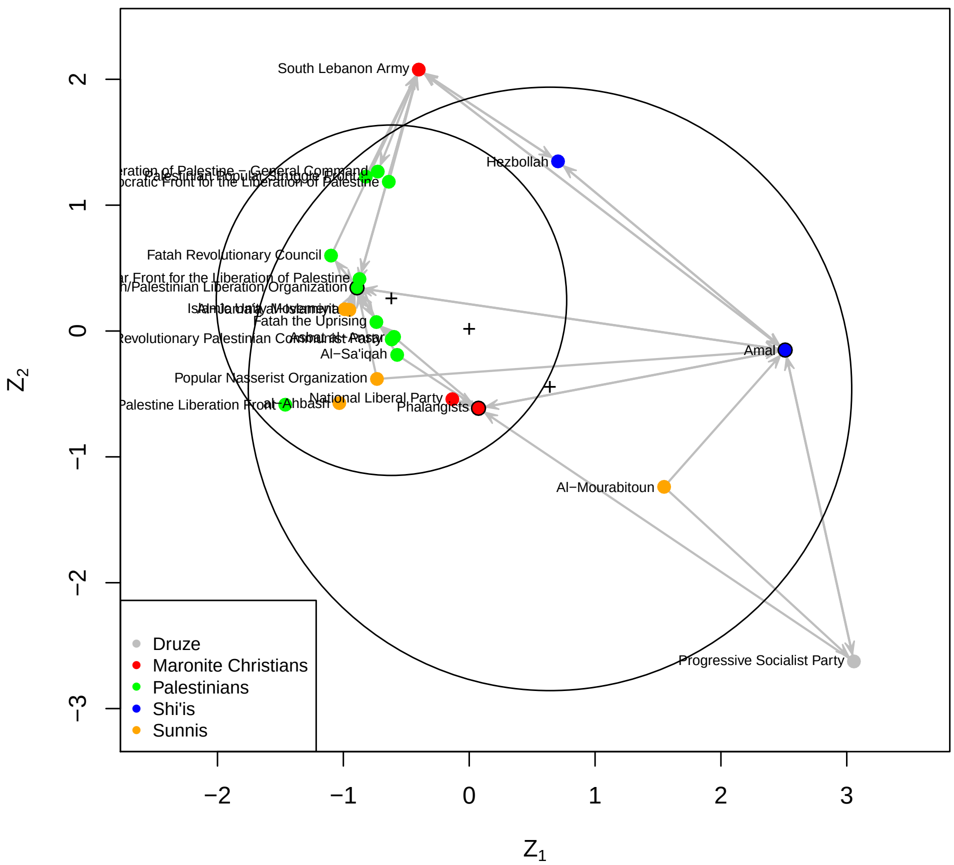

Figure 3: Latent Position Cluster Model

Notes: Latent dimensions are scale-free. 3 crosses mark the origin of the two latent dimensions (0,0) and the center of the 2 clusters.

3 Discussion

From the perspective of the literature on inter-rebel violence, this study produces several substantive insights. This is because the best-fit models in Table 4 include a number of covariates that other scholars have presented as causes of rebel hostilities. In this section, I discuss each of these variables' marginal effects, and, where possible, connect my findings to the literature. I also interpret the clustering model's output from the perspective of historical accounts of the conflict.

Popular organizations, defined as those that have the support of the majority of the ethno-religious community they belong to (Sunni, Shi'ite, etc.), are, on average, roughly 9 times more likely to an other randomly chosen rebel group than groups that do not have majority support from their ethno-religious community.[9] This is in line with the argument of Pischedda (2015), that groups facing "windows of opportunity"—that is, which have an advantage over other co-ethnic rebels in reaping the support of their broader ethnic community—are more hostile towards other groups.

Groups that control valuable natural resources are, on average, roughly 400 times more likely to attack another group than resource-poor groups. This supports the arguments of Eck (2010) and Fjelde and Nilsson (2012), that natural resources enlarge groups' capacity for violence, leading to more attacks on other rebels. Fjelde and Nilsson (2012) report a positive coefficient for groups controlling oil reserves and a negative one for groups controlling gemstones. Given that my own data does not distinguish between the type of resource, it is likely that the positive coefficient I estimate is due to the dominating effect of oil in this sample. Indeed, there are few gemstone-endowed regions in Lebanon for rebel groups to exploit, as there in the data of Fjelde and Nilsson (2012).

