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

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December 11, 2016

Abstract

When do rebel groups fight each other? How is conflict between rebel groups structured? 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 predict conflict between 22 rebel groups in Lebanon's Civil War, specifically in the period 1980-1991. My best-performing Exponential Random Graph Models predict that groups that command support from the ethnic group they belong to, control valuable natural resources and territory, and use terrorist tactics are more likely to attack other rebels. On the other hand, my analysis finds that groups that are able to reach an agreement with the state are less likely to attack other rebels. My findings are relevant to policy-makers deciding which rebel groups to support, particularly in conflicts where opposition to the state is fragmented.

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1 Introduction

To end conflicts like that in Syria, 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—the state and the opposition. 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 increases, and conflicts become more multidimensional, it becomes both necessary and possible to move the field forward.

One topic that has recently attracted the attention of civil war scholars is that on violence between rebel groups. Indeed, looking at the conflict in Syria, one might ask: why is the Islamic State in war with other rebel groups fighting the Syrian government, like al-Nusra? Why, in turn, do both of these groups fight the Free Syrian Army? Anecdotal evidence suggests that the Syrian war is not unique—a large number of civil wars involve conflict between different groups, all of which are in conflict with the state (Kalyvas, 2003). Setting-out to uncover the correlates of inter-rebel violence, recent studies have sketched the profile of the groups most likely to attack other rebels (Cunningham, Bakke and Seymour, 2012; Eck, 2010; Fjelde and Nilsson, 2012; Pischedda, 2015); 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. Undoubtedly, these findings advance our understanding of inter-rebel conflict. That said, the research design they employ suffers 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 ties. This allows me to summarize useful information about inter-rebel group violence through edgelevel and network-level statistics. Clearly, this is not possible under a conventional regression framework. Furthermore, a network approach allows me to consistently and efficiently estimate the effect of node-level, dyad-level, and higher-level covariates on hostilities between rebel groups, by applying a key tool of social network analysis: the exponential-family random graph model (ERGM) (Besag, 1975). Because the ERGM treats the observed network as a draw from a multivariate distribution, unlike regression models, it does not require independent nodes and ties to unbiasedly and consistently estimate the effects of exogenous parameters on the network (Cranmer and Desmarais, 2011). In other words, replicating the studies above after restructuring the data as dyads and including dyad-level features would not rectify the harm done; regression estimates would still exhibit bias and noise, whereas ERGM estimates would not.

The conflict I apply these tools to is the Lebanese Civil War; in particular, the years 1980-1991. This choice is made for three reasons, each allowing this study to make a separate contribution. First, the Lebanese conflict was unique in the number of groups involved, as well as the variation in their religious, ethnic, and political identity, as well as their capacity, objectives, and strategies. This is convenient from a statistical perspective: the presence of multiple groups enlarges the sample, thereby allowing for more consistent and efficient estimates of quantities of interest. Similarly, the frequent hostility between groups with different features makes for a sufficiently dense network and covariates with common support. This enables identification of covariate effects.[1] 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.

Second, the Lebanese conflict lasted long, claimed many lives, destroyed the economy, shaped future regional politics, and drew-in many countries. Despite that, there is little con-

[1] If hostilities are rare, thereby resulting in 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.

sensus surrounding the conflict's many dimensions. Through examining one of the conflict's dimensions—the dynamics between rebel groups—this study aims to shed some light on the conflict's complex history. Specifically, I contribute descriptive statistics on the network of inter-rebel violence, which can be used to complement qualitative accounts of the conflict. In addition, I contribute predictive models of hostilities among rebel groups that are relatively accurate. Although 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 the probability and impact of further violence.

Third, the Lebanese Civil War bears some similarities with the ongoing Syrian war: the large number of rebel groups, the variation in their ethnic, religious, and political preferences, and their ties to foreign governments. More importantly, and perhaps as a result of the above, the Syrian conflict has reached a stalemate, with neither the government nor any rebel group being able to dominate. Coupled with foreign powers' diverging preferences over the conflict's outcome and the resources they channel to support different groups, knowing how each group will respond to changes in the conflict network is crucial to policy-makers on all sides. For example, if Iran's objective is to maximize conflict among rebel groups, so as to divert damage away from the allied Syrian regime, Iranian policy-makers will want to know what covariates predict inter-rebel hostilities. Similarly, if the US's objective is to channel resources to groups unlikely to use them against other rebels, Congress will want to know how the interaction of groups' resources with group covariates affects the likelihood of hostilities. My approach can provide suggestive answers to both of these questions.

