Distribution Agreement

Signature:

______________________________________ ______________

Nathan Dwight Edwards Date

Criminal and Insurgent Patterns of Violence are Empirically Equivalent: The Case of Drug Violence in Mexico

By

Nathan Dwight Edwards
Master of Arts

Political Science

Dan Reiter
Advisor

David R. Davis
Committee Member

Danielle F. Jung
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

Criminal and Insurgent Patterns of Violence are Empirically Equivalent: The Case of Drug Violence in Mexico

By

Nathan Dwight Edwards
M.S., Georgia Institute of Technology, 2004
B.S., Georgia Institute of Technology, 2002

Advisor: Dan Reiter, Ph.D. University of Michigan

An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Arts
in Political Science
2014

Abstract

Criminal and Insurgent Patterns of Violence are Empirically Equivalent: The Case of Drug Violence in Mexico
By Nathan Dwight Edwards

Are insurgent groups and organized criminal groups distinct? Contemporary research on intrastate conflict suggests they are, by neglecting the subject of organized crime. Qualitative analysis of several groups demonstrates operational and organizational similarities between them. I argue that their macro-level patterns of violence are empirically equivalent. Previous studies have shown that the frequency of violent attacks by insurgencies conform to a power-law distribution based on the notion of interdependent cells aggregating and disaggregating over time. In this study, I find the frequency of violent attacks by organized criminal groups in Mexico from 2006 to 2010 is also well characterized by a power-law distribution at the national level and at the state level where fighting between the groups and the state is particularly fierce. My findings suggest insurgencies and organized criminal groups are part of the same class when analyzed from the perspective of complex systems. Additionally, we must be cautious in using analytical tools associated with central tendencies when analyzing conflict data characterized by a "fat-tailed" distribution of unusually large events.

Criminal and Insurgent Patterns of Violence are Empirically Equivalent: The Case of Drug Violence in Mexico

By

Nathan Dwight Edwards
M.S., Georgia Institute of Technology, 2004
B.S., Georgia Institute of Technology, 2002

Advisor: Dan Reiter, Ph.D. University of Michigan, 1994

A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Arts
in Political Science
2014

Acknowledgments

I would like to thank Kristen for her unwavering support in this endeavor. I would also like to thank the rest of my family for their love and encouragement throughout this process. Lastly, I would like to thank each of my thesis advisor and committee members for their insight and guidance. You have helped challenge me to make this research project what it is.

Contents

Figures

Tables

Introduction

In July, 2009, the criminal organization La Familia Michoacána simultaneously attacked federal police stations in eight cities as swift retribution for the capture of a high-ranking member of their organization earlier that day. They killed three federal police officers, two soldiers, and wounded 18 other federal officers firing automatic weapons and grenades from armored S.U.V.s (Grinberg and Trevino 2009). Two days later it emerged they had followed their attack by kidnapping, torturing, and murdering twelve federal agents, leaving the bodies on the side of the road with a sign saying, "Come for another. We will be waiting for you here" (Finnegan 2010). La Familia first gained prominent attention in 2006 when they rolled five severed heads onto the floor of a dance club in Uruaban, Michoacán leaving a sign at the scene, "La Familia doesn't kill for money, it doesn't kill women, it doesn't kill innocent people—only those who deserve to die. Everyone should know: this is divine justice" (Finnegan 2010). According to a senior American in Mexico city, La Familia "is looking more and more like an insurgency and less like a cartel" (Finnegan 2010).

Are insurgent groups and organized criminal groups distinct? Contemporary research on intrastate conflict suggests they are, by generally neglecting the subject of organized crime. Qualitative analysis of several insurgent and organized criminal groups demonstrates operational and organizational similarities between them (Makarenko 2005; Shelley and Picarelli 2005). I argue their macro-level patterns of violence are empirically equivalent. In short, the distribution of the severity of an attack by organized criminal groups in Mexico from 2006 to 2010, measured in terms of casualties per attack, is power-law distributed—with the same scaling parameter as global terrorism and several politically-motivated insurgencies.

Classically, organized crime runs protection rackets and provides illicit goods and services (Schelling 1967). However, organized criminal groups (OCG) in Mexico do not adhere to these basic assumptions of profit-motivated illicit behavior by generating a spiral of violence to unparalleled proportions. Since 2006, Mexico has suffered over 80,000 drug-related homicides, including over 1,100 military and police casualties (Astorga and Shirk 2010; Graham 2013). Such violence greatly exceeds the standard threshold of 1,000 casualties scholars use to define the onset of a civil war. It even surpasses the median number of deaths (19,000) in all civil wars from 1945 to 1999 (Sambanis 2004).

The past few decades have seen the emergence of transnational organized crime and the embrace of criminal activities by terrorists. Several scholars have examined the overlap between organized criminal groups and terrorist groups along a spectrum conceptualized as the 'crime-terror continuum' (Ballina 2011; Cornell 2007; Dishman 2005; Hutchinson and O'malley 2007; Makarenko 2005; Rosenthal 2008; Shelley and Picarelli 2005). Two traditionally separate phenomena increasingly exhibit similar operational and organizational characteristics. As Shelley (2006) notes, "the artificial distinction that has been made between crime and terrorism is based on an antiquated concept of both." Some argue that Mexico faces a "criminal insurgency"—insofar as organized crime uses violence against the state to achieve a goal of profit without government interference (Bunker 2011; Grillo 2011; Metz 2007; Sullivan and Elkus 2010). For instance, La Familia Michoacána and Los Zetas, two Mexico's most notorious organized criminal groups, employ guerrilla tactics in combat against the state, use decentralized networked structures, seek varying levels of popular support, and threaten the sovereignty of the state one neighborhood and firm at a time. Others argue insurgencies are adapting methods and capabilities from organized crime and terrorist groups with evidence from the conflicts in Iraq and Afghanistan (Kilcullen 2006; Manwaring 2008; Metz 2007; Robb 2007). A few scholars argue that blanket government crackdowns change the incentive to avoid conflict facing organized crime causing increased violence (Lessing 2012; Rios 2012). The implication is that we have reached the point of diminishing returns as we continue to refine outdated typologies of violent non-state actors.

The gap in the literature yet to be filled is a quantitative analysis of the extent to which organized crime is similar to other violent non-state actors. Previous research based on qualitative evidence suggests an overlap in operational and organizational capabilities of groups such as Abu Sayyaf in Philippines, IMU in Uzbekistan, PKK in Turkey, FARC in Colombia, or La Familia Michoacána in Mexico. These organizations straddle the profit-versus-politics dichotomy that characterizes most non-state actor taxonomies. The motivations and methods used to obtain their objectives previously separated organized crime from terrorist groups and insurgencies. As Hoffman (2006) notes, a criminal’s violent act is not intended to create psychological repercussions beyond the act itself or to influence an audience beyond the victim. In contrast, insurgents and terrorists employ violence to mobilize popular support or influence target audiences within a broader strategy of psychological warfare. However, classic conceptual distinctions are insufficient for dynamic environments with evolving organizational strategies by violent non-state actors. They provide little leverage in understanding why criminal organizations have become so violent. The political, historical and rhetorical baggage of such concepts has prompted awkward imbroglios such as Mexico's government repudiation of U.S. Secretary of State Hillary Clinton's remarks in 2010 that their drug violence increasingly has the hallmarks of an insurgency (Ghattas 2010).

In this study I adopt a more empirical approach to analyzing the behavioral similarities between violent non-state actors. More specifically, I relax the assumptions of politically-motivated violence in the Clauset and Wiegel (2010) model of insurgency to include profit-motivated violence by organized crime. The analytical model generates hypotheses of the frequency distribution for the severity of organized criminal attacks: that they are well characterized by a power-law with a scaling parameter, $\alpha = 2.5$. That is, on a log-log plot the cumulative distribution of attacks will be a straight line with a slope of -2.5 over a large range attack severity. The unit of analysis is violent attacks with at least one casualty. The data are then the number of casualties as a result of each attack. I then use the Clauset, Shalizi, and Newman (2009) method of maximum likelihood and goodness-of-fit tests based on the Kolmogorov-Smirnov statistic to discern whether the data are power-law distributed at the country level. I also test the power-law hypothesis at the state level by using a Bayesian hierarchical model to examine state-level geographic variation in Mexico. I find two different measures of organized criminal violence at the national level in Mexico from 2006 to 2010—government data from Mexico's National Security Council and the Political Instability Task Force Worldwide Atrocities Dataset—are well characterized by a power-law distribution. At the state level, areas where conflict is severe between organized criminal groups and the government are also well characterized by a power-law distribution.