Controlling territory increases the probability that a group attacks another group by roughly 400%. Again, this finding is in line with Fjelde and Nilsson (2012), who argue that controlling territory adds to groups' strategic capacity, thereby enabling them to scale-up their hostilities towards competitors. This is because territorial control allows the group to harness the resources of civilians, including manpower and valuable information.

Reaching an agreement with the state means that a group is, on average, roughly 98% less likely to attack another group. This is in contrast with the argument of Eck (2010);

[9] All of the marginal effects I report are based on output from the second column of Table 4. Implied in each statement is that all other covariates (binary) are kept at their reference category. As such, the effects I report are what is sometimes referred to as "first differences". Henceforth, to conserve space, I do not provide full intepretations of marginal effects.

that groups in negotiation with the government will try to eliminate other groups, in order to be the sole recipients of state concessions. That said, the author cautions us that the evidence in support of her argument is non-robust. As such, it is possible that the negative association I report is generalizable outside the Lebanese case.

Terrorist tactics increase a group's likelihood of initiating hostilities against another rebel group by roughly 270%, on average. On the other hand, a group that engages in ethnic cleansing is roughly 99% *less* likely to attack another group. Both of these findings are novel, thus pointing to the necessity of incorporating rebel tactics into theories of inter-rebel violence. Puzzlingly, although there is a wide literature on rebels' tactics in fighting against the state, it has not been integrated with the emerging literature on inter-rebel violence. Since theory-building is beyond this study's scope, I leave it up to the literature to modify existing theories so as to account for the above correlations.

I now return to the output from the LPCM (Figure 3). The lack of tight clustering around sectarian lines reflects the highly complex nature of the Lebanese Civil War: multiple rebel groups from each of several ethnic and religious sects, with cross-cutting political preferences within sects and substantial variation in resources and strategies. Naturally, this presents a tough setting for establishing clear patterns. Furthermore, the aggregated nature of the edges across 12 years of a dynamically evolving conflict might obscure clusters from distinct phases in the conflict. Nevertheless, there are some patterns in Figure 3 worth interpreting.[10]

The narrower cluster seems to pick-up the significant infighting among Palestinian groups, a unique feature of the Lebanese conflict. At the same time, the close positioning of the Palestinian groups emphasizes their similarities across many dimensions. Indeed, where it not for the extreme organizational fragmentation and "plague of initials" that civil war encourages, several of these Palestinian groups might have consolidated into one group (Bakke, Cunningham and Seymour, 2012). The presence of 4/5 Sunni groups in the first cluster is also

[10] As with Principal Component Analysis, where researchers often label and interpret the k most important principal components in a way that is informed by their theory, interpreting the clusters identified by LPCMs is at the researcher's discretion. The historical information in this paragraph is from O'Ballance (1998).

interesting. In addition to the occasional alliances between Palestinian and Sunni groups (e.g. Popular Nasserist Organization joining PLO in 1976 Damour offensive), it is possible that shared religion creates more shared features between them, which the latent model detects. The only Sunni-labeled group outside the first cluster, Al-Mourabitoun, actually had mixed membership historically – containing, Sunnis, Shias, Maronites, and Druze – and also perpetually formed alliances with groups from all sects but the Maronites. Of further interest is the presence of 2/3 Maronite groups in the narrow cluster. Their adjacent presence might be explained by the fact that the National Liberal Party's militia joined forces with the Phalangists in 1976, then were eliminated by them in 1980. As for these Maronite groups being placed in the same cluster as the Palestinians and Sunnis, this might be owed to shared tactics: much like the more extreme Palestinian groups (e.g. Al-Sa'iqah), the Phalangists used terrorism and ethnic cleansing, as in the Karantina and Tel al-Zaatar massacres.

