DYNAMIC NETWORKS OF VIOLENCE: PEOPLE POWER AND THE MEXICAN CRIMINAL CONFLICT

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Abstract. This study presents an aggregated analysis on the evolution of armed conflict in Mexico. The criminal war in Mexico is complex: Drug Trafficking Organizations vie for control against one another and against government actors. This cycle of violence is characterized by a set of interlocking interactions between armed actors. Existing research, however, typically ignores the interdependencies inherent to these networks. Using a new collection of machine-coded event data, we generate conflict networks representing each quarter period from 2006 to 2012. We then apply a relatively new approach, the bilinear network autoregression model to explore changes in the model over time. Importantly, we demonstrate how these networks capture the independent nature of the Mexican conflict and test an important substantive question of whether protests can predict the probability of violence between armed actors within the network.

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Introduction

Network analysis is a critical tool for capturing dependencies inherent to the development of social phenomenon. The concept of social network analysis began as early as the 1930s with Jacob Moreno's *Who Will Survive?* and has developed into a rich and diverse field. In Political Science, network analysis has now been utilized to study a diverse range of topics: trade, intergovernmental organizations, sanctions, internal conflict, political behavior.[1] Yet, unfortunately, a majority of studies in Political Science still rely on the standard dyadic framework. We argue that conflict evolution is a process conditioned on the relative effects of actors' behavior and is thus best conceptualized via a network approach.

Sociologists have long established that to understand an actor's behavior you have to understand the context in which they operate as well as interpret their interactions with one partner in light of all interactions across all other partners. Conflict scholars are interested in questions that mirror these exact patterns, such as: which actor is driving the violence within a multi-actor conflict? Did a government crackdown cause anti-government coordination or chaos between armed groups? Are civilian challenges towards non-state armed actors causing an increase or decrease in violence? These questions precisely illuminate the need to apply the appropriate methodological approach to pressing questions in our field.

Our paper, however, is not merely a methodological exercise. We are also motivated by a rich, underdeveloped theoretical question: do nonviolent protests influence the evolution of violence between armed actors? A recent wave of research in peace studies has illuminated the efficacy of non-violent strategies in contexts of repression. Chenoweth & Stephan (2011) maintains that non-violent campaigns are more likely to succeed in overthrowing a leader than violent campaigns. This research, however, is primary focused on so-called

[1] For examples, see Dorussen & Ward (2010), Cao (2009), Cranmer et al. (2014) and for an overview of network analysis in Political Science see Ward et al. (2011).

maximalist campaigns wherein an entire population unites under the singular cause of removing a (usually corrupt) leader from power. This previous focus on maximalists movements spurs scholars to explore the capacity of non-violent actions at the local level.

We are particularly interested in the link between protests and violence in the Mexican case. The Mexican Criminal conflict began in 2006 and has continued to trouble the socio-political landscape of Mexican life. Different estimates place number of drug-related deaths well over 100,000 from 2006-2012. Violence in Mexico is driven by competitive drug trafficking organizations (DTOs) which vie for control for access to resources, transportation routes, and civilian influence. Yet, even in these risky conditions, Mexico has exhibited a rich civic society committed to take action, often through nonviolent protests, to inspire change.

In this paper we utilize an original database of actor-coded conflictual events in Mexico. We investigate whether nonviolent protests influence the likelihood of violence between armed actors. To do so, we generate a conflict network at the quarterly level for the time period 2006-2012 and incorporate novel protest data which documents the number of protests against violence at the state level during the Mexican Criminal Conflict.

Existing Literature

More often than not, stories of armed conflict, war, or widespread criminal violence shine a spotlight on those actors who initiate injustices or wield power through collective violence against a given population. Recently, however, this narrative has begun to change. With the various uprisings across the previous 5 years–the Tunisian revolution, the Egyptian revolution, the Syrian Civil War, the Yemen revolt, the 2013 protests in Turkey, and the 2014 protests in Venezuela (just to name a few)–attention has shifted to recognize the power of the population to influence environments of extreme violence and repression.

A diverse range of conflictual episodes occur around the world: coups, civil wars, drug wars, refugee crises, border disputes. While media attention might focus on civilians fleeing or to cooperating with whichever armed actor wields the greatest power in their region, a truer picture reveals a vast range of civilian responses to violence. Mass anti-regime movements are an important form of civilian response in some cases but civilians might also engage at the local level through self-defense forces, community watch groups, civil society efforts, or nonviolent campaigns in their home town.

Compared to the number of studies focusing on economic (Collier & Hoeffler, 2004), political (Humphreys & Weinstein, 2008), and identity-based (Cederman et al., 2010) drivers of conflict intensity and duration, existing research has largely neglected the role of civilians in restraining or influencing the behavior of armed actors. A large body of research has explored the origins of collective action and mobilization, (Gurr 1970; Opp 1988, Tarrow 1994, Tucker 2007) and recent scholarship has assessed the effectiveness of "maximalist campaigns" (Chenoweth & Stephan, 2011) to show that countries are more likely to be democratic following nonviolent campaigns. However, as articulated by Celestino & Gleditsch (2013) even the macro-level relationship between nonviolent campaigns and state-level outcomes such as democracy or regime transitions remains unclear. Importantly, Celestino & Gleditsch (2013) show that nonviolent campaigns destabilize regimes, but that the trajectory of peace and democracy following such campaigns is conditional on the precise actions employed by campaign organizers.

