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

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Abstract.

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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. **?** 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 maximalist campaigns

[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).

wherein an entire population unites under the singular cause of removing a (usually corrupt) leader from power. The implications of this incites scholars to explore the capacity of non-violent actions at a local level.

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 2006-2013 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 (**?**), and identity-based (**?**) 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.

1. People Power & Conflict Evolution

Little empirical evidence that protests should "work" in contexts of high violence.

- no relationship- protest might have other effects (community building, government response through speeches or meetings).
- no relationship- protestors are targeted due to their activism, potentially resulting in fewer protests over time, but with no clear consequences for violence between armed groups.
- decreased violence- Protests delegitimize armed actors: Protests demand that the government invest greater resources in the prevention of violence, resulting in fewer conflictual events and raising the political costs of violent engagement.
- decreased violence- Protests delegitimize armed actors- Protests delegitimize non state actors which minimizes the effectiveness of coercion against civilians.
- increased violence- protests raises the costs of inaction so government more likely to show up & fight hard in the next round (instead of going about peaceful means of action).

The Mexican Criminal Conflict

The Mexican case is the key country case for this study. The internal war in Mexico is a criminal conflict, driven by territorial disputes over trafficking routes and land and collusion between government officials and Drug Trafficking Organizations (DTOs). Drug trafficking is not a new phenomenon but over the last decade it has has been at the root of a complex conflict affecting 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 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 became known as 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

[2]Shirk (2011)
[3]According to Mexico's National Statistics Institute (INEGI).
[4]Nathaniel (2013)

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 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

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

are often 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 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 cleaned 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 events in Mexico.[7]

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]

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[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. Very recently this data became publicly available; we are currently investigating its use for this study.

[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).

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 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.

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

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 2004-2013, we 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.

In addition to correcting for the number of conflictual events over time, we also correct for the vague coding descriptors found in the original data. To do this, we read the stories and coded whether a specific criminal group, cartel, or cartel member was mentioned. We then code the new actors' names and list any relevant actor involved in the conflictual event. A variety of other news sources, blogs, and area expert knowledge were used to complete this new set of actor codings. If we could not locate any resources that allowed me to identify which cartel, or actor, was involved in the event, we utilized a pre-existing data set containing the locations of cartels over time. This data set was created by Viridiana Rios and Michele Coscia and records locations of cartels down to the municipal level. An example of the territorial changes for the Sinaloa Cartel are shown in Figure 1.[13] Exploiting online newspapers and blogs, they develop a mechanism that uses unambiguous query terms to classify the areas in which criminal organizations operate.

[13]Maps and data provided by Viridiana Rios, which can be accessed online, see Coscia & Rios (2012).