Mexico is a crucial test of the potential overlap between criminal and politically-motivated violence. The key feature that makes violence in Mexico a critical case study is that all the criminal organizations are profit-seeking in contrast to other cases like Colombia or Afghanistan where criminal organizations are intermixed with politically-motivated organizations. The data does not exist to separate the violence of criminal organizations from politically-motivated ones within those conflict zones. In other words, previous studies on power-law distributions in conflict have not examined a case at the purely criminal end of the crime-terror spectrum. Mexico is such a case; and even if it is not, the empirical analysis does not depend on homogenous profit-motives of organized criminal groups. Thus, the Mexican case provides greater evidence that violent non-state actors generate similar patterns of violence.

Analysis of power-laws is part of the science of complex systems. It is used to analyze the characteristics of a particular class of systems defined by the presence of unstable dynamics, the interaction of a large number of interdependent units and the nonlinearities between micro- and macro-level events (Bohorquez et al. 2009; Sornette 2006). Instead of performing analysis on central tendencies in order to estimate the influence of variables on the severity of individual events, this approach examines the global distribution of extreme events or “fat tails.” This method of analysis has already been used to examine the distribution of casualties in different types of conflict: inter-state, intra-state, and global terrorism (Bohorquez et al. 2009; Cederman, Warren, and

Sornette 2011; Cederman 2003; Clauset and Gleditsch 2011; Clauset and Wiegel 2010; Clauset, Young, and Gleditsch 2007; Dobias 2009; Johnson et al. 2006).

Three implications follow from my findings. First, organized criminal groups, insurgencies, and terrorist groups exist within the same class such that they generate equivalent patterns of violence. This “universal pattern,” as Bohorquez et al. (2009) refer to it, is exhibited by loosely organized groups engaged in asymmetric warfare and applies independently of politics, ethnicity, ideology, terrain and according to my findings, profit. Second, we need to be cautious in using analytical tools associated with central tendencies and assumptions of normal distributions in the study of conflict because of the presence of rare and extreme events. Lastly, a macro-level analysis of frequency distributions for extreme events can prove useful in a wider array of conflict studies. Extreme events are not anomalies that defy scientific generalization, but are rather part of a pattern understudied by social sciences.

This paper is organized into five sections. First, I discuss the conceptual similarities between types of violent non-state actors. Second, I consider the existing scholarship on power-laws within human conflict. Third, I develop a model of organized criminal group behavior based on Clauset and Wiegel’s model of politically-motivated violence, and generate empirically testable hypotheses. Fourth, I describe the research design and examine the results of violence in Mexico at the state and national level. Lastly, I discuss the results and conclude with further implications.

The Landscape of Violent Non-state Actors

For organized crime there "appear to be as many descriptions…as there are authors" (Albanese 2000, 410). Though Albanese refers only to organized crime, this observation also applies to the Hoffman's (2006) conceptualization of terrorism and insurgency. As Hoffman notes, a criminal's violent act is not intended to create psychological repercussions beyond the act itself or to influence an audience beyond the victim. Albanese defines organized crime as a continuing criminal enterprise that rationally works to profit from illicit activities; its continuing existence is maintained through the use of force, threats, monopoly control and the corruption of public officials. This rational approach implies that organized crime lacks an ideology or political agenda. Any security threats posed by the criminals' violent activities is inadvertent rather than deliberate (Mandel 2011). This goal-seeking assumption logically leads to a behavioral expectation: organized crime seeks to avoid violent confrontation wherever possible because it is costly and disruptive to business. Moreover, such criminals have traditionally shown little interest in fomenting mass-casualty attacks (Dishman 2001). Yet, scholars find the avoidance of violent confrontation or employment of mass-casualty attacks is not always the case (Bailey and Taylor 2009).

Hoffman (2006) defines terrorism as the deliberate creation and exploitation of fear through violence or threat of violence in the pursuit of political change. This definition is further refined into five principal characteristics: political motives and goals, violence and threats of violence, the use of these as psychological effect for an audience beyond the immediate victim, the use of such actions by an organization or an individual on behalf of an organization, and their perpetration by a non-state entity. Young and Findley (2011) further emphasize that the key feature distinguishing terrorism from other forms of political violence like genocide is the psychological effect on the target audience as distinct from an effect on the immediate victim.

Fearon and Laitin define insurgency as a "technology of military conflict characterized by small, lightly armed bands practicing guerrilla warfare from rural base areas" (2003, 75). Insurgents share the same characteristics as guerrillas but typically use coordinated informational (e.g. propaganda) and psychological warfare efforts to mobilize support against an established government, imperial power or foreign occupying force (Beckett 2001). Killcullen (2006) generalizes the concept of insurgency as "a struggle to control a contested political space, between a state (or group of states or occupying powers), and one or more popularly based, non-state challengers." In his conceptualization, the insurgent attempts to challenge the status quo while the counterinsurgent reinforces the state to defeat the challenger. On the other hand, the insurgent also attempts to preserve the status quo of ungoverned spaces or to repel an occupier such as the Taliban in Afghanistan—an inversion envisaged in classical counterinsurgency theory.

The difficulty with the classical conceptualizations of non-state actor violence—organized crime, terrorism and insurgency—is their considerable overlap across several dimensions. This is due both to the broad definitions as well as the behavioral evolution by non-state actors in diverse environments. These concepts have become particularly convoluted due to their wide popular usage in both policy-making circles and popular vernacular, sometimes making academic discourse difficult. To address this confusion, scholars have generated a plethora of new terms—irregulars, global guerrillas, system disrupters, extra-legal organizations or violent entrepreneurs, to name a few—that simply shift the emphasis of certain conceptual dimensions into new boxes. Classical concepts become less relevant as groups engage in patterns of behavior that can be classified within many different conceptual definitions. A number of recent studies of political violence suggest that scholars must engage the ambiguities and avoid studying specialties of violence such as terrorism or civil war (Findley and Young 2012; Kalyvas 2003; Tarrow 2007). Particularly in warring states, terrorists and insurgents resort to crime to fund their operations but also seek out criminal networks for specialized support such as weapons, document fraud or money laundering. Conversely, criminal organizations are known to employ violence similar to that used by terrorist groups as a bargaining strategy with the state. Even Al Qaeda—the archetype of modern terrorism—engages in illicit criminal activities and has conducted guerrilla attacks on military forces, blurring distinctions among the classic concepts.

Conceptual Overlap of Violent Non-State Actors

I next examine similar behavioral patterns and characteristics of violent non-state actors, including organized crime, terrorism and insurgency. While this paper takes an empirical approach to analyzing the violence of organized criminal groups, the justification for applying a model of organizational dynamics derived from the study of insurgencies and terrorism to organized crime requires a minimum degree of behavioral overlap. Several scholars argue that there is a continuum between purely criminal and purely ideological non-state behavior, with hybrid groups able to exhibit characteristics of both (Ballina 2011; Dishman 2001, 2005; Hutchinson and O'malley 2007; Makarenko 2005; Manwaring 2008; Shelley and Picarelli 2002). Hybrid groups like the FARC in Colombia, PKK in Turkey, LTTE in Sri Lanka, Abu Sayyaf in the Philippines and Los Zetas in Mexico exhibit a combination of both criminal and ideological goals as they pursue their organizational goals through violent means.

First, violent non-state actors *are not recognized legal entities* in international or domestic politics. They generally do not wear uniforms or identifying insignia to distinguish themselves from noncombatants. The deliberate mixing with civilians and other non-combatants belies their lack of desire for formal legal status. They operate outside the law and therefore do not have the ability to enforce contracts or obtain international recognition. Of course, there are examples where a government recognizes a violent non-state group in order to negotiate a cessation of violence. Such examples typically arise after civil wars (e.g. Sierra Leone) but recently have included a negotiated settlement between organized criminal groups in El Salvador (Ramsey 2012). Even though Mexican law enforcement and military fight Mexican organized criminal groups, the groups are not legally recognized entities with which the government can negotiate a cessation of violence. Any reduction in violence is due to government countermeasures or informal negotiation with no binding power.