Building on the research agenda motivated by macro-level studies, we investigate the link between nonviolent action and violence at the local level. The focus of this study is two-fold. First we discuss the importance of considering conflict processes through a network framework. In doing so, we suggest that networks of conflict constitute a meaningful outcome of interest and depart from the great majority of the literature which focuses on dyadic outcomes to measure conflict intensity or duration. Second, we contribute to a growing scholarship concerned with whether or not people-power driven actions and campaigns influence trajectories of violence and stability.

People Power & Conflict Evolution

There is little empirical evidence that protests should or should not "work" in contexts of high violence at the sub-state level. There are several possible logics linking protest and violence between armed groups.

First, there might be no relationship between protests and violence. Protest might have other benefits and thus persist for reasons outside of the stated goals driving protest organizers. For example, non-violent activism via protest can stimulate community between survivors of violence and foster a sense of purpose and belonging in the midst of crisis. Additionally, protests against insecurity and issues of violence might be targeted at both types of armed actors (i.e. the state and the non-state challenger), these actors could respond to protests through other means outside of violent strategy. Non-state armed groups might make public appeals to civilians, saying that they are there for civilians' protection. Similarly, governments can respond with media campaigns, speeches, or through a general effort to try to divert political attention from violent events. A second mechanism driving a null relationship between protests and violent events is the high level of risk for protestors. Following a protest, participants might be targeted because of their activism, possibly resulting in fewer protests over time but with no clear consequences for violence between armed groups.

Second, protest participants might achieve their stated aims and decrease violent contestation in their region. If protests successfully demand that the government invest greater resources in the prevention of violence, then we would expect fewer incidents of violence following protests. If protests also demand that non-state actors stop warfare with the state, this manifests as a public disapproval of attempts by the non-state group to coerce or control the civilian population. With enough discontent, protests disrupt the ability of non-state actors to operate in their region.

Finally, protest could lead to an increase in violence. As violence between armed actors (state and non-state) increases, non-state actors often victimize civilians to highlight the government's inability to protect the population. Even if protestors demand a non-violent solution to warfare, a final plausible logic connecting protest and violence is that protest raises the cost of government inaction so that government armed actors are more likely to visibly fight hard in the next round of contestation. This logic would suggest an antagonistic government actor, one who is politically motivated to demonstrate competency through violent policy.

The Mexican Criminal Conflict

The internal war in Mexico is a criminal conflict driven by territorial disputes over trafficking routes and land. Drug trafficking is not a new phenomenon but over the last decade it has affected all levels of Mexican society. After the fall of the Colombian cartels in the 1990s, the landscape of violence related to drug trafficking completely shifted in Mexico as cartels gained new territorial control. Since this time, Mexican drug cartels have become the largest foreign supplier of methamphetamine and marijuana to the United States, effectively dominating the drug market. In fact, estimates claim that the drug trade employs over half a million people and generates roughly 4% of Mexico's annual GDP.[2]

Although Mexican drug cartels have controlled the drug trade for decades, it was not until the 2006 election of Felipe Calderón that drug-related violence began to soar and civilians found themselves under fire. In 2006, Calderón became president and ushered in a new policy against the cartels. With support from the United States, the Mexican government initiated a massive campaign to combat drug-related violence. Violence soared

[2] Shirk (2011)

and between 2006 and 2011 and homicides nearly tripled from 10,452 to 27,213.[3] Sending armed actors into an already armed, violent, and competitive situation, Calderon's strategy was a failure. It did not address the fundamental needs of civilians or establish trusted local institutions where citizens could seek support in the realms of justice and security. Instead, these policies complicated the security situation even more and created an unstable environment for reporters, government officials, and civilians.

The failure of "Calderón's War" is partially attributable to the fact that DTOs are complex, with overlapping rivalries, family histories, splintered subgroups, and territorial disputes that drive their violent methods of political action. DTOs are also engaged in extensive corruption networks across different levels of the government and throughout the Mexican territory. The influx of federal troops into areas of high criminal activity added further complication to pre-existing corruption. Because police in Mexico receive low pay (about $9,000 to $10,000 a year), their loyalty can often be bought by cartels; however, when bribery doesn't work, cartels routinely punish government officials with violence.[4] Since combat and corruption between federal troops and cartels began, over forty mayors and numerous government officials have been murdered while increasing numbers of missing persons have been reported across Mexico as a result of cartels' increasing use of kidnapping. Government corruption, civilian victimization, and a silenced media are severe problems deeply embedded in the conflict.

Because of the cartels' brutal methods of punishment and gain, journalists and other forms of citizen representatives have been hesitant to report on these events. Journalists have not only been afraid to report out of fear that they *might* be punished; in fact, they have been targeted and killed numerous times. In 2010, Carlos Santiago, an intern photographer for the Mexican newspaper El Diario, based in Ciudad Juarez, was shot and killed. This was the second journalist from El Diario to be targeted. The other was

[3]According to Mexico's National Statistics Institute (INEGI).
[4]Nathaniel (2013)

Armando Rodrguez, a writer who worked the police beat and was killed in front of his own home. Following these deaths, the newspaper's editor drafted a plea to drug traffickers asking why they were being targeted. The article was published on the front page of the paper.[5] Then, on April 28, 2012, Regina Martínez, a journalist for the national news outlet Proceso, was found dead in her home in Xalapa, Veracruz. This series of murders is indicative of a larger phenomenon across Mexico. According to the International Press Institute and the Mexican journalists' group "Periodistas de a Pie," 103 journalists have been killed between 2000-2015 and 25 have disappeared. Since 2010, Mexico has been considered as deadly for journalists as Iraq; yet, these crimes continue with impunity. The Mexican case thus presents a relevant, timely, and difficult case for measuring the evolution of nuanced relationships between different violent actors. This study describes how the investigation of these relationships is possible.