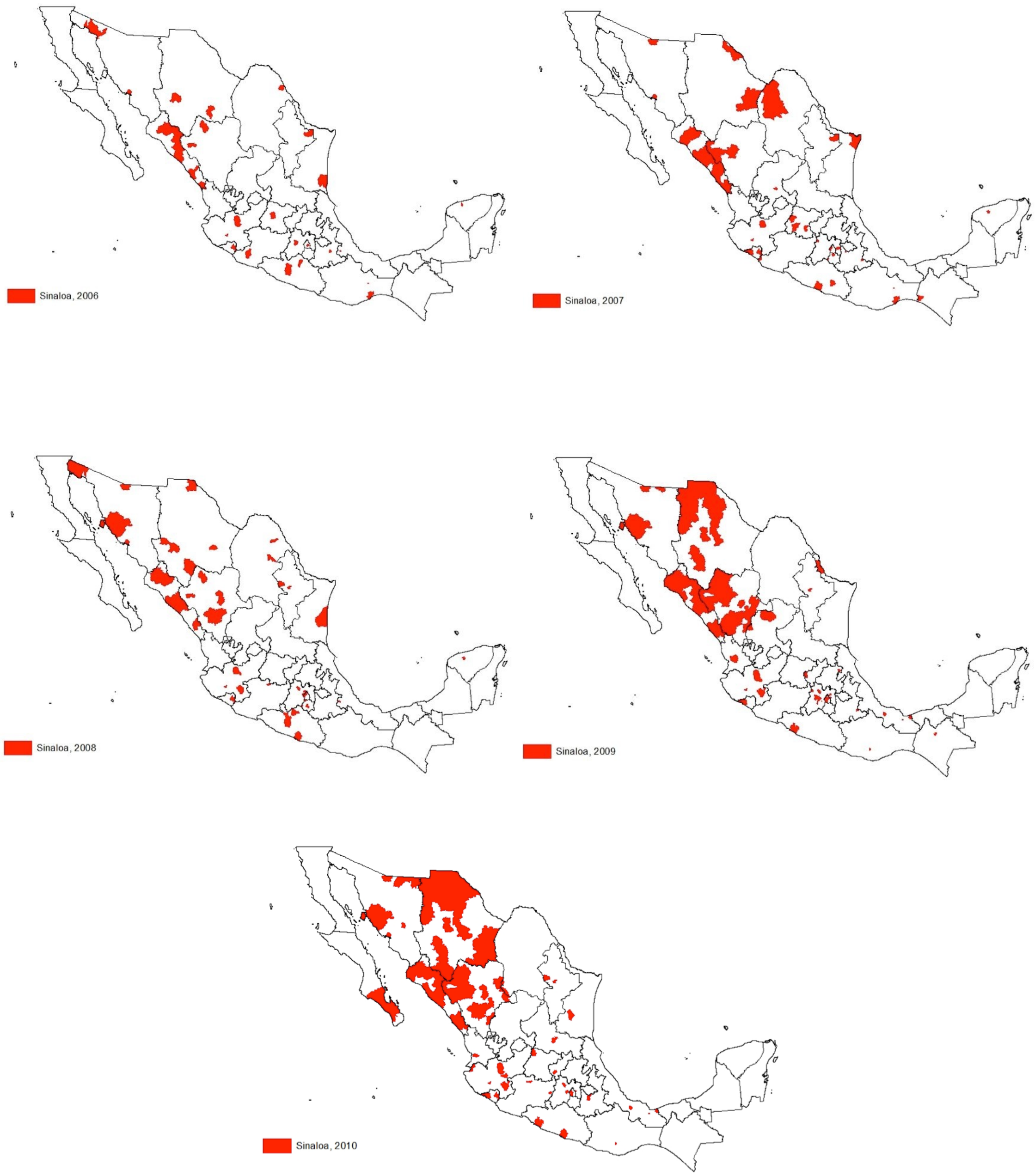

Figure 1. Sinaloa Cartel's territorial movements from 2006-2010

The end result is a collection of 1,052 actor-coded violent events from 2004-2012. The general trend of this data fits the pattern we observe in other data based on homicide rates.

Figure 2. 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. 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 show that the Sinaloa cartel engages in violence against the highest number of competitors as well as against the federal government's armed forces. After walking through these connections and the ways in which they evolve over time, we turn to relationships *unobserved* in the raw data: i.e reciprocity and clustering.

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 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.

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

These matrices reveal a variety of interesting dynamics in the data, as shown in the network graphs of Figure 3, Figure 4, and Figure 5. First, Figure 3 shows the network graph for the first year of the data. Beginning as early as 2005 to 2007, there is a substantial increase in the number of actors in the network. For simplicity, the actors are simply coded as DTO or Government actors. Government actors include different branches of the armed forces and government.

Figure 3. The evolution of the Mexican criminal conflict, 2005. 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.