Using data on a network of 22 rebel groups during the period 1980-1991, with hostilities between groups modeled as directed edges, I uncover several correlations that speak to the literature. As shown by other scholars, groups that command support from the ethnic community they belong to, as well as groups that control valuable natural resources and/or territory, are, *ceteris paribus*, 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. Finally, I contribute two novel associations between group covariates and the likelihood of inter-rebel violence: groups that use terrorist tactics attack other groups with a higher probability, while the opposite holds for groups using ethnic cleansing tactics.

The rest of this study is structured as follows. Section 2 introduces the data and presents descriptive statistics at the node level and network level. Section 3 displays the results of my model-fitting. Section 4 discusses the significance of my results vis-á-vis the literature.

2 Data and 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 (1975-1980).

Because the non-state (rebel) actors involved in the War were 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) ties in the network are indicators of hostilities between groups, coded using MAROB variables on "inter-organization conflict" (Asal, Pate and Wilkenfeld, 2008, p. 30).[2] I should note that my ties are *binary* indicators of hostility by group i towards group j, not counts of hostilities. Similarly, there is no temporal dimension to the ties; 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.

[2]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).

The network is graphed in Figure 1, with colors representing the 5 ethnic groups to which the rebel organizations belong.[3] Table 1, in turn, provides network-level descriptive statistics. Several patterns are worth noting. First, the network graph is neither overly sparse, nor dense. This is confirmed by the density calculation in the table: for two randomly chosen rebel groups i and j, there is an 8% chance that i attacked j sometime during the Lebanese Civil War. Nevertheless, for a conflict network, this is relatively dense—compare it, for example, to that of international conflict in the period 1990-2000.

One factor contributing to the network's sparsity is that 4 out of the 22 nodes are isolates. Interestingly, 3/4 of isolates are Palestinian—the ethnic group with the largest number of factions in the conflict—yet other Palestinian groups are more hostile (e.g. Fatah/PLO). This is consistent with perceptions of Palestinians as the most strategically diverse ethnic group in the War. Indeed, it might not surprise Lebanon scholars that Palestinians' wide range of preferences and tactics maps into a lot of within-Palestinian variation in hostilities.

Another pattern to note is that many ties are mutual. This is intuitive, given that we are studying a civil conflict network—with little constraints on rebels' strategies other than resources, we should expect violence to be met with violence. This stands in contrast to international conflict, whereby domestic political constraints (laws, elections), and international political constraints (treaties, sanctions) limit states' abilities to attack each other. Again, this is confirmed by the high dyadic and edgewise reciprocity scores (0.93 and 0.54, respectively) in Table 1.

[3] I use the terms node, vertex, rebel group, rebel organization, militia and faction interchangeably.