Data Challenges in The Mexican Case

The quality of data on the Mexican criminal conflict remains mixed and generally suffers from underreporting. We know that there have been several key actors in this conflict over the years, including the Gulf Cartel, Juarez Cartel, La Familia Michoacana, Los Zetas, Sinaloa Cartel, and the Tijuana Cartel. However, because Mexican drug cartels are sometimes in conflict with one another and infiltrated by government officials, it is difficult to attribute responsibility for homicides or other violent events to one cartel or actor versus another. Although the noisiness of this data might seem daunting, it presents an opportunity for researchers to explore how they may improve data and knowledge about violent situations in contexts where it is often dangerous to do the costly on-the-ground "legwork" that is generally necessary to accrue such information.

At present, the majority of data on violence in Mexico is based on homicide rates. Homicide data is produced from four main sources: Mexico's National Institute of Statistics

[5]For a full interview with the editor see Gladstone (2010).

and Geography (INEGI), the National System of Public Security (SNSP), the Mexican Federal Government, and La Reforma. In the beginning of the conflict (typically demarcated by Calderón's assumption of the Presidency), national newspapers carried death counts related to drug violence. *La Reforma* continues to maintain drug-related homicide data; however, transparency behind the methodology of this data collection remains uncertain. It is not known, for example, how the newspaper decides whether a homicide is drug-related or not. Mexico's INEGI has data based on death certificates, which allows one to acknowledge the manner of death (such as bullet wound). This data, however, is unable to attribute which homicides are linked to crime and which are unrelated. The National System of Public Security also has crime data based on local prosecutor reports, but its reliability is questionable due to the mixed incentives for governments to accurately report information. Finally, the federal government also has released data known as the "Database of Alleged Homicides Related to Organized Crime." This database has information on executions and violence against authorities. Altogether, these data present several difficulties: first, they are not updated in real-time. To better understand the heterogenous evolution of civil conflict, researchers need to be able to describe conflict dynamics as they unfold. An additional, major criticism is that these data do not further our understanding about who is directly or indirectly responsible for these crimes.[6]

Acknowledging the shortfalls of pre-existing data, our analysis improves upon existing data by providing actor event data. While we can only provide a rough estimation of actors involved in each conflictual event, this is a considerable advancement from the current status quo of knowing little to no information about which actors are engaged in which violent events in Mexico.[7]

[6] This information summarizes an article will fuller details on the subject in *Letras Libras*. See Ley (2012). Melissa Dell uses this government data to assess whether or not PAN victories divert drug traffic to alternative routes predicted by the shortest paths in a networked trafficking model. The aim of Dell (2011), however, is not to create actor-based event networks.

[7] The only other data similar to this format is from a project of machine-coded data of Spanish newspapers created by Javier Osorio and Alejandro Reyes. This data is currently unavailable.

ICEWS Data and The Mexican Criminal Conflict. A key goal for this study is to leverage machine-coded reports to construct a network of armed actors that represents conflict over time in Mexico. In order to construct this network study, we use the ICEWS actor-coded event data. The ICEWS event data is part of a larger project designed to operate as a crisis warning system for policymakers.[8] This database has enabled policymakers and researchers to forecast conflictual events around the world.[9] The machine-coded event data are gleaned from natural language processing of a continuously updated harvest of news stories, primarily taken from Factiva^{TM}, an open source archive of news stories from over 200 sources around the world. The baseline event coder is called JABARI, a java variant of TABARI (Text Analysis By Augmented Replacement Instructions) which has been developed by Philip Schrodt and colleagues.[10] This approach combines a "shallow parsing" technology of prior coders with a richer exploitation of syntactic structure.[11]

The models create each data point by obtaining three components of the news story: the sender of the event (i.e., who initiated the action), the receiver or target of this action, and then the event type itself. We subsetted this data according to relevant "violent" cameo codes in order to gain access to all events relating to any armed actors such as rebels, insurgents, government, and the police. These events, in essence, capture any type of violent conflict between different actors. The event type itself is coded according to the Conflict and Mediation Event Observation (CAMEO) ontology.[12] The main distinguishing feature of CAMEO is its use of mediation related event codes. CAMEO does not assume that a meeting is a peaceful interaction, for example, but is able to decipher whether meetings between actors are related to mediation, or negotiation. CAMEO also includes

[8]For a summary, see O'Brien (2010).

[9]Ward et al. (2013)

[10](see http://eventdata.psu.edu/)

[11]This has increased accuracy (precision) from 50% to over 70%, as demonstrated in a series of ongoing (informal) evaluations of its output by human graders. Peak human coding performance is reported to be around 80% (King & Lowe, 2003).

[12]See Gerner et al. (2009) for the full summary of the project.

four categories for violence (structural violence, unconventional violence, conventional force, and massive unconventional force) as well as a rich system of sub-categories.