The inability to rely on the law ensures that such groups must govern themselves. Scholars have identified several mechanisms of governance by groups that employ violent tactics. Hamas and Hezbollah coax contributions by providing aid, to which a participant will lose access if he or she fails to contribute (Berman 2009). Organizations require costly signals of a potential member's commitment, which when judged acceptable give the new member access to local public benefits (Berman and Laitin 2008). Ethnicity and religion can facilitate within-group cooperation for those who operate outside the law (Bernstein 1992; Landa 1981). In his study of organized criminal groups, Skarbek (2011) finds that the use of threats and violence funds governance by increasing the costs for refusing to participate. He quotes a 17-year veteran of the Mexican Mafia: "Tens of thousands of gang members adhered to what we said…And it was then that we realized the true potential of the Mexican Mafia…because of the finances generated by taxation: Taxation, extortion, protection—they all fall under the same umbrella" (American Public Media 2008). An organization's power to tax is at the heart of Tilly's (1985) argument that government war making and state making is analogous to organized crime. Both governments and organized criminal groups operate as a protection rackets, but the government's actions appear legitimate. Violent non-state actors develop highly sophisticated but nevertheless informal mechanisms of governance—costly signals of membership, taxation, and social sanctions based on ethnicity or religion—that are independent of the organization's political or profit motivations.

Second, violent non-state actors *threaten the sovereignty of the state*. Terrorists and insurgents intend to replace the existing social and political order within a state, or at least a significant geographic area in the case of secessionist movements. On the other hand, organized criminal groups threaten state sovereignty at the micro rather than the macro level. "Rather than trying to depose a government in a major stroke or prolonged revolutionary war, as some insurgents have done, gangs and other TCOs [transnational criminal organizations] more subtly take control of turf one street or neighborhood at a time or one individual, business, or government office at a time” (Manwaring 2008, 105). Any conceptualization of state sovereignty must include some aspect of border control, economic regulation, legal system legitimacy and a monopoly on violence. Bruneau (2005) argues that organized criminal groups challenge each of these dimensions of state sovereignty in five principal ways: straining government capacity by overwhelming police and legal systems, challenging state legitimacy through corruption and inability to provide public goods and services, acting as surrogate governments in so-called ungoverned areas, dominating the informal economic sector, and infiltrating police and non-governmental organizations to further their goals. The fact that organized criminal groups do not use public statements or charters with the goal of overthrowing a government does not imply that their actions do not challenge several dimensions of sovereignty. In comparison to organized crime, terrorism may have a more direct and immediate impact on society, but both undermine the state sovereignty in the long term. “The terrorist threat is rather like smallpox—when it erupts it is immediate and devastating in its impact; transnational organized crime, in contrast, is rather more like AIDS—it breaks down the defences of the body politic, using corruption as a selectively targeted instrument to weaken or neutralize law enforcement, the judiciary, and even the government as a whole” (Williams 2007).

Third, violent non-state actors *adopt similar organizational structures*. They eschew rigid hierarchies in favor of hybrid networks. This similarity is crucial for the organizational dynamics model I use in the quantitative analysis of Mexican organized criminal violence. According to Powell (1990), networks are an institutional form of organization different from markets and hierarchies. Unlike market interactions, networks endure. Hierarchies have recognized dispute settlement authority that is not conferred upon any member of the network. Often, networks constructed in the real world display hybrid patterns drawn from all three ideal types. Networks are ubiquitous in the world around us and have become “the intellectual centerpiece of our era” (Kahler 2009). A network in its most basic form is a set of interconnected nodes. The nodes can be individuals, groups, organizations or even states. The links between the nodes create a structure, or persistent pattern of relations, that in turn serves to provide opportunities for collective action. In their widely cited definition, Podolny and Page define a network as “any collection of actors ($N \geq 2$) that pursue repeated, enduring exchange relations with one another and, at the same time, lack a legitimate organizational authority to arbitrate and resolve disputes that may arise during the exchange” (Podolny and Page 1998, 59). Distinguishing networks from hierarchies is less clear, but the features of networks include “relative flatness, decentralization and delegation of decision making authority, and loose lateral ties among dispersed groups and individuals” (Zanini and Edwards 2001, 33).

The fundamental dilemma that drives violent non-state actors to adopt hybrid network structures is the tradeoff between concealment and coordination, or as Kenney (2009) refers to it, the *secrecy-efficiency dilemma*. To protect their operations from competitors or government enforcement, violent non-state actors must conduct their operations in secret. The need for concealment encourages minimal contact between members and information sharing on a need-to-know basis. Yet members must also communicate and coordinate activities to make decisions, conduct operations, distribute resources and arbitrate disputes. Networked forms of organization provide advantages over markets or hierarchies in managing this dilemma (Kenney 2007). Using networks to segment members into loosely organized, functionally-specific compartments minimizes potentially destabilizing contact between members. As Sanderson (2004) explains, such an organizational structure enables tremendous operational flexibility: it can set up or close down operations overnight, maintain distance between operational and planning cells, move and use resources quickly and clandestinely, and operate without headquarters approval. This does not imply that organized criminal groups, terrorists and insurgencies all adopt the same network. Rather, I argue similar preferences and constraints in addressing the secrecy-efficiency dilemma drives similar organizational structures for violent non-state actors regardless of the political or profit motivations. “The strategic architecture of Los Zetas [Mexican criminal organization]—organization, motive, practices, and policies—resemble that of a political or ideological insurgency” (Manwaring 2009, 32). For example, consider the modern militaries as an example of state organizations under similar constraints with highly variable goals and motivations. Each state’s military varies in levels of hierarchy, functional components and capabilities; yet, scholars analyze them as similar units because they all adopt the same Prussian-style bureaucratic staff system. Similarly, violent non-state actors embrace networks as the basic organizational structure and adapt as needed to local conditions.

Fourth, violent non-state actors *employ guerrilla tactics* against the state. Guerrilla tactics include assassination, kidnapping, hit-and-run attacks, bombings of public gathering places and small-unit raids. Violent non-state actors start from an inherent asymmetric balance of power with respect to the state. Guerrilla tactics are the hallmark of a weaker force against a stronger opponent. Thus, guerrilla tactics are a manifestation of the asymmetric power relationship without any connection to the organization's motives. In fact, nearly a third of the 37 groups on the U.S. State Department's "Designated Foreign Terrorist Organizations" list could just as easily be categorized as guerrillas (Hoffman 2006). The State Department specifically cited the challenge of making meaningful distinctions between these categories, arguing the "line between insurgency and terrorism has become increasingly blurred as attacks on civilian targets have become more common" (U.S. Department of State 2003).

Terrorists and insurgents are generally known for employing guerrilla tactics, but organized crime increasingly demonstrates a capability for and occasionally a desire to employ such tactics against their enemies. Examples range from Pablo Escobar's Medellin Cartel attacks against the Colombian government during the 1980s and 1990s and the Italian Mafia's strategy of car bombs and assassinations against state officials in the 1990s to Los Zetas engaging in terror tactics against the Mexican state more recently. Since the upsurge in violence beginning in 2004, Mexican organized criminal groups have been known to attack civilians, to utilize grenades in urban settings, and employ rocket-propelled grenades (RPGs), vehicle-borne IEDs, and armor-piercing ammunition (Brands 2009; Bunker 2011; Sullivan and Elkus 2010). They also employ sophisticated, complex attacks on military and police garrisons, raids on prisons to free members, and simultaneous attacks on government forces throughout their territory (Turbiville 2010). Such tactics are no doubt in part due to the estimated 100,000 Mexican soldiers who have deserted since 2000, many of whom are suspected of being involved with criminal organizations (Turbiville 2010). The involvement of former military professionals has surely increased organized crime's ability to engage in such tactics. For example, Los Zetas was founded by 31 Mexican Special Forces members who deserted to become Gulf Cartel enforcers. With the success of Los Zetas, each of the organized criminal groups in Mexico has developed its own paramilitary-style enforcer group that employs guerrilla tactics such as La Linea for the Juarez Cartel (Grillo 2011).

The commonly held view that organized crime does not violently confront the state with political objectives is increasingly questionable. In the early 1990s, dozens of high-level state officials were killed in bombings and assassinations by the Italian Mafia in response to a massive government crackdown on their organizations (Shelley and Picarelli 2002). Similar patterns of violence erupted in Colombia in the late 1980s and early 1990s when Pablo Escobar attempted to thwart any U.S.-Colombia extradition treaty by engaging in attacks on state institutions, such as the bombing of the DAS Building in 1989 (Chepesiuk 2003). Bailey and Taylor (2009) argue that organized crime is capable of challenging the state, not to assume its governing powers, but to attain political objectives nonetheless. Specifically in Mexico, criminal organizations target state officials and institutions to pre-empt interference in their illicit activities and in response to government crackdowns. For instance, La Familia coordinated simultaneous attacks on eight federal police stations across Michoacán, killing 12 federal agents (Finnegan 2010). Other Mexican criminal organizations like Los Zetas employ traditional squad infantry tactics by assaulting army or police patrols in pitched battle for hours and then melting away into the countryside or urban forests (Grayson 2011; Sullivan and Elkus 2008). As profit-motivated organizations, Mexican organized crime is evidently willing to incur the considerable costs of organizing collective action to confront the state through the use of guerrilla tactics.