The wider cluster contains the only two Shi'ite groups, Amal and Hezbollah, though they are placed far apart. This could be owed to Hezbollah forming as a splinter of Amal due to disagreements over secularism, as well as their frequent infighting (esp. 1987 – 1989). Since all Palestinian (and Sunni) groups are included in the broader cluster with Amal and Hezbollah, the positioning of the two Shi'ite groups can also be interpreted through their attitude towards the Palestinian issue. Indeed, Amal exchanged attacks with Palestinian groups (see War of the Camps), with which Hezbollah was historically aligned. Amal's hostile stance to Palestinian groups might also explain why it is placed much further from the narrow cluster than Hezbollah is. Finally, the only Druze group's (PSP) placement outside the broader cluster and at maximal distance from other nodes can be interpreted through their shifting alliances and opportunistic tactics. Similarly, the only other group outside the broader cluster, the Maronite South Lebanon Armys, also differed drastically from other groups: though it was initially aligned with the other Christian groups, it broke away, and it acted mostly as a proxy actor for Israel.

4 Concusion

Following the civil war literature's recent shift to the study of inter-rebel conflict, this article reviewed and demonstrated the advantages of a network approach. This was done by applying several tools from network analysis to the case of Lebanon's Civil War, specifically the period $1980 - 1991$. In particular, a network graph and descriptive statistics at the node-, dyad-, triad-, and network-level were used to confirm several patterns detected in historical accounts of the conflict: a dense pattern of hostilities, high reciprocity and low transitivity in hostilities, infighting within religious sects, and the existence of 3 central rebel groups. Furthermore, Exponential Random Graph Models were used to predict inter-rebel hostilities, and found that groups that command support from the ethno-religious sect they belong to, control valuable natural resources and territory, and use terrorist tactics are more likely to attack other rebels, while groups that are able to reach an agreement with the state are less likely to attack other rebels. Finally, a Latent Position Cluster Model was employed to uncover clusters in the network and detected 2 sub-conflicts: a narrow cluster that includes the infighting among Palestinian groups and their Sunni allies and a broader cluster that includes the hostilities between rival Shi'ite groups.

My approach has implications for (inter)national policy-makers seeking to predict or influence inter-rebel hostilities. For example, given foreign powers' diverging preferences over the ongoing Syrian conflict's outcome and the multitude of groups involved in the conflict, knowing how each group will respond to changes in network structure is crucial to policy-makers on all sides. If Iran or Russia's objective is to maximize conflict among rebel groups, so as to divert damage away from the allied Syrian regime, they will want to know what covariates predict inter-rebel hostilities. Similarly, if the US's objective is to channel resources to groups that will use them against the regime and not other against rebels, policy-makers will want to know what covariates predict a reduction inter-rebel hostilities. By building on my approach with more fine-grained data, it is possible to tackle these policy questions.

My approach also suffers from two limitations, which lend themselves to an equal number of suggestions for future research. First, the aggregated nature of my edges across 12 years of conflict might cause me to pool distinct phases of the Lebanese Civil War into one phase. Though this is not improper from a statistical perspective and, in fact, provides more degrees of freedom and a denser network for estimating my ERGMs, it increases the risk of null results. For example, if nodal covariate x caused rebels to be more violent in the first half of the period in question, but less so in the second half, we might find a null effect by estimating the effect of x using data from the whole period. Another issue that pooling network data creates relates to the elimination of rebel groups during the period in question. If elimination is driven by some of the nodal covariates in my regressions, predicting hostilities against groups that no longer exist might bias my estimates. A remedy to these issues is modeling the network dynamically and using longitudinal ERGMs to predict hostilities across time. Unfortunately, this task is highly challenging and largely an area of ongoing research (Krivitsky and Handcock, 2014).

The second limitation of my approach is that my estimates are correlational, not causal. This is owed to the observational nature of my network data and the lack of a causality-oriented research design. However, it might be possible to exploit sources of random variation at the rebel-group level to identify some causal effects. For example, shocks to rebels' resources due to poor weather, economic conditions, or unforeseen foreign intervention might allow us to estimate the causal effect of rebel groups' resources on inter-rebel hostilities. That said, one is hard-pressed to think of random shocks for other node-level covariates (e.g. agreement with state), let alone higher-level covariates for the network. For this reason, the most obvious way to advance the use of network analysis in civil conflict studies – with network graphs and descriptive statistics, ERGMs, and LPCMs – is to apply these tools to additional conflict networks. I leave this exciting task to future research.

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