To begin to understand how to leverage the ICEWS data for country-level network analysis, we have taken a subset of data from the larger ICEWS corpus. We constructed a SQL query to gain data subsetted according to all four "violent" cameo codes as well as any actions related to all armed actors such as rebels, insurgents, government, and the police. Through the process of reviewing and cleaning the ICEWS data in preparation for my analysis, we encountered two key problems with the data. The first problem relates to the vague nature of the actor names in the data, which we improve upon via manual re-coding. The second problem we identify incentivizes ICEWS programmers to improve the parsing algorithm used in the creation of the original data. While there are many unique actor names, the bulk of these descriptions are likely too vague for network construction. For example, the majority of cases relating to criminal violence use descriptors such as: "Armed Gang," "Armed Opposition," "Attacker," "Hitman," "Drug Gang," "Armed Band," and "Criminal." A number of other cases have actor names such as "Men" or "Citizens" as well as Military descriptors.

To improve on these issues, we subset the data to include the raw text available from the larger ICEWS database. Then, using a subset of cases from 2004-2012, two human coders reviewed each individual case. This task includes two main goals: to label events as they relate to specific drug cartel actors in the area and to address aggregation problems in the data. In addition, we coded for duplicate cases. We identified that this data has fewer duplication issues than previously found in other ICEWS data (such as protests) but has a number of complex aggregation and parsing problems.

The end result is a collection of 1,052 actor-coded violent events from 2006-2012. The general trend of this data fits the pattern we observe in other data based on homicide rates.

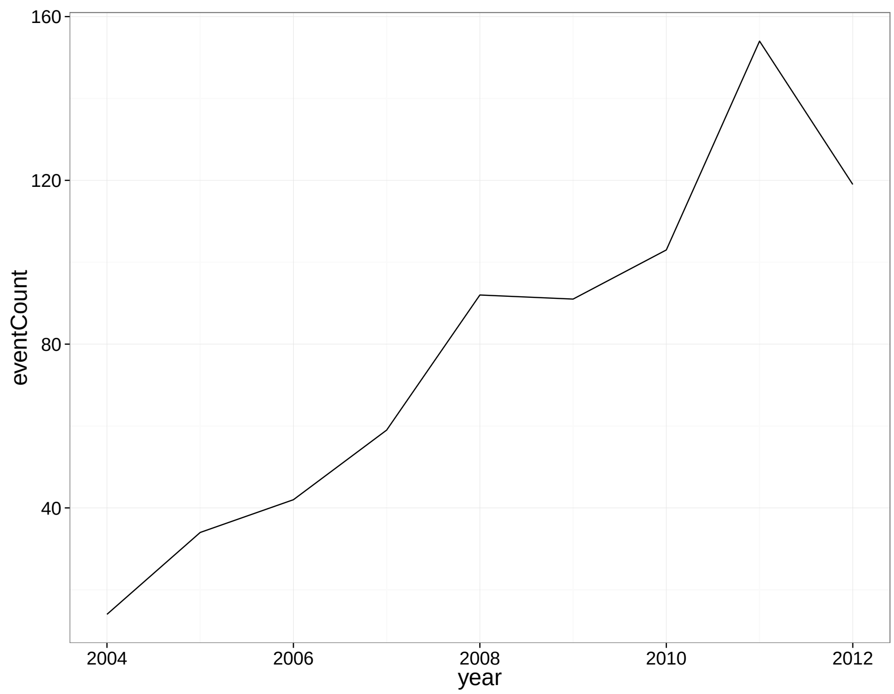

Figure 1. Counts of conflictual events over time in Mexico 2004-2012.

Creating a Conflict Network in Mexico

Next, we demonstrate how networks can capture the behavior of armed groups within the Mexican conflict. We focus our description on network graphs representing the behavior of disaggregated actors at the yearly level.[13] These networks, discussed below, reveal important relationships between actors, relationships that are otherwise missed by traditional dyadic frameworks. In a simple, descriptive and systematic way, we are able to show which DTOs were involved in the most conflict relevant to one another. We also show that both the Sinaloa Cartel and the Zetas become active players in the network at different moments in the Mexican Criminal Conflict.

To begin, we create sociomatrices for each year of the cleaned data. These sociomatrices can be thought of as a summary of interactions between all actors involved in conflictual

[13]Due to sparsity issues in the current stage of our modeling we aggregate different state actors (such as federal government and federal police) into a general "federal government" category. We are, however, able to investigate changes overtime in the network at the quarterly level of analysis

events within a year. Given that there are n actors in a year we construct an n x n sociomatrix Y. The number of conflictual dyadic interactions for any actor i and j is simply the number of events between those two actors during each given year. The resulting matrix is an undirected, symmetric matrix, as represented below.

$$\begin{bmatrix} & actor_i & actor_j & actor_k & actor_l & actor_m \\ actor_i & 0 & 2 & 0 & 0 & 0 \\ actor_j & 2 & 0 & 0 & 2 & 1 \\ actor_k & 0 & 0 & 0 & 0 & 4 \\ actor_l & 0 & 2 & 0 & 0 & 4 \\ actor_m & 0 & 1 & 4 & 4 & 0 \end{bmatrix}$$

These matrices reveal a variety of interesting dynamics in the data, as shown in the network graphs of Figure 2. For simplicity, the actors are simply coded as DTO or Government actors. Government actors include different branches of the armed forces and government. In the original data, we have different types of government actors such as local police, federal army and federal police. For our analysis we aggregate state actors into three levels of government: Municipal, State, and Federal groups.