Organized crime may not only confront the state with violence to preserve unfettered access to illicit activities; it also may influence audiences beyond the victim—the primary feature of psychological warfare. The conventional view is that criminals use violence as means to further personal financial gain, while terrorists or insurgents use violence to convey a message beyond the victim to a broader audience. “Unlike terrorism, the ordinary criminal’s violent act is not designed or intended to have consequences or create psychological repercussions beyond the act itself…the criminal is not concerned with influencing or affecting public opinion.” (Hoffman 2006, 36). Yet the violence perpetrated by organized criminal groups in Mexico often has the intent of influencing popular opinion and government policy. The change in government policy sought by organized criminal groups is not related to ethnic or religious grievances, as is often the case with terrorists and insurgents, but instead the softening of government pressure on their illicit activities. Martin (2012) examines over 1,400 narcomessages in Mexico—written communiqués associated with criminals’ violent attacks designed to influence public opinion—over a 12-month period to find that influencing government policy and public opinion was a primary motive behind 30 percent of the messages. The distinction between politically-motivated and profit-motivated violence is not as clear-cut as it used to be as violent non-state actors attempt to influence audiences beyond their immediate victims about government policies.

Fifth, violent non-state actors *exploit numerous and diverse revenue streams to fund their operations*. The rich literature on lootable resources—high-value, easily transportable commodities—consistently show insurgents take advantage of natural resources to fund their organizations (Humphreys 2005; Ross 2004; Snyder 2006; Weinstein 2005). As subsides for insurgencies from the great powers dried up after the Cold War, the insurgents wielded their capacity for violence and popular support to extract revenue by controlling lootable resources. The literature on a “crime-terror” nexus indicates an increasing trend of terrorist groups adopting illicit activities, including extortion, kidnapping, and trafficking drugs and other illicit commodities to support their operations. Despite the difficulty in acquiring hard data, the available research suggests that kidnapping, money laundering, and fuel and oil scams are activities that demonstrate the greatest intersection between organized crime, insurgents and terrorists (Oehme 2008). Terrorist groups like Abu Sayyaf in the Philippines, the Islamic Movement of Uzbekistan and PKK in Turkey are prime examples of such groups that have evolved from ideologically-driven terrorist groups into a mix of profit- and politically-motivated terrorism. Recent studies on Mexican and Central American organized crime demonstrate that these groups are diversifying their profit-generating activities beyond merely cocaine trafficking. The evidence demonstrates organized criminal groups in Mexico now traffic in medicinal and illicit drugs, cigarettes, weapons, automobiles, immigrants and intellectual property (Beittel 2011; Brands 2009; Grayson 2011). Some criminal organizations are maneuvering even beyond an expertise in commodity trafficking to control industrial resources through mineral extraction and oil bunkering (Grillo 2011; Sullivan and Elkus 2011). For instance, La Familia and its successor group Knights Templar have been found exporting iron ore mined in Mexico to Chinese mills. Many studies demonstrate that insurgents and terrorists engage in drug trafficking or other criminal activities, while organized criminal groups are expanding their revenue streams beyond commodity trafficking to exploit resources like oil and minerals. Violent non-state actors continue to diversify their revenue streams such that insurgents and terrorists no longer rely merely on third party donors or revolutionary taxes, and criminal organizations no longer rely solely on drug trafficking or local protection rackets.

A common objection to a comparison of revenue streams is that insurgencies rely on "taxes" from the population, while organized crime and terrorism do not. Insurgents tax the population in order to fund their operations, but also to provide basic governance and social services in order to maintain popular support. Gambetta's study (1996) shows that extortion—or a tax on businesses—is a fundamental feature of the Italian Mafia. More generally, Mancur Olson's (1993) "stationary bandit" model explains how a group that encompasses a particular community with a long time horizon and a credible threat of violence will use extortion through "taxes" and provide basic governance such as enforcing deals, adjudicating disputes and protecting property. On the other hand, a roving bandit with a short time horizon will extract all the resources from the community. This model applies not only to insurgents but also to criminal organizations such as the Mexican Mafia in the California prison system (Skarbek 2011) or La Familia in the Mexican state of Michoacán (Grayson 2010). From this perspective, insurgents and organized criminal groups are stationary bandits that exploit a region's resources and extort its people through some form of taxation. The spectrum of taxation spans pure exploitation to provision of government and social services. Where a violent non-state actor falls within that spectrum depends not only on local conditions but also on the organization's ability to credibly threaten violence that supersedes the state's monopoly on violence.

Lastly, violent non-state actors *seek varying levels of support from the population*. This dimension of overlap is the most controversial and has yet to be examined in any depth either quantitatively or qualitatively in the case of Mexico. Our classic concept of insurgency is prominently influenced by its communist orientation during the Cold War and by early theorists such as Mao Zedong and Che Guevara. The precondition for success in each of Mao's three phases of guerrilla warfare is popular support, which is why Mao advocated terrorism tactics against recalcitrant people unwilling to support the insurgency. Conversely, in order to secure popular support the insurgents must provide services other than the threat of violence or extortion. This principle is often called "warfare through welfare."

Organized crime typically seeks no popular support and is viewed as a parasite on the population. The criminals draw resources from the population by relying on violence or fear without providing anything in return. The parasite analogy is often invoked in this context because it renders its host (i.e., the state) vulnerable to other diseases but does not actually kill it. However, many studies demonstrate that organized crime does provide services to subsets of the population. Important work on the governance of organized crime shows that early Sicilian Mafia protected land and enforced contracts (Gambetta 1996). Organized crime provides similar services in Japan (Hill 2006) and post-Soviet Russia (Varese 2005). Skarbek (2011) shows that criminal organizations can administer governing institutions rather than simply having a parasitic relationship with the population. For example, in 1992 the Mexican Mafia began to regulate drive-by shootings in Los Angeles by threatening to kill any gang member involved in unauthorized shooting. Following the implementation of this rule, drive-by shootings declined by between 15 percent and 50 percent, depending on the community (Skarbek 2011, 10). Mexican criminal organizations have been known to make donations of food, medical care and schooling to impoverished people within their territory (Beittel 2011). A few criminal bosses "have gained the reputation of giving away money to their followers. Furthermore, they are seen to be the town's principal benefactors [creating businesses and generating employment], in stark contrast to the older elites and even the state" (Malkin 2001, 112).

Olson's "stationary bandit" model provides a useful method of evaluating the relationship between a violent non-state actor and the population. That relationship exists along a continuum from purely parasitic to long-term institutional governance. The services that organized criminal groups provide to the population, while not widespread or common throughout the criminal underworld, demonstrates that there can be a degree of similarity between insurgencies and organized crime with respect to their relationship with the people.

Fat Tails and Violence

William Safire (2009) notes in his etymology of the term, a "fat tail" occurs when there is an unexpectedly thick end or "tail" toward the edges of a distribution curve, indicating an irregularly high likelihood of catastrophic events. The assumptions of normality do not work so well when it must be stretched include unforeseen wars, pandemics, terror attacks, tsunamis, or debt defaults (Bremmer and Keat 2009). The power-law is one such distribution with a fat tail used extensively to study the occurrence of rare events.

Power-law distributions of empirical phenomena are not well characterized by their average or typical values because rare events occur with far more frequency than would be predicted under a normal distribution. The Gaussian distribution features probability density tails that decrease too quickly relative to the size of the event. The decrease in likelihood for extreme events occurs much more gradually for power-law distributed phenomena than for Gaussian tails (Figure 1). The fundamental difference between distributions relies on the assumptions of correlations among events. In a normal distribution the data are assumed to be *independent-additive*. When events are *independent-multiplicative* they generate a lognormal distribution. When events are *interdependent-multiplicative*, power-law distributions occur because positive feedback processes lead to extreme outcomes occurring more frequently than 'normal.'