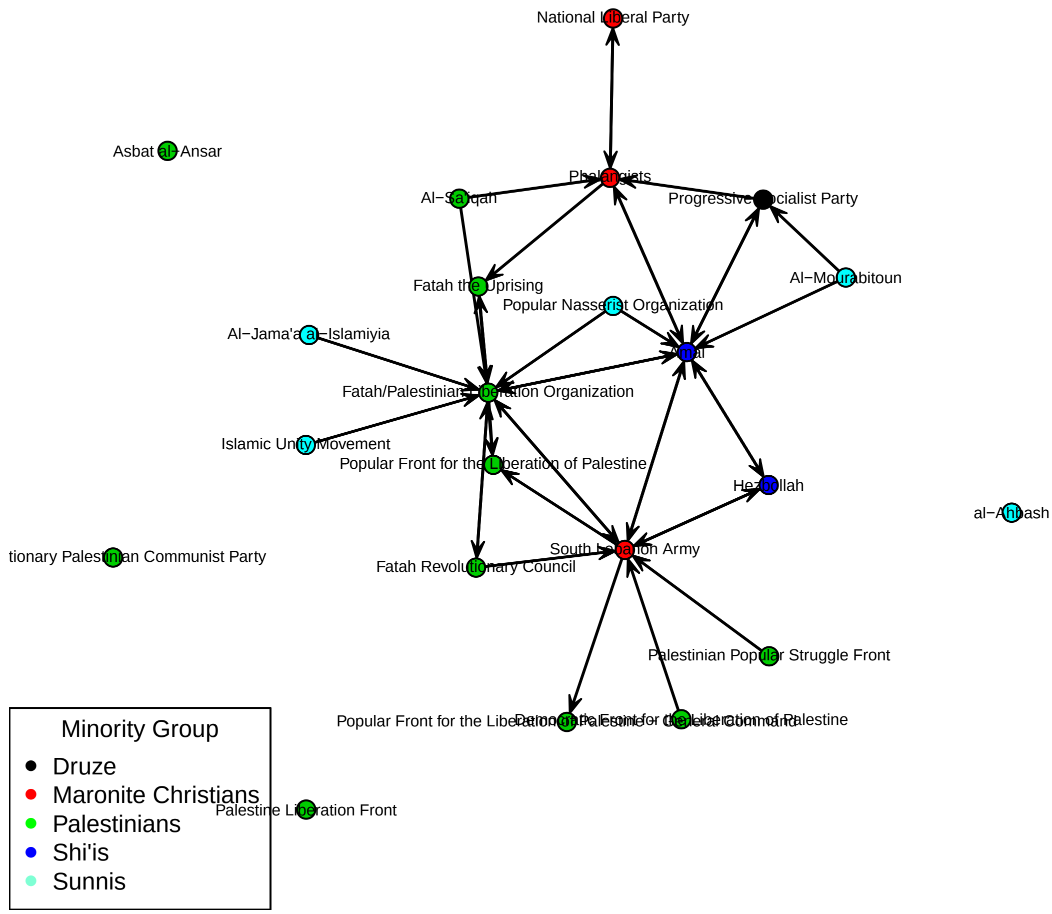

Figure 1: Directed Network Graph — Inter-Rebel Hostilities in Lebanon's Civil War

Table 1: Network-Level Descriptive Statistics

Nodes	Edges	Dyads	Density	Dyadic Reciprocity	Edgewise Reciprocity
22	37	462	0.08	0.93	0.54

Finally, it is worth noting that there is significant infighting within ethnic groups; namely, Palestinians vs. Palestinians, Shi'ites vs. Shi'ites, and Christians vs. Christians. This differentiates the Lebanese War from current conflicts in the region, where sectarian divisions are the main predictor of alliances and hostilities.[4]

Moving on to a more thorough analysis of the network's structure, Table 2 provides measures of network centralization à la Freeman (1979), using different centrality measures. These range from 0.13 for Betweenness Centrality to 0.41 for Information Centrality, potentially hinting at a central role for a small number of rebel groups.

Table 2: Network Centralization, by Centrality Measure

Indegree	Outdegree	Betweenness	Bonacich Power	Eigenvector	Stress	Information
0.32	0.17	0.13	0.31	0.33	0.17	0.41

This is further investigated in Table 3 and Figure 2. Both indegree and outdegree exhibit a right-skewed distribution, with some nodes (e.g. the 4 isolates) attaining the minimum of 0, while others the maxima of 8 and 5. This is also reflected in the mean of both degree distributions being (weakly) greater than the respective median, and the standard deviations being relatively high. That said, given that $\sigma_{ID} > \sigma_{OD}$, rebel groups are more heterogeneous in terms of being the target of hostilities than initiating them. Finally, it is worth noting that, owing to the aforementioned mutuality of hostilities, there is a strong positive correlation

[4] Moreover, current conflicts in the Middle East seem to be a complete reversal of the pattern observed in the Lebanese one: the only within-group violence is Sunni-on-Sunni (e.g. IS vs. al-Nusra in Syria), while there is no Palestinian-on-Palestinian, Shi'ite-on-Shi'ite and Christian-on-Christian violence.

(0.84) between indegree and outdegree, which is mirrored in the steep slope of the scatterplot in Figure 2.