In 2007 to 2008, shown in Figure 2, the number of conflictual events between the Sinaloa Cartel and the Federal government increase. Additionally, the federal government faces a greater number of events from the Gulf Cartel. We also observe a jump in the number of cartels involved in the network, as new actors such as the inclusion of the Juarez Cartel. The year 2008 is a significant year in the drug war. President Felipe Calderón, following is inauguration in 2006, cracked down on DTO's in the western region of Mexico. A major consequence of his "mano dura" (strong hand) policy was increased volatility in the region. The Gulf and Sinaloa cartels are known to have been heavily challenged at this time and internal pressures inside the Sinaloa Cartel's rank began to build. While the networks do not capture strife internal to an actor-group, observe than in 2008 the

Sinaloa Cartel is involved in many reciprocal conflictual events with all levels (municipal, state, and federal) of government.

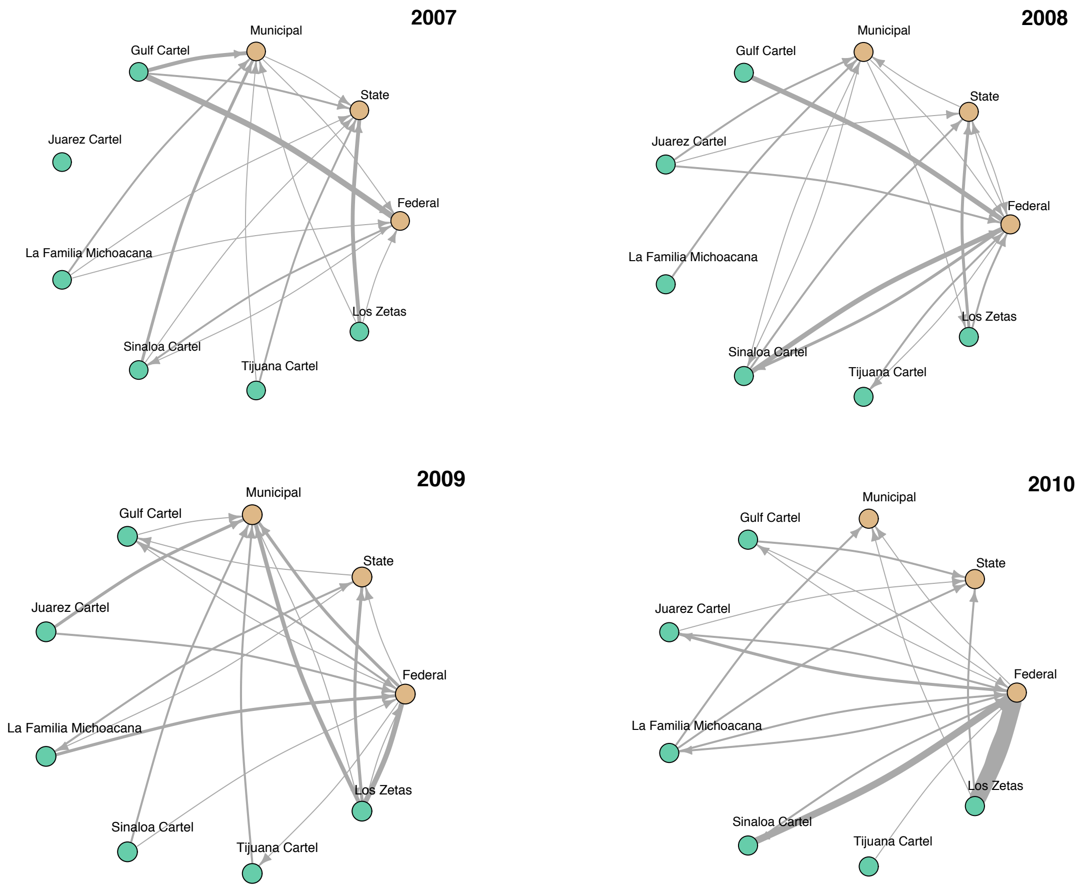

Figure 2. The evolution of the Mexican criminal conflict, 2007-2010. Orange nodes are government actors, teal corresponds to criminal organizations. The links (grey lines) are weighted by the number of conflictual events for that year.

Figure 2 we also see evidence that supports qualitative accounts of the Gulf Cartel. Namely, that due to the increased independence of their former violent enforcer group, the Zetas, as well as increased targeting from the Government, the Gulf Cartel weakened over time. Indeed, in these graphs the Gulf Cartel is not nearly as active in 2010 as they are in 2007. Similarly, the graphs reveal that conflict involving the Zetas increases over time, by 2010 the DTO experiences high levels of violence with federal forces.

Modelling Approach

To model the evolution of this type of longitudinal network a number of network analytic tools have been developed. One of the most prominent of these approaches is the stochastic actor-oriented model developed by Snijders (2001). Within his agent based approach the linkages within a network are the result of decision making by actors operating under some utility function. The SAOM technique has become a popular technique to modeling longitudinal networks in political science (e.g., see Manger et al., 2012; Berardo, 2013; Kinne, 2016). The temporal exponential random graph model (TERGM) developed by Hanneke & Xing (2007) and introduced to political science by Cranmer & Desmarais (2011) is a similar approach used to model binary longitudinal relational data (e.g., see Cranmer et al., 2012; Corbetta, 2013). TERGM and SAOM share a similar mathematical core, the exponential random graph model (ERGM), but differ in their estimation approach and in how they deal with temporal dynamics (Leifeld & Cranmer, 2015).[14]

Another popular approach to modeling longitudinal networks has been to specify dynamic latent variables, in which each $\mathbf{Y}_t$ is modeled as a function of actor specific latent variables (e.g., see Hoff (2005); Durante & Dunson (2014); Sewell & Chen (2015)). The goal of this approach is to collapse information contained in the network about higher-order dependencies to a lower dimensional latent space. Embedding the network information onto this lower dimensional space has the added benefit of providing meaningful visualizations of how likely actors are to interact with each other due to network influences. Examples of these dependencies include concepts such as reciprocity and transitivity that are familiar to the international relations literature. Broadly, these dependencies can be placed along two dimensions: second and third-order dependencies.