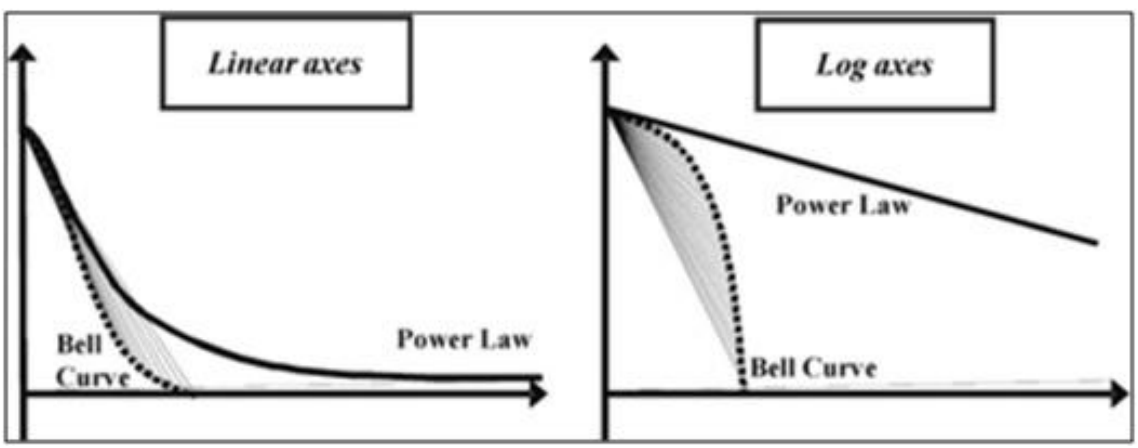

Figure 1. Gaussian vs. Power-Law Distributions.

The Gaussian distribution (bell curve) is a reasonable approximation of power-law distributions only for small events. The larger or more extreme the event, the more the Gaussian distribution underestimates its likelihood. The probability of an event occurring is displayed along the y-axis and the severity of the event along the x-axis. Source: Adriania and Mckelvey 2011.

Examining sample means under the assumption of normal distribution-like tail behavior can be misleading when an analyst attempts to describe the probability of observing the most extreme events in the sample (Pickands 1975; Smith 1987). These problems become more severe when data is characterized by "fat-tailed" probability density functions that produce unusually high frequencies of extreme events (Clauset, Shalizi, and Newman 2009). While scholars typically rely on the assumptions of the normal distribution because of the Central Limit Theorem, it is important to keep in mind the theory refers to the normality of the means of random variables drawn from a given distribution, not the normality of the tails (Sornette 2006). The Central Limit Theorem refers to the normality of the sample means, not the extreme events at the tail of the distribution. Methodological techniques that are useful for characterizing central tendency often provide bad quantitative results of the behavior at the observed sample tails (Alfarano and Lux 2010).

For instance, if I were to fit a normal distributional form to the data on drug-violence in Mexico by the federal government (described in the next section), I would conclude the probability density of violence is described by a bell shaped curve with a mean of $\mu=3$ and a standard deviation of $\sigma=3.4$. That is, organized criminal attacks cause three casualties on average per attack and the standard deviation of that value is slightly more than three people. There is nothing mathematically incorrect about this description of the data, but that would imply the probability of ever observing a rare event—such as the atrocity in August 2010, where the bodies of 72 migrant workers were found in a ranch in Tamaulipas—is astronomically small ($p < 10^{-50}$) as to be essentially impossible.

From this perspective, the fact that atrocities like this do occur appears to be such an anomaly that it must be explained based on unique characteristics and contextual factors that will likely never combine again.

An alternative perspective is provided by the emerging science of complex systems to evaluate empirical phenomenon of power-laws. Power-law distributions are found and studied across numerous areas of the natural sciences including earthquakes, solar flares, neuron behavior, power outages, spatial population distributions, and the hyperlink structure of the internet (Ball 2004; Clauset, Shalizi, and Newman 2009). Scholars investigating these natural phenomena have demonstrated that rare events in a fat tailed distribution are not "outliers" from which generalizable inferences cannot be drawn and thus require event-specific and contextual explanations (Sornette 2006). Instead, extreme events are simply a pattern of behavior not well characterized by Gaussian models.

A theory developed within physics—self-organized criticality (SOC)—is considered one of the primary mechanisms by which power-laws emerge in nature (Bak, Tang, and Wiesenfeld 1987). Bak et al. demonstrated a certain class of dynamical systems constantly reorganize themselves into a critical state where fluctuations of any size occur defined by a power-law relationship. As their metaphor and model, they used a stream of grains of sand dropped onto a sand pile. The steady input of grains of sand, energy or other inputs drives the system into a state of *criticality* between order and chaos, in the sense that sand grains on the surface are just barely stable. One grain of sand with the right combination of microscopic forces can cause an avalanche of any size. The system is *self-organized* in the sense that it reaches this steady state without any outside shaping forces. SOC explains the behavior of systems with slow build-up and rapid avalanche-like release of energy, such as earthquakes and forest fires. The ‘avalanche-like’ events occur with sizes that scale as power-laws. Moreover, SOC theory demonstrates that systems at a critical state do not depend on the finely tuned details of the system to cause the emergence of critical state behavior.

A discovery that an empirical quantity follows a power-law distribution suggests unusual mechanisms for their origin, e.g. long-range correlations, long-term memory effects, or positive feedbacks (Clauset and Wiegel 2010). Bak et al. (1987) argue power-law signatures are characteristic of a particular class of systems, defined by highly unstable dynamics and dominated by the interaction of large number of independent units, and strong nonlinearities in the process that links micro-level actions to macro-level events. The presence of power-law scaling also suggests the equality of underlying mechanisms for events across the entire scale (Dobias 2009).

Richardson (1948, 1960) was the first to find the distribution of casualties in “deadly quarrels”—major wars—follows a power-law with respect to frequency and severity. The power-law relationship indicates the doubling of severity of war measured by total casualties decreased the probability of it occurring by a constant factor on a logarithmic scale. That is, the fundamental mechanism characterized underlying the generation of war sizes are characterized by nonequilibrium processes through which small wars become large wars (Cederman, Warren, and Sornette 2011). Large wars are not outliers in a stable system that typically generates small wars, but a natural outcome of an unstable system of interdependent states where military actions cause positive feedback.

More recently, power-law characteristics have been observed in several studies on human conflict. Cederman et al. (2011) find the power-law distribution characterizes the relationship between an interstate war's severity and frequency from 1495 to 1990. Both Cederman (2003) and Roberts and Turcotte (1998) argue SOC best explains Richardson's Law of inter-state conflict where the doubling of war severity decreases its frequency by a constant factor. It must be noted that SOC is a general theory with different possible micro-foundations. For instance, Cederman (2003) examines spacio-temporal factors while Johnson et al. (2006) rely on the dynamics of organizational components.

Building upon this analysis of inter-state conflict, scholars find a similar pattern of violence arising *within* conflicts: including Iraq, Afghanistan, Colombia, and global terrorism from 1968 to 2008 (Clauset and Wiegel 2010; Clauset, Young, and Gleditsch 2007). They argue SOC applies to the dynamics of asymmetric warfare as the cause for why we observe a similar pattern of violence across many intra-state conflicts (Bohorquez et al. 2009; Dobias 2009; Johnson et al. 2006). The severity of violence conforms to a power-law distribution with a scaling parameter of $\alpha \cong 2.5$, independent of the underlying religion, ideology, politics, ethnicity, or terrain of the particular conflict (Johnson et al. 2006). These studies suggest patterns of human conflict both *between* and *within* states depart dramatically from assumptions of the Gaussian models when examined from a macro-perspective—there is no average level of violence in war, insurgency, or terrorism. Furthermore, the parsimonious relationship between the severity and frequency of attacks is governed by a single parameter.

Though there are studies of the distribution of violence for insurgencies and global terrorism, there is no work on the distribution of organized criminal violence. This study aims to extend previous work on the power-law distribution of violence by applying the same analytical approach to organized crime in Mexico.

Model of Organized Criminal Violence

As previously argued, organized criminal groups exhibit many similarities in tactics, capabilities and organizational structure as insurgencies and terrorist groups. Many qualitative studies consistently show violent non-state actors adopting similar organizational structures. The motivation of a violent non-state actor group—whether politics or profit—does not drive the entire behavioral profile of the organization. In order to quantitatively compare organized crime to insurgencies or terrorism, the model I use must be independent of organizational motivations other than the use of violence in pursuit of those objectives. Therefore, I use a model of organizational dynamics derived from politically-motivated organizations (insurgencies and terrorist groups) to explain the pattern of violence by a profit-motivated organizations. The organizational dynamics model avoids relying on the vagaries of an organization's political goals or its methods of acquiring illicit profits. Instead, it captures how the interdependent component parts of an organization dynamically interact to generate an emergent behavior, in this case with respect to the macro-level pattern of violence. Please refer to Appendix A for details on my formal model and its solution. In this section I will briefly discuss its conceptual roots and the minor changes I have made to apply it to the violent behavior of organized crime.