Table 3: 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	

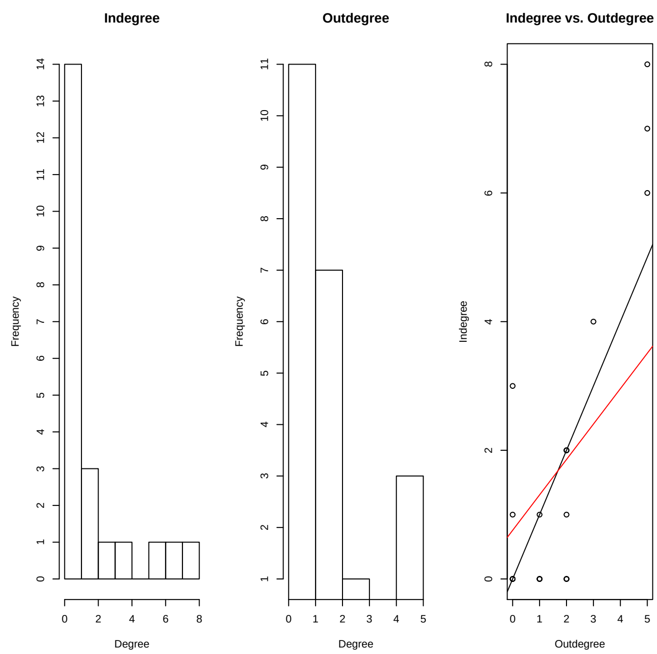

Figure 2: Degree Histograms & Scatterplot

At this stage, we can zoom-in on the node-level. Table 4 displays different centrality scores for each rebel group. Across most measures, 4 groups stand out: Amal, Fatah, the Phalangists and SLA. In addition, the first 3 of these groups are also identified as cutpoints. Indeed, as O'Ballance (1998) notes, these are groups that are included in virtually every account of the conflict. Moreover, these groups are the biggest factions from the three ethnic groups most active in the conflict—Amal from the Shi'ites, Fatah from the Palestinians, and the Phalangists and SLA from the Maronite Christians.

However, if we look at the Eigenvector and Information Centrality measures, we see some high-scoring groups outside these four. For example, Hezbollah and PNO have a higher Eigenvector Centrality score than the Phalangists. This is because they attack groups that are very central—they both attack Amal, and Hezbollah also attacks SLA, while PNO attacks Fatah. As such, they become central in the Bonacich (1972) sense, via their enemies' centrality. Similarly, PFLP has nearly the same Information Centrality score as the Phalangists, even though it scores lower on all other measures. This is entirely due to the fact that PFLP is attacked by SLA, one of the most prestigious groups. (In fact, it is the only tie PFLP has.) In short, Table 4 shows how using multiple and complementary measures of actor centrality improves our understanding of the complex dynamics in networks.

Table 4: Centrality Scores by Group

Group	ID	OD	Betweenness	Bonacich	Eigenvector	Stress	Information
al-Ahbash	0	0	0	0	0	0	0
aJaI	0	1	0	-1.70	0.13	0	0.65
al-Mourabitoun	0	2	0	0.85	0.23	0	0.87
al-Saíqah	0	2	0	-1.28	0.20	0	0.95
Amal	7	5	60.67	-0.43	0.48	78	1.45
Asbat al-Ansar	0	0	0	0	0	0	0
DFLP	0	1	0	-0.21	0.12	0	0.64
FRC	1	2	0	-1.92	0.25	0	0.97
Fatah Uprising	2	2	4.33	-1.28	0.13	7	1.13
Fatah	8	5	56.50	-2.13	0.39	73	1.54
Hezbollah	2	2	0	-0.21	0.27	0	0.97
IUM	0	1	0	-1.70	0.13	0	0.65
NLP	1	1	0	0.43	0.07	0	0.59
PLF	0	0	0	0	0	0	0
PPSF	0	1	0	-0.21	0.12	0	0.64
Phalangists	4	3	27.67	0	0.22	37	1.24
PFLP	3	0	0	-0	0	0	1.14
PFLP-GC	1	0	0	0	0	0	0.64
PNO	0	2	0	-1.70	0.28	0	0.97
PSP	2	2	1.33	0.43	0.22	3	1.03
RPCP	0	0	0	0	0	0	0
SLA	6	5	42.50	-0.64	0.37	52	1.46

Another feature worth exploring is whether there is a triadic structure to the conflict, and whether triads are balanced. Conflict networks tend to be balanced, and this one should be no exception. Indeed, in Figure 1 we see preliminary evidence of this: many triads do not display mutuality among all of their nodes. Similarly, a triad census reveals that the two types of triads that are balanced in the Davis-Leinhardt classification scheme, 102D ($\{(i,j)\}$) and 300 ($\{(i,j),(j,i),(j,k),(k,j),(i,k),(k,i)\}$), amount to roughly 8% of triads in the network.

Finally, it is worth exploring components of the network. There are 13 of them, the largest of which contains 9 groups. Figure 3 is a network graph of that component. It contains 41% of groups in the conflict, so it cannot exactly be considered "giant". However, inspecting the groups in that component, we discern the 4 key organizations identified above (Amal, Fatah, the Phalangists and SLA), along with 3 other groups that assume a key position in any narrative of the conflict: the only Druze group (Progressive Socialist Party), the only other Shi'ite group (Hezbollah), and the only other Maronite Christian group (National Liberal Party). As such, it seems that the largest component of the network suffices to explain a large part of the conflict. Indeed, in some classic historical accounts of the conflict (e.g. O'Ballance (1998)), one will find little to read about the groups outside this component.