Second-order dependencies refer to what is often described as reciprocity in the context of directed relationships. This concept has particular relevance in the conflict literature,

[14] Also of note is that the TERGM approach has recently been advanced to handle weighted edges (Desmarais & Cranmer, 2012; Wilson et al., 2015).

as we would expect that if, for instance, the Gulf Cartel behaved aggressively towards the Mexican federal government that this would induce the Mexican government to behave aggressively in return. An example of a third-order dependency is transitivity, which follows the familiar logic of "a friend of a friend is a friend". In binary data, transitivity describes the dependence among three actors i, j, k in which i and j are more likely to be linked if linkages already exist between $i - k$ and $j - k$. The principal idea behind these dependencies is that knowing something about the relationships between $i - k$ and $j - k$ may reveal information about the relationship between $i - j$, even if it is not directly observed.

While both the ERGM based and latent space approaches effectively incorporate statistical interdependence among the actors, the ERGM based approaches assume that this effect is homogeneous among all dyads. The latent variable based approach allows heterogeneity between dyads. The downside, however, of earlier work using the latter approach is that explicit parameterizations of the effect of reciprocity and transitivity could not be calculated due to the simple structure of the latent variables. Instead all of the information contained within those higher order dependences was collapsed into a lower dimensional latent space.

In this paper, we utilize a bilinear network autoregression model that bridges some of the benefits of these two approaches (Hoff, 2015; Minhas et al., 2016). This approach allows us to explicitly operationalize network dependencies such as reciprocity and transitivity while still allowing for heterogeneous higher order effects between dyads. The core of this modelling framework can be thought of as related to a simple vector autoregression model but generalized to matrices. For example, let $\mathbf{Y} = \{Y_t : t = 1, \ldots, T\}$ represent a time series of networks. Hoff (2015) developed a matrix autoregression model for $\mathbf{Y}$ in which its expectation, M_t, depends on Y_{t-1} via a bilinear transformation:

$$M_t = \{\mu_{i,j,t}\} = AY_{t-1}B^T$$
$$\mu_{i,j,t} = a_i^T Y_{t-1} b_j = \sum_{i'} \sum_{j'} a_{ii'} b_{jj'} y_{i'j't-1}$$

The matrices A and B can be thought of as "influence parameters". The value of $a_{ii'}$ describes how predictive the actions of country i' at time $t-1$ are of the actions of country i at time t. The value of $b_{jj'}$ describes how predictive the actions directed at country j' at time $t-1$ are of the actions directed towards country j at time t. In our application of this model, $\mathbf{Y}$ is a time series of event count matrices, thus we utilize a Poisson model, specifically, $y_{ijt} \sim Poisson(e^{\mu_{i,j,t}})$, where $\mu_{i,j,t}$ is as above, except with $\tilde{y}_{i,j,t} = \log(y_{i,j,t-1} + 1)$. Additionally, in our case here we also seek to predict y_{ijt} with additional endogenous and exogenous variables, thus we utilize a model with the form: $\mu_{ij,t} = \theta^T z_{ij,t} + AY_{t-1}B^T$. To estimate this bilinear model, we utilize a block coordinate descent algorithm in which we iterate finding the conditional maximum likelihood estimate of $(\theta,\ \hat{A})$ and $(\theta,\ \hat{B})$ using iterated weighted least squares.

Variables. The dependent variable in our study is the conflict event network which results in directed, count-matrices for each time slice in our data. For our analysis we only examine the years 2006-2012, due to limitations in the protest data. Additionally we were able to disaggregate the data into quarterly periods, but at the same time aggregated state related armed actors into three main groups- municipal government, state government, and federal government.

At present, we include several covariates of interest. First we include a measure of protests which is our key independent variable. Our protest data is constructed from a new data set, "The Mexican Protest Against Crime Database" collected by Ley (2015). This data records the number of protests against violence in each state during per year for the time period of 2006-2014. Creating a protest variable for the network analysis is straightforward: we simply match states across the protest data and the conflict event data. In doing so, we create a protest count for the number of protests in a DTO's region of operation. Figure 3 shows Ley (2015)'s data for the whole time period.

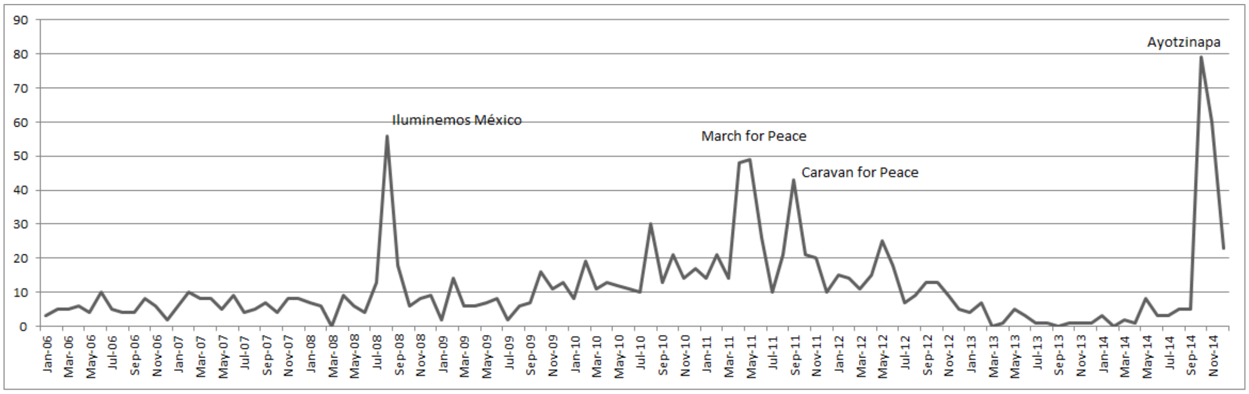

Figure 3. Counts of protest events over time in Mexico 2006-2014.