Johnson et al. (2006) propose a coalescence-fragmentation model of the internal dynamics of a modern insurgent organization. They find the steady-state behavior of violent attacks conform to a power-law distribution with a scaling parameter of $\alpha = 2.5$ using computer simulation and a steady-state analytical solution. The coalescence-fragmentation model is based on the notion that the total attack capability of a modern insurgent force is being continually redistributed. This force is made of *attack units*, with each unit having an *attack strength*. An *attack unit* is a group of people, weapons, explosives, or even information. *Attack strength* is the average number of people killed as a result of an attack by a particular unit, either from a one-sided attack or two-sided clashes. At any particular time, the total attack strength is distributed among the various attack units—their relative attack strength evolving from an ongoing process of coalescence (i.e. combining attack units) and fragmentation (i.e. breaking up of attack units). These processes are driven by a combination of deliberate decision making and opportunistic actions by both the insurgent force and the government force. For example, separate attack units may coalesce prior to an attack or fragment by blending in with population or retreating to impassable terrain to avoid government crackdowns. The important feature is that the motivations driving the coalescence and fragmentation processes are exogenous to the model.

Within the model, each attack unit has a random probability of being involved in an attack. This probability of attack is insensitive to the attack strength of the unit or its age. In a conflict underway for a long time or steady-state, the model assumes the distribution of attacks is proportional to the distribution of attack strengths of the insurgent force. It is this distribution that is well characterized by a power-law. This assumption is the key to the link between evolving dynamics of an organization and its violent behavior.

Based on the Johnson et al. (2006) model, Clauset and Wiegel (2010) generalize their finding by constructing an aggregation-disaggregation model of the dynamics of an organization prone to terrorist attacks composed of cells that merge and fall apart according to probabilistic rules. Their more elegant closed-form analytical solution generates the same result but with fewer assumptions: a power-law distribution of attacks in the steady-state as a universal feature. Their solution demonstrates that insurgencies and terrorist groups generate the same pattern of violence when examined through the lens of organizational dynamics.

I extend Clauset and Wiegel's (2010) model of terrorist violence to organized criminal violence with only subtle modifications to their assumptions. Their model assumes "there is a pool of N radicalized individuals that are 'inclined' towards terrorism" (Clauset and Wiegel 2010, 3). Since the model applies to a complex system of interacting units, the assumption of political motivation driving the violence is overly strict. In other words, the model focuses on the ecology of organizational units rather than the underlying motives of violence. Thus, the model does not critically depend on politically-motivated violence as opposed to profit-motivated violence from organized criminal groups. Indeed, the authors stress that the results are independent of ideology, religion, or geography. Furthermore, Johnson et al.'s model, proved to be a sub-class of models from the generalized Clauset and Wiegel model, only assumes an attack unit is a "group of people, weapons, explosives, machines, or even information which organizes itself to act as a single unit" (2006, 13). Again, this assumption does not require politically-motivated intentions in order to apply organizations "inclined" towards violent attacks.

I also relax Clauset and Wiegel's second assumption that terrorists can form cells of any size with each cell composed of a number of individuals. Instead, criminals can form cells of varying size composed of a number of individuals. These criminal cells, or attack units, are continually redistributed as they confront their competitors. Thus, the model characterizes a dynamically evolving organized criminal group as it aggregates and disaggregates in its pursuit of violence.

However, relaxing these two assumptions does not substantively change the Clauset and Wiegel model results. Thus, the model captures the steady-state behavior of dynamically evolving criminal groups which allows me to generate quantitative predictions of behavior. Based on this adapted model, I develop the following hypotheses:

H1(a): The distribution of drug-related casualties in Mexico is well characterized by a power-law.
H1(b): The scaling parameter α is equal to 2.5.

Mexico has substantial geographic variation in organized criminal violence. The violence clusters in areas where OCGs compete to control valuable *plazas*—areas or corridors through which drug-traffickers control production, storage, and transportation of illicit narcotics. These areas include border states with the U.S. near the consumer market and Pacific coastal states where narcotics arrive from South America. *Plazas* are valued not only in their role for drug-trafficking but also as a method of "taxing" local businesses and other drug-traffickers for its use. As organized criminal groups compete over *plaza* control, it leads to greater violence. As Rios (2012) has shown, higher violence incentivizes the government to crack down harder, replacing local law enforcement with the military and federal police. The increasing levels of violence between criminal groups or between criminal groups and the state can be characterized as asymmetric warfare. States on the Yucatán Peninsula or southern Baja coast with low-value *plazas* for narcotics distribution encounter little violence from OCGs. Therefore, I would not expect to observe characteristics of asymmetric warfare in those locations. For states with high-value *plazas* on the border with the U.S. and Pacific coastal states, I would expect to observe characteristics of asymmetric warfare. This leads to the following hypothesis:

H2a: The distribution of drug-related casualties is well-characterized by a power-law in states with valuable plazas.
H2b: The power-law exponent parameter α is equal to 2.5 in those states.

Research Design

I use two different data sets on organized criminal violence in Mexico: one collected by the Mexican government and the other by the Penn State Event Data Project. The unit of analysis is violent attacks with at least one casualty. Attacks with no casualties are treated as non-events. I use both data sets to test the hypotheses of the distribution of violent attacks at the national and state level. In the following section, I discuss the two data sets, the methods of analysis, and the results.

Mexican Government Data

Mexico's National Security Council (Consejo de Seguirdad Nacional, CSN), a federal institution within the Mexican security establishment, collected and made public the total number of drug-related homicides from December 2006 until December 2010 on a monthly basis and disaggregated to the municipal level (CSN 2011). The time-series cross-sectional data cover 1,167 of a total 2,450 municipalities in Mexico. A homicide is classified as drug-related if federal security-related institutions deem it likely to be related to drug-trafficking organizations within Mexico. The Mexican government no longer releases updated measures for this database after bad publicity. The characteristics used to determine a drug-related homicide is based on the nature of the victim, the event, and the method of violence (i.e. execution, mutilation, etc.). The data are imperfect. For instance, data were tallied before the homicide investigations had been officially concluded, indicating that a homicide could have been classified as drug-related but ultimately excluded in an updated version of the dataset (Rios 2012). The data also do not provide the time of day, age or gender of victim, signs of physical torture, or tallies of decapitations.

Despite its limitations, the CSN database offers greater precision of drug-related violence at the local level over time compared to alternative sources. In fact, other scholars have used the data as the primary source for empirical analysis of violence by organized crime in Mexico (Rios 2012). Homicides are categorized into three types of violence: drug-related executions (*ejecucciones*), violent confrontations (*enfrentamientos*), and aggression targeting authorities by organized crime groups (*agresiones*). Drug-related executions are characterized by extreme violence to the victim (decapitation, dismemberment, mutilation, burning) or events involving more than two victims. This category is the classical way to understand drug-related violence, with targeted executions linked to drug-trafficking. Violent confrontations are events between members of criminal groups, "caused by antagonisms with other groups or differences within the same groups." This category describes casualties generated from turf battles between criminal organizations or between traffickers and authorities as a result of law enforcement operations. Events of aggression targeting authorities define an event when the target is a government installation or assassination of individuals employed by the government. Executions account for 89.3 % of the total number of casualties recorded, while confrontations account for 9.1 % and aggressions 1.6 %.

From 2007 to 2010, the total number of drug-related homicides by organized crime reached 34,610 (CSN 2011). This number is more than four times greater than the total of 8,901 such killings identified during the previous six years from 2001 to 2006 (Rios and Shirk 2011). Violence by organized crime is estimated to account for 45% of all intentional homicides in Mexico since 2007 (Rios and Shirk 2011). The increase in violence began in 2005, but a major spike occurred in 2008 with a 140% increase in organized crime related homicides to 6,864 from 2,860 in 2007. After another jump of more than 40% to 9,774 in 2009, the number of homicides reached a new record in 2010 with 15,047, an increase of 54% from the previous year.