3 Model-Fitting

In this section, I fit an array of ERGMs to the network, in an effort to maximize model fit. In choosing terms to include in my models, I look to the emerging literature on inter-rebel violence. However, I also build on the literature by including nodal covariates from the MAROB dataset whose predictive power has not yet been explored.

Before incorporating covariates, though, I explore the effect of other ERGM terms. Interestingly, all but one of these terms either cause the model to be non-estimable, do not improve model fit, or contribute very little to our understanding of the network—as mea-

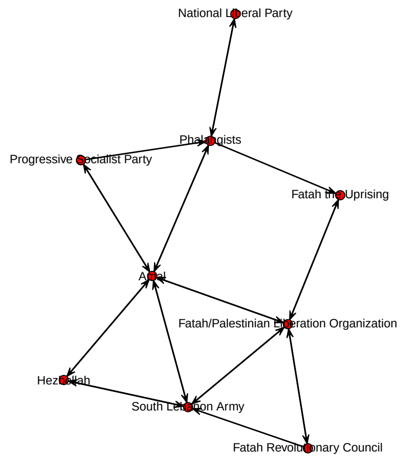

Figure 3: Largest Component — Network Graph

sured by a reduction in residual deviance, AIC or BIC. Namely, adding cyclical, transitive or other triangle-related terms causes the model to not converge. Similarly, the MCMC diagnostics for edgewise and dyadwise shared partners terms are alarming. Finally, sender and receiver effects, in addition to being non-identified for many groups, make a small and costly–in terms of degrees of freedom—reduction in residual deviance.[5] The only exception is the term for mutual ties, which improves model fit drastically. Recalling that hostilities in conflicts are very often mutual—documented above for the case of Lebanon—this is not surprising.

Far more interesting is the output from the models with nodal covariates. Guided by the literature, I carried-out an extensive search through the variables included in the MAROB dataset. Starting from the Erdos-Renyi model, supplemented with a term for mutual ties, I progressively added nodal covariates in an effort to minimize Residual Deviance.[6] Table 5

[5] Output validating all of these claims is suppressed to conserve space.

[6] All of my nodal covariates terms are estimated effects for *out*-edges (`nodeocov()`). This is because the literature on inter-rebel violence frames all of its hypotheses as the effect of *group i having feature x* on its likelihood to attack other groups.

shows the results of this search, through a series of ANOVA comparisons. Every model from the third one onwards adds a nodal covariate, and all models aside from the penultimate make a statistically significant improvement in fit. Overall, at the cost of only 8 degrees of freedom, Residual Deviance drops from 640 to 157.

Table 5: ANOVA

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>|Chisq|)
Edges (Erdos-Renyi)	1	640.47	461	640.47	0^{***}
+ Mutual	1	414.70	460	225.77	0^{***}
+ Terrorist Tactics	1	24.53	459	201.24	0^{***}
+ Popular (=BIC-min.)	1	30.48	458	170.77	0^{***}
+ Ethnic Cleansing	1	3.49	457	167.28	$0.06^{\cdot}$
+ Control Resources	1	5.03	456	162.24	0.02^{*}
+ Control Territory	1	0.95	455	161.30	0.33
+ Agreement w/ State	1	4.36	454	156.93	0.04^{*}

Nevertheless, Residual Deviance is only one of many criteria for model selection. Therefore, I supplement my search for the best-fitting model by examining BIC and AIC. Table 6 shows output from the BIC- and AIC-minimizing ERGMs. Incidentally, the latter model is the same as that which minimizes Residual Deviance. However, the BIC-minimizing ERGM includes four nodal covariates less. Substantively, this is an important difference, because the excluded covariates—Ethnic Cleansing, Control Resources, Control Territory, Agreement with State—have been presented as determinants of inter-rebel violence in previous studies. I return to this point in the next section.

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 Markov Chains that produced the reported output 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.

[7] I surpress MCMC diagnostic tables, autocorrelation plots and traceplots to conserve space.