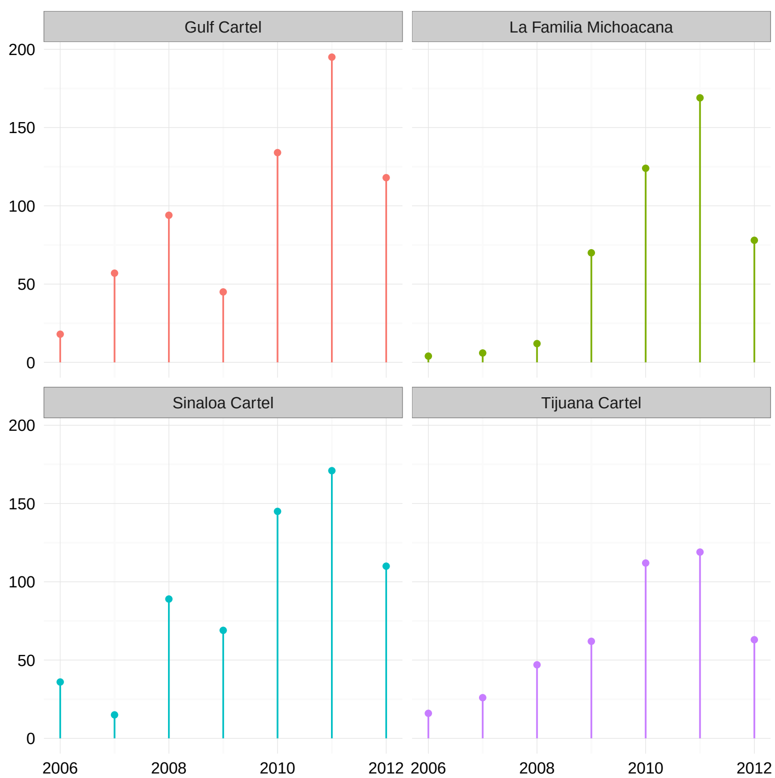

Figure 4. Counts of protest four for the Gulf Cartel, La Familia Michoacana, Sinaloa Cartel and the Tijuana Cartel from 2006-2012.

Our other measures are network-related variables. We include a betweenness score,which is generated on the previous iteration of the network and thus acts as a nodal time-varying covariate for each year in the model. The primary motivation here is to test whether actor-level effects, such as being a large "sender" of the conflict, can best predict future conflict. Next we include a measure of reciprocity to account for the straightforward idea that adverse actions by one party towards another are likely to be met in kind. Additionally, we include a measure of transitivity to test whether the likelihood of i initiating conflict with a third party decreases if that third party is already involved in a direct conflict with an actor that i is in conflict with. Last, we include a lagged version of the dependent variable, and a control variable for whether or not the actor in the network is a Drug Trafficking Organization.

(Preliminary) Results

Figure 5 highlights the results from our bilinear autoregression model. The first parameter here represents the effect of the lagged dependent variable. The positive effect here is not surprising as all it indicates is that actors engaged in a higher number of conflicts in the last period are more likely to be engaged in a high number of conflicts in the next. The second parameter from the top, $Conflict_{ji,t-1}$, highlights the role of reciprocity in this network. Here we see that conflictual actions do tend to be reciprocated in this network. The third parameter, $Conflict_{ijk,t-1}$, provides an estimate of the level of transitivity within the network. Our expectation was that this effect would be negative but there is not enough evidence to make any claim here.

More interestingly, when it comes to the effect of protests we find that there is a positive association between protest and future conflict. This is evidence for the idea that increased protests raise the short term costs of inaction for government actors, and in this case, mobilize the Mexican government to respond more harshly to DTOs in time period following protest events. Since a majority of the recent work on non-violent action has been at the level of maximalist campaigns, this finding also highlights the importance of studying protests at different levels of analysis in order to understand the conditions under which protest might not be effective in reducing violence.

The betweenness centrality measure shows that actors involved in conflicts between many groups are more likely to initiate conflict in the next period. This allows us to capture the aggressive tendencies of groups like the Sinaloa cartel who drive the evolution of violence in the network by engaging in conflicts with multiple warring parties.