Despite the overall increasing levels of violence, there is substantial geographic and chronological variation. The highest levels of violence are found along the major drug trafficking routes and production locations. Four states—Chihuahua, Sinaloa, Guerrero, and Baja California—accounted for 84% of all drug-related violence from 2007 to 2010 (Rios and Shirk 2011). Roughly 40% of drug-related violence since 2006 occurred in just ten of Mexico's 2,450 municipalities. The bottom 2,350 municipalities only accounted for 28% of the violence. Violence also varies over time with spikes of more than 100% in seven states. For example, from 2009 to 2010 Tamaulipas saw an increase in drug-related homicides to 1,209 from 90, Nayarit 377 from 37, and Nuevo León 620 from 112 (Rios and Shirk 2011).

There are several advantages to using this data. First, the data are official government sources with nation-wide access to data rather than media reports on high-profile events or events near the U.S.-Mexico border. Second, the government data captures events with both few casualties such as a single law enforcement officer killed to many casualties such as the slaughter of dozens of migrant workers. Third, the disaggregated data at the municipality-month level of resolution provides the highest level of precision on the number of casualties during the period of explosive growth in drug-related violence. One potential disadvantage of using government data is that it may be systematically biased due to under-reporting for political purposes or over-reporting to justify government budgets. Nevertheless, biases of over- or under-reporting do not affect the α parameter under investigation in a power-law distribution.

I conduct an empirical analysis on a subset of events denoted as *Confrontation* and *Aggression*, excluding those denoted as *Executions*. That is, I strictly use events where criminal traffickers or government authorities—and not civilians—are targets, so as to more closely capture the dynamics of organized criminal groups engaged in asymmetric warfare. The data for *Executions* include many observations with several hundred casualties per observation, which are aggregations of multiple attacks in a municipality during a single month. In other words, this data classification combines several high casualty events into a single observation, creating the illusion of a rare event when in fact it is an aggregation of several events. The aggregation-disaggregation model generates hypotheses for the distribution of attacks with varying casualties, not an aggregation of events over a period of time. Because I am unable to parse the data further to individual attacks, I decided to subset the data to the municipality-month which closely proxies the hypotheses from the model. The *Aggression* and *Confrontation* data include 1,232 attacks with a total of 3,699 casualties.

The subset of data that aggregates Aggression and Confrontation events are denoted in Figure 2. First, note the substantial variation in violence between states. The Yucatán peninsula is far less violent than the northern border states of Chihuahua, Nuevo León, or Tamaulipas. Second, states with the most violence border the United States or have ports along the Pacific Ocean where South American narcotics are often transported into Mexico. Organized criminal groups violently compete over lucrative territory for drug transportation and distribution.

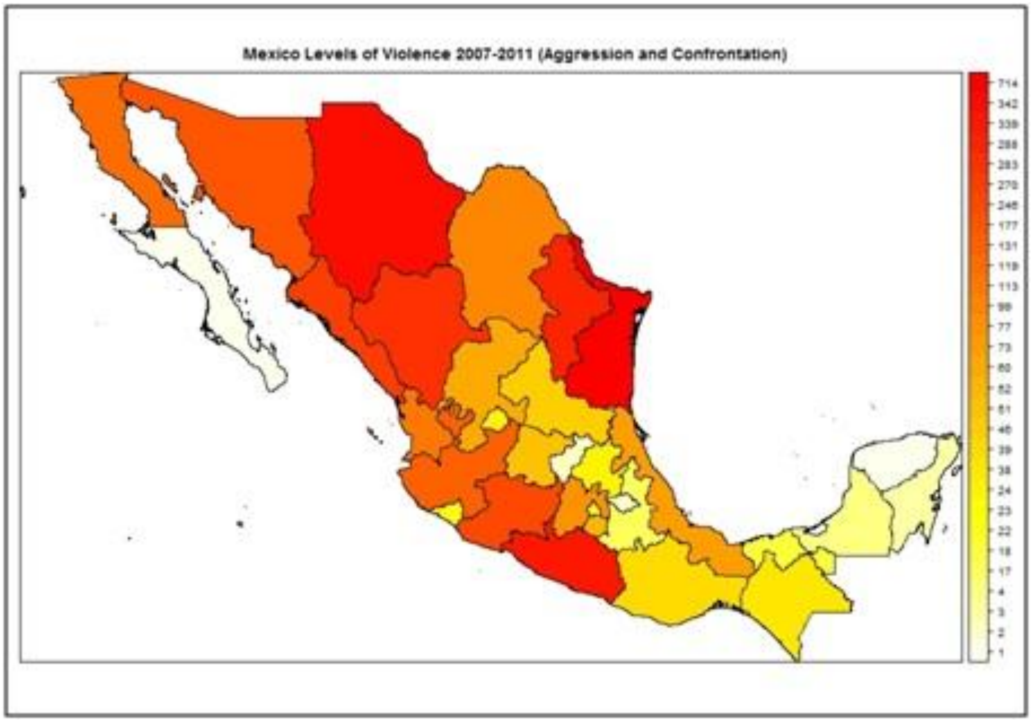

Figure 2. Levels of Drug-Related Violence in Mexico 2007-2010.

The data displayed geographically aggregates two categories of casualty counts from the CSN government data. The two categories are "violent confrontations" between organized criminal groups and "aggression" targeting authorities by organized crime. States depicted in red experienced the most violence in these two categories while those depicted in white experienced almost no violence of this kind.

Political Instability Task Force Data

I use a another measure of organized crime related violence in Mexico as a robustness check because each observation is this second data set is an individual attack. The data are derived from the Political Instability Task Force Worldwide Atrocities Dataset (Penn State University 2012) covering a period from January 2005 to June 2012, using human coders rather than automated methods. Each event describes the deliberate killing of non-combatant civilians in the context of a wider political conflict, with five or more civilians casualties reported in the media. The PITFWA data comprise violent attacks by Mexican organized criminal groups with 1,741 victims in 159 violent attacks over a period of eight years—a small portion of the total number of drug-related homicides.

Each PITFWA data observation is a single violent attack that adheres to the assumptions and hypotheses of the aggregation-disaggregation model. Still, these data have disadvantages. First, they miss many small events not reported in the media. The threshold for inclusion in the dataset is an event with 5 casualties, excluding low-casualty attacks that are over-represented in a power-law distribution. Second, the database uses human coders to find and select the observations for inclusion, potentially introducing bias or systematic missing data. Third, the measure has far fewer observations than the CSN dataset. The statistical method of inference is still valid for this number of observations at the country level, but is highly problematic for inferences at the disaggregated state level.

Both the CSN and PITFWA data capture rare events with small differences due to reporting discrepancies and classification schemes. For instance, in June of 2010 in Chihuahua, two dozen masked men raided the Faith and Life Center where they systematically executed several people with automatic weapons. The PITFWA data coded this attack with 19 casualties compared to 17 casualties for the CSN data. Or consider the same month in state of Chihuahua where the PITFWA data coded a single event with 12 casualties across the entire state compared to the CSN data which coded violent attacks as two events—3 casualties in Chihuahua City and 9 casualties in Madera. For another example, the bodies of 72 migrant workers were found in a ranch in San Fernando, Tamaulipas in August, 2010. A survivor of the massacre told investigators the Los Zetas criminal organization kidnapped and then killed the people after they refused to work for Zetas. The PITFWA data coded the event as a single observation with 72 victims. The CSN coded the event as a single observation with 76 victims for the town of San Fernando during the entire month of August 2010—72 non-combatant civilians killed in one attack and four other non-combatant civilians killed at other times during the month. Descriptive statistics on each data set are displayed in Table 1.

Table 1. Descriptive Statistics for Two Sources of Violence in Mexico

Data Source	Mean	Std. Dev.	Min	Max	N	Total Victims
CSN	3.0	3.4	1	39	1232	3699
PITFWA	11.0	10.3	5	72	159	2051

The CSN and PITFWA data are displayed in Figure 3 and Figure 4 respectively. Each plot shows log-log plots of the fraction of all recorded events of organized criminal violence with x or more victims, $P(X \geq x)$, versus x. That is, as the log of the event size increases (as measured by casualties), there is a corresponding decrease in the log of the likelihood that such a large event will be observed. Note that my analysis seeks to discern whether the decrease is linear and what the slope is on a log-log graph. The minimum number of casualties in an attack is 5 in the PITFWA data set and 1 in the CSN data set. The maximum number of casualties in an attack is 72 in the PITFWA data set and 39 in the CSN data set. The size of each data set, N, indicates the number of violent attacks recorded. Note that the data are time-invariant, in that each data set is a vector of integers where each number denotes casualties from a violent attack.