Table 6: Best-Fit Models

	BIC	AIC / Res. Dev.
	(1)	(2)
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

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

A final class of models worth exploring are latent positioning models. Given that this is a conflict network, one might expect nodes to group into clusters representing opposing sides of the conflict. These sides could have emerged due to political, regional, religious, ethnic or other divisions between the rebel groups. In theory, a latent positioning model has the ability to identify the existence of such clusters and assign nodes to them. In particular, this task could be aided by the wealth of nodal covariates in the data. Thus, I fit a model to position the groups into two clusters, using all of the nodal covariates identified above as significant predictors of hostilities. Interestingly, the model's output is completely uninformative. Figure 4 shows maximum likelihood estimates of the latent positions of each rebel group, with capital letters abbreviating the ethnic group they belong to. The two clusters that the model fits are concentric circles, and are centered around 0 on both dimensions. Moreover, many groups fall outside both clusters, while ethnic group identity seems to not matter in predicting cluster membership. I return to this in the next section.

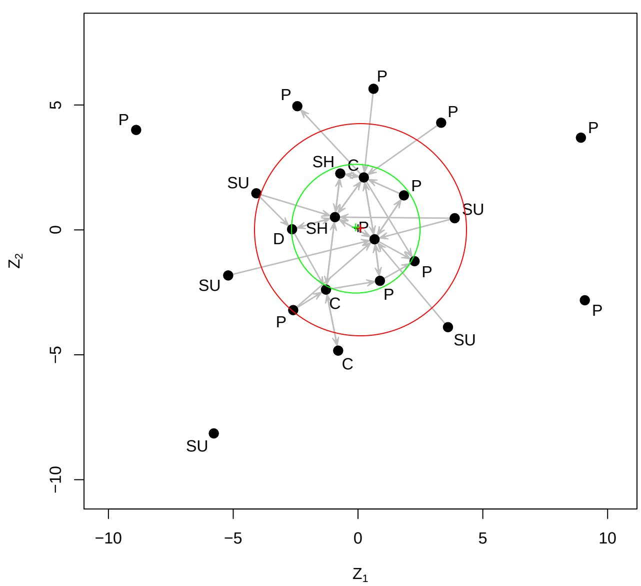

Figure 4: MLE Positions from Latent Positioning Model with 2 Clusters

Notes: C: Christian, D: Druze, P: Palestinian, SH: Shi'ite, SU: Sunni

4 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 6 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.

Popular organizations, defined as those that have the support of the majority of the ethnic 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 ethnic community.[8] 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.

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

[8] All of the marginal effects I report are based on output from the second column of Table 6. 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.

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); 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, and thus point 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.

Finally, it is worth returning to the output from the latent positioning model. The algorithm's failure to cluster the nodes informatively reflects the highly complex nature of the Lebanese Civil War: multiple rebel groups from several ethnic communities, with different political preferences, resources and strategies clashing against each other. This makes for a multidimensional conflict that cannot be modeled as a cleavage along a single line, whether ethnic, sectarian or political. Clearly, this was common knowledge to scholars of the War. In this manner, Figure 4 serves as a visual reminder of the need for quantitative tools such as network analysis to be carefully integrated with in-depth qualitative research.

References

Asal, Victor, Amy Pate and Jonathan Wilkenfeld. 2008. "Minorities at risk organizational behavior data and codebook version 9/2008." *Online at: www. cidcm. umd. edu/mar/data. asp* .

Besag, Julian. 1975. "Statistical analysis of non-lattice data." *The statistician* pp. 179–195.

Cranmer, Skyler J and Bruce A Desmarais. 2011. "Inferential network analysis with exponential random graph models." *Political Analysis* 19(1):66–86.

Cunningham, Kathleen Gallagher, Kristin M Bakke and Lee JM Seymour. 2012. "Shirts today, skins tomorrow dual contests and the effects of fragmentation in self-determination disputes." *Journal of Conflict Resolution* 56(1):67–93.

Eck, Kristine. 2010. Fighting Our Friends Instead of Our Enemies: Explaining Armed Conflict Between Rebel Groups. In *Paper for presentation at the 51st Annual Meeting of the International Studies Association, New Orleans, LA, February.* pp. 17–20.

Fjelde, Hanne and Desirée Nilsson. 2012. "Rebels against rebels explaining violence between rebel groups." *Journal of Conflict Resolution* 56(4):604–628.

Freeman, Linton C. 1979. "Centrality in social networks conceptual clarification." *Social networks* 1(3):215–239.

Kalyvas, Stathis N. 2003. "The ontology of political violence: action and identity in civil wars." *Perspectives on Politics* 1(03):475–494.

O'Ballance, Edgar. 1998. *Civil war in Lebanon, 1975-92.* Macmillan.

Pischedda, Costantino. 2015. Wars Within Wars: Understanding Inter-Rebel Fighting PhD thesis Columbia University.