In 2006 and 2007, shown in Figure 4, the number of conflictual events increase. Both federal agencies and municipal forces are more active in the conflict. We also observe a jump in the number of cartels involved in the network, as new actors such as La Familia Michoácana, the Mexican Mafia, and the military begin to take part in the conflict. In the period between 2007-2009, the networks reflect a change in the government policy at that time. By 2006 Calderón was elected president and implemented a militarized strategy, sending federal police and troops into the most contested regions. By 2007, we see that the relationships become more complex as cartels begin to interact with one another. This sufficiently reflects what we now know to be true: following Calderón's 2006 efforts, violence increased due to grueling competition between newly fragmented cartels.

Figure 4. The evolution of the Mexican criminal conflict, 2006-2007. 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.

In 2008, similar dynamics are in motion, but it is difficult to decipher the various roles played by the different levels of government. Earlier, both federal and municipal governments seem similarly involved, but by 2008 and 2009 the municipal government has a broader connectivity to diverse actors while the federal police seems to become more limitedly engaged with the Sinaloa Cartel. Overall, density increases across these networks overtime.

To further assess how different levels of government change their role in the network over time, Figure 6 presents the eigenvalue centrality for each actor. Eigenvector centrality is calculated by assessing how well connected an actor is to the other actors of the network. Specifically, those with the highest eigenvector centrality are well-connected to other actors who are also well-connected across the network. In this case we can consider an actor with high eigenvector centrality to be a key player in the conflict.

Figure 5. The evolution of the Mexican criminal conflict, 2009-2011. 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 6 reveals an interesting story of coordination between different levels of government. In 2004 both the municipal police and the federal police have similar levels of eigen centrality. In 2005 they both decrease, with a larger decrease for the municipal police. In 2006 we see that both actors have very high centrality, indicating a deep involvement in the conflict. This reflects the Calderón strategy: sending federal forces into local areas to help bolster security enforcement and combat the cartels. We then see these two actors diverge. Federal police stay highly central in the network in 2007 while the municipal forces seem to back down. At this year these two actors experience the biggest gap in centrality, signaling that coordination between the two levels of governments decreases as federal forces take over combat operations relative to municipal security forces.

Figure 6. Eigen centrality at the yearly level (2004-2009) for both municipal police and federal police

By 2008, we see a stark shift as municipal forces are once again involved in the conflict while federal forces seem to back down. This is particularly interesting because at this time it becomes well known to the public and to the government that Calderón's strategy has largely failed, causing more violence rather than stemming it. Figure 6 shows that after federal forces are very active from 2006-2007, in 2008 they then recede and the municipal police become more active in the network. Finally, the year 2009 shows closer centrality scores than 2008 and 2007, signaling that perhaps these two levels of government begin to cooperate again.

Without the re-structuring of the event data into networks we would not be able to see the ways in which different levels of governments interact over time. This approach offers a more complete picture of these dynamics than has previously been possible and enables future research to examine what factors influence government coordination within the network.

Latent Space Analysis

A further analysis of these networks allows us to answer questions about the probability of interaction between actors in a network. While there are several approaches to social network analysis, we employ the latent space approach. Latent space approach is most useful when the main goal is to understand the role of individual actors in the network. Specifically, the latent space approach can identify interactions that are unobserved in the raw data. This approach is presented by Hoff et al. (2002) and has been used in political science in several applications.[14]

The essential idea of the latent space is to capture third-order dependence. A common example involves relationships within a triad i, j, k. If we know that i considers j a friend and j is a friend of k, then the probability that k will also be a friend of i is likely to be higher than for a random person outside of this triad, since i and k are at least indirectly connected in the friendship network by virtue of their separate linkages to j. Thus, information about the relationships in the first two dyads of a triad can usually reveal something about the relations in the third dyad. Third-order dependence, or the "unobserved," latent social space then becomes a highly useful concept. The latent space can be thought of as a probability space, whereby observation of two links, i-j and j-k, suggests that i and k are not too far away from each other in this social space and therefore are also likely to have a link between them. Since third-order dependence is an expression of the underlying probability of a link between two actors, we do not observe the complete

[14]For examples regarding political conflict see Dorff & Ward (2013) or Metternich et al. (2013)

set of all of these network characteristics, but we can infer them from the pattern of dyadic linkages. If we can map out the latent positions of each actor in the "social space," we can then assume that the ties in the network are conditionally independent.