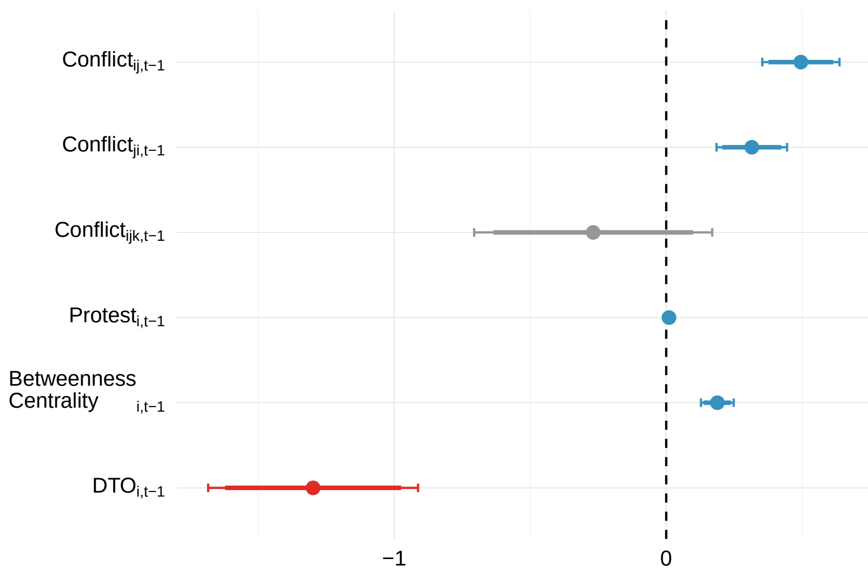

Figure 5. Regression results from Bilinear Autoregression Analysis. Darker colors indicates that the coefficient estimate is significantly different from zero at a 95% CI, while lighter the same for a 90% CI. Grey indicates that the estimate is not significantly different from zero at either of those intervals.

In figure 6, we show the results of our influence parameters from the autoregressive analysis. The network on the left represents the sender influence parameters and the right the receiver. A linkage between two nodes within these figures indicates that their autoregressive effect was significant at a 95% confidence interval. Specifically, the link from the Tijuana Cartel to the Gulf Cartel, in the leftmost figure, indicates that the Tijuana Cartel is more likely to engage in conflicts with actors in the network that the

Gulf Cartel is engaged in conflicts with. From the receiver influence parameter space, the directed link from the Gulf Cartel to the Sinaloa Cartel indicates that the Gulf Cartel is more likely to receive conflictual events from actors that are sending those types of events to the Sinaloa Cartel.

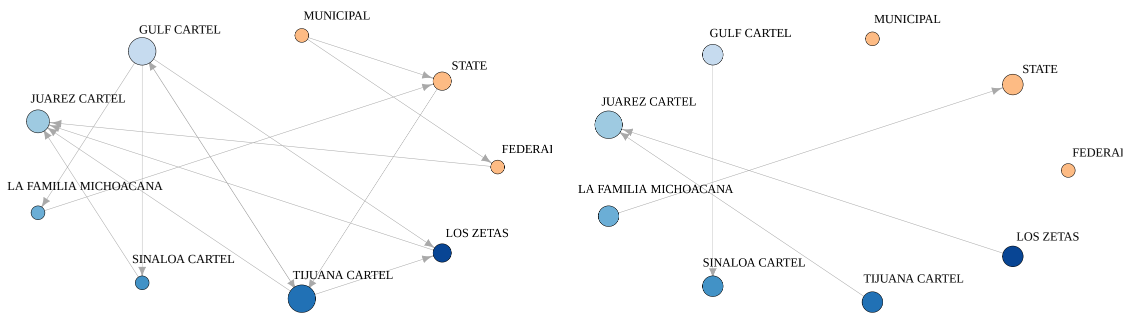

Figure 6. Sender (left) and Receiver (right) Influence Estimation

Conclusion

First, our study contributes to growing literature on the role of nonviolent action in conflict settings and is the first of its kind to directly investigate the effects of protest on the development of a conflict network. Our results support a cautious research agenda to further investigate how nonviolent actions might actually be associated with a short term increase in conflict, rather than a decrease. This does not, by any means, suggest that nonviolent movements in Mexico have been entirely ineffective, but this does suggest that the short term effects of protests might be very different from the long term effects. Additionally, our study highlights a weakness in existing literature: at present we know very little about the differences in the temporal effects of protests or the mechanisms that drive them.

Second, this study makes a significant data contribution: this data approach can enhance the broader study of civil conflict. Using area-expertise to improve machine-coded data produces a replicable strategy across countries throughout the world. Machine-coded data allows for this kind of cross-cutting replicability, enabling researchers to rely on similar news sources in different regions, employ consistent methods of parsing and cleaning, and create national-level dynamic data as I have done here. The implications for this are notable: thus far in political science, country-level data is often limited by its uniqueness, i.e., researchers focus on regional data sets with details about a specific pre-determined set actors and related events (such as the Armed Conflict Location & Event Data Project (ACLED) data project).[15] Larger projects such as the Uppsala Conflict Data Program (UCDP) data collection project are focused only on armed conflict, and are updated with less frequency.[16] The analysis shown here demonstrates that this kind of data can provide critical and timely information on crisis events.[17]

Finally, our study demonstrates how the creation of network data can identify meaningful connections between actors that are not directly observable in the original data. This approach provides information about unobserved conflict and cooperation–a critical advancement in an age of media bias and underreporting of events in violent contexts. The study of conflict evolution as a network process reveals that when these dependencies in the data are ignored, researchers cannot deeply investigate how, and why, violent actors change behavior over time. As the promise and value of a frequently updated and detailed machine-coded dataset remains high, future work should build upon the insights found in the creation of network data and the use of latent space models. Utilizing these approaches allows researchers to track critically important events quickly and effectively, and to produce knowledge that can support efforts by civilians, governments, activists, and policymakers to deescalate conflicts.

[15] See Raleigh et al. (2010) for data details.

[16] For a discussion of both ACLED and UCDP see Eck (2012).

[17] There are efforts at Duke's Wardlab to create similarly fine-grained data in other regions such as China.

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