Formally, if we are interested in modeling an n x n sociomatrix that contains dyadic data, we might do so with a typical linear regression approach:

$$y_{ij} = \beta' x_{i,j} + \epsilon_{i,j}. \tag{1}$$

While this approach is certainly common, it assumes the errors, $\epsilon_{i,j}$ are independent. In employing the General Bilinear Mixed Effects modeling (GBME) approach, we alter the assumption of the errors and instead assume that the errors $\{\epsilon_{i,ji} \neq j\}$ have a covariance that is exchangeable under identical permutations of the indices i, j. We then assume normality, which implies that the residuals can be represented as a linear random-effects model with sender (a_i) and receiver (b_j), and dyadic y_{ij} effects:

$$\begin{gathered}
\epsilon_{ij} = a_i + b_j + \gamma_{i,j} \\
\begin{bmatrix} a_i \\ b_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ba} & \sigma_b^2 \end{bmatrix} \right) \\
\begin{bmatrix} \gamma_{i,j} \\ \gamma_{j,i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\gamma^2 & \rho\sigma_\gamma^2 \\ \rho\sigma_\gamma^2 & \sigma_\gamma^2 \end{bmatrix} \right).
\end{gathered} \tag{2}$$

This allows us to estimate the following moments:

$$
\begin{aligned}
E(\epsilon_{i,j}^2) &= \sigma_a^2 + \sigma_b^2 + \sigma_\gamma^2 \\
E(\epsilon_{i,j}\epsilon_{j,i}) &= \rho\sigma_\gamma^2 + 2\sigma_{ab} \\
E(\epsilon_{i,j}\epsilon_{i,k}) &= \sigma_a^2 \\
E(\epsilon_{i,j}\epsilon_{k,j}) &= \sigma_b^2 \\
E(\epsilon_{i,j}\epsilon_{k,i}) &= \sigma_{ab}.
\end{aligned} \tag{3}
$$

where σ_a^2 represents dependence among dyadic observations with a common sender, σ_b^2 represents dependence among measurements having a common receiver, and ρ is the correlation of measurements within a dyad, or *reciprocity*. To adjust for other types of data, such as the count data used here, the error structure can be altered so that the dyadic data are conditionally independent given the random effects but are unconditionally dependent:[15]

$$
\begin{aligned}
\theta_{i,j} &= \beta' x_{i,j} + a_i + b_j + \gamma_{i,j} \\
E(y_{i,j}|\theta_{i,j} &= g(\theta_{i,j}) \\
p(y_{1,2}...y_{n,n-1}|\theta_{1,2}...\theta_{n,n-1}) &= \prod_{i \neq j} p(y_{i,j}|\theta_{i,j}).
\end{aligned} \tag{4}
$$

Following Hoff (2005), we can define the unobserved, K-dimensional vector z_i for each node i in the network. By modeling the interaction of two nodes as an increasing function of their proximity in the latent space, we include patterns of transitivity, balance, and clusterability into the network. Formally, we can incorporate this into the model by adding the inner product $z_i' z_j$ to the linear predictor:

$$\epsilon_{ij} = a_i + b_j + \gamma_{i,j} + z_i' z_j. \tag{5}$$

[15] Where g(·) is the inverse-link function. This is a summary of the full specification provided in Hoff & Ward (2004) and Hoff (2005).

Because we are interested in modeling a temporal network, we extend on the GBME framework and employ an AME model. The Additive and Multiplicative Effects model (AME) model is a relatively new technique that is a generalization of the Generalized Bilinear Mixed-Effects model explained above. The model is an extension of the Social Relations Model:

$$f(Y_{i,j}) = \beta' \mathbf{x_{i,j}} + \alpha_i + b_j + \epsilon_{i,j} \tag{6}$$

where $f(.)$ is a general link function corresponding to the distribution of Y, $\beta' \mathbf{x_{i,j}}$ is the standard regression term for dyadic and nodal fixed effects, α_i, b_j are sender and receiver random effects, and $\epsilon_{i,j}$ is an IID error term. The AME model further decomposes the error term as follows. If we assume the matrix representation of deviation from the linear predictors and random effects is $\mathbf{M} + \mathbf{E}$, such that the matrix $\mathbf{E}$ represents noise, and $\mathbf{M}$ is systematic effects. By matrix theory, we can decompose $\mathbf{M} = \mathbf{UDV}'$ such that $\mathbf{U}$ and $\mathbf{V}$ are are n x n matrices with orthonormal columns, and $\mathbf{D}$ is an n x n diagonal matrix. This is called the singular value decomposition of $\mathbf{M}$.

We then write the AME model for a given value $Y_{i,j}$ as being a function of a latent sociomatrix Z that follows a Gaussian AME model:

$$z_{i,j} = \beta' \mathbf{x_{i,j}} + \alpha_i + b_j + \mathbf{u_i} \mathbf{D} \mathbf{v_j'} + \epsilon_{i,j} y_{i,j} = g(z_{i,j}) \tag{7}$$

An important innovation with the AME, as compared to previous network estimates is the ability to handle longitudinal datasets. The AME with dyadic data treats each different slice of data as independent, save for those dependencies captured by the nodal and multiplicative random effects, as well as those controlled for by fixed effects.

Key Variables. The dependent variable in our study is the conflict event network. At present, we include four predictor variables. The first two are eigenvector centrality and betweeness scores. These variables are generated on the previous iteration of the network and thus act 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. Third, we include a control variable for whether or not the actor in the network is a Drug Trafficking Organization. Last, we include a protest variable.

Our protest data comes 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 a municipality during each month for the time period of 2006-2014. Creating a protest variable for the network analysis is straightforward: we simply match municipalities 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 7. Counts of protest events over time in Mexico 2006-2014.

(Preliminary) Results

We present the results for four AME models, each with the inclusion of an additional variable, and plot the results below. We faced several challenges in our modeling process. First, the AME approach, at present, is restricted to analysis of binary and ordinal data. This was fairly easy to work around: we simply transformed our networks of event counts into a "low", "medium," and "high" ordinal variable. Secondly, our approach is limited by sparseness in the networks. The number of events for each network-year are low so it is difficult to incorporate a large number of parameters without running into overfitting issues. For example, we tried to incorporate other variables in the model including more robust fixed effects but were unable to reach convergence. At present, we find some support that centrality positively predicts violence, perhaps suggesting that key actors are responsible for perpetuating violence. This might especially be true in the case of

Mexico, in which major organizations such as the Sinaloa DTO have been responsible for challenging, and ultimately dismantling, smaller DTO competitors. At present, we find little support that protests influence DTO behavior.

Figure 8. Results from AME Analysis

Conclusion

There are several main conclusions to draw from this study. First, there are important takeaways for future research regarding the Mexican conflict itself. At present, the future of the Mexican criminal conflict is indeterminate. Civilian death counts remain high, and it is unclear whether government strategies are working. This study demonstrates that networks can reveal insight about cooperation between different levels of government and highlight the ways in which this coordination changes over time.

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).[16] Larger projects such as the Uppsala Conflict Data Program (UCDP) data collection project are focused only on armed conflict, and are updated with

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

less frequency.[17] The analysis shown here demonstrates that this kind of data can provide critical and timely information on crisis events.[18]

Finally, this study shows how the creation of network data, and particularly the use of latent space models, can actually 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.

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

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

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