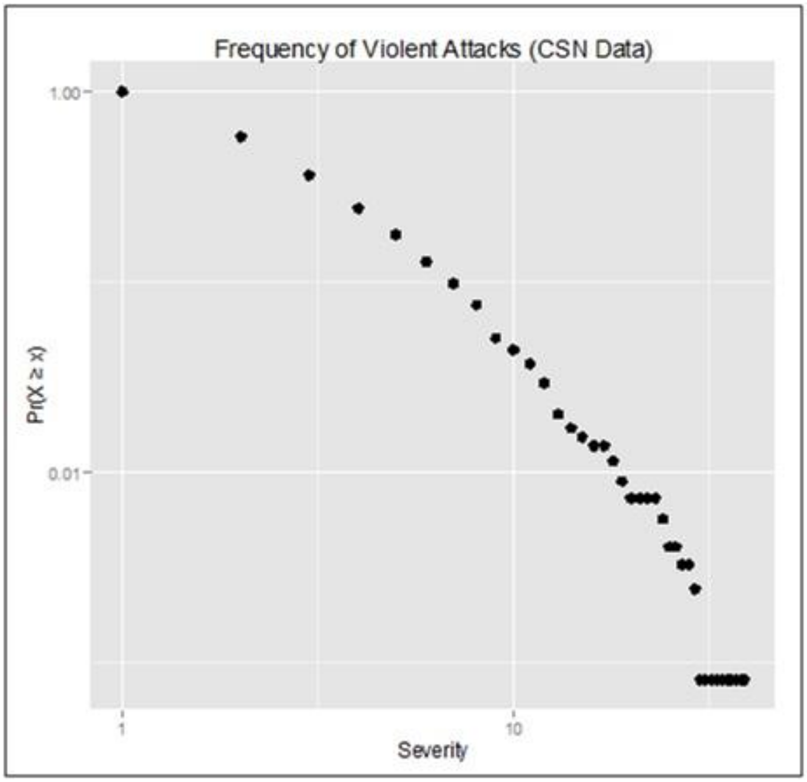

Figure 3. Log-log plot of drug-related attacks in Mexico (CSN data).

This plot displays the cumulative distribution of *P(X ≥ x)* of total number of deaths from events of size greater than *x,* for organized criminal violence in Mexico. The data are derived from the CSN database distributed by the Mexican government.

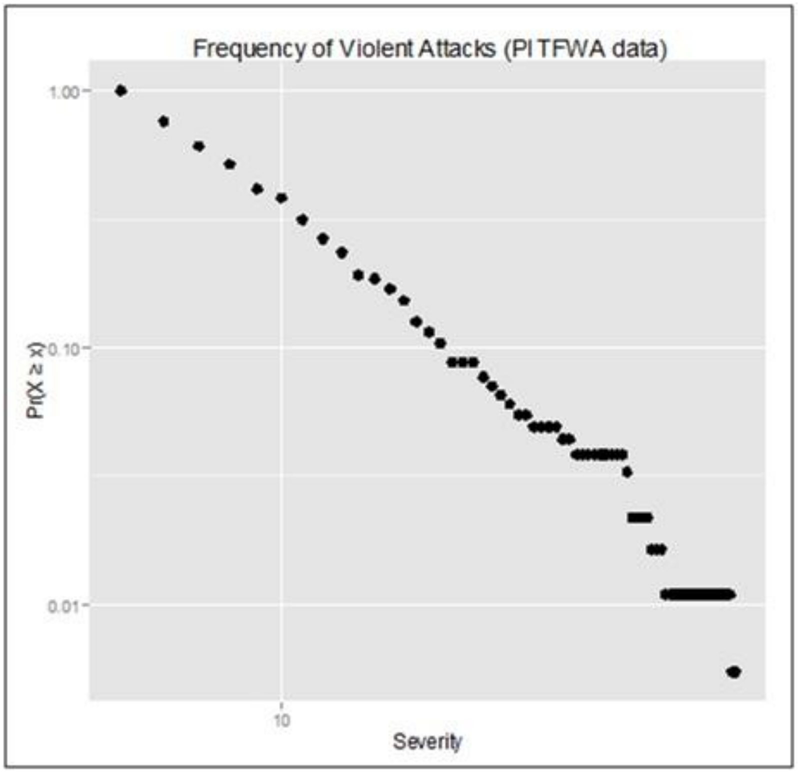

Figure 4. Log-log plot of drug-related attacks in Mexico (PITFWA data).

This plot displays the cumulative distribution of *P(X ≥ x)* of total number of deaths from events of size greater than *x*, for organized criminal violence in Mexico. The data are derived from the PITFWA database distributed by Penn State University.

In the rest of this section I address several critiques of these datasets that could be raised. First, the government data or media-reported mass casualty events may be systematically biased. Potential biases include over- or under-reporting of casualties for political reasons and limited data-scraping of media outlets or inter-coder reliability in the case of the PITFWA data. However, the advantage of focusing on the scaling parameter α alleviates concerns of possible over- or under-reporting of casualties. The scaling parameter is "insensitive to systematic over-reporting and under-reporting of casualties. That is because any systematic multiplication of the raw numbers by some constant factor, has no effect on the α value the at emerges from the log-log plot" (Johnson et al.

2005, 37). Such systematic multiplication merely shifts the intercept, leaving the slope, or α, unchanged.

Second, the two data sets on violence capture different phenomena, and further are not mutually supporting as I claim. Therefore, the similar α estimates between data sets could be a coincidence. The PITFWA data measure mass-casualty attacks against civilians reported in the media, while the CSN data measure attacks against other criminal groups or state officials. However, the threshold for the tail distribution (x_{min}) provides a scope condition on any inferences captured in both data sets by speaking only of rare events where civilians, criminals, or security officers were killed. Asymmetric warfare includes violence against civilians, such that previous studies on macro-level patterns of violence in Iraq, Afghanistan, and Colombia include civilian casualties in the data.

Third, even with similar tail thresholds, organized crime generates different α estimates compared to the analytical, simulated and empirical estimates of previous studies. That is, the parameter estimates are not quantitatively uncovering a common pattern of violent non-state actors, but rather reflect fundamentally different mechanisms behind profit-motivated violence compared politically-motivated violence. A corollary to this point is that the severity of violence generated by organized crime is far lower than violence generated by terrorists and insurgencies. The profit motive of organized crime may indeed limit the rare events of violence (in the hundreds and thousands of casualties), but not because it is a different mechanism. The aggregation and disaggregation of attack units for violence on the surface qualitatively describes the behavior of organized crime as they seek to gain power, protect their territory, and confront any threats. From this perspective, there is no a priori reason why organized crime theoretically *cannot* engage in violence with casualties that approach war in other countries.

Fourth, the statistical evidence cannot conclusively demonstrate the data derive only from a power-law distribution. The data, while conclusively not exponential or Poisson distributed, cannot be entirely rejected as lognormal. The evidence is mixed because I can reject lognormality with a tail threshold but cannot reject the hypothesis when there is no tail threshold. However, within the Bayesian analysis of state-level data, the evidence indicates states with α estimates closer to 2.5 are in fact power-law distributed and not drawn from alternative distributions.

Lastly, the complex system of multiple organized criminal groups in Mexico fighting each other and the government violates the assumption of a unitary organization in the aggregation-disaggregation model. However, political conflicts of insurgencies or global terrorism all have a complex system of multiple groups with differing agendas engaged in warfare. Those cases exhibit a power-law distribution of violence in spite of violating this model assumption. This could indicate the model is more generalizable to a system of organizations or that the assumption is an unnecessary restriction.

Analysis of Results

Country-Level Analysis of Violence

I use the Clauset et al. (2009) method to evaluate an empirical power-law distribution. The procedure follows three general steps. First, estimate the power-law scaling parameter, α, and tail threshold, x_{min}. Second, calculate a goodness-of-fit between the data and the power-law using synthetically created datasets. Third, compare the power-law with alternative distributions to evaluate whether other distributions fit the data better.

Power-law distributions describe a mathematical relationship of event frequency and event size. More formally, I can write that

$$\mathrm{p}(x) \propto Cx^{-\alpha} \tag{0.1}$$

where x is the size of the event over a reasonably wide range of x, with α as positive coefficient. The parameter C is a normalizing constant. Alpha, α, is the *exponent* or *scaling parameter*. The α in equation (0.1) is the slope of the cumulative density function when plotted in a log-log graph. As the scaling parameter decreases, events in the tail distribution become less rare. In this way, α provides an efficient means of conveying how "fat" the tail distribution is and how likely I am to observe extreme events. The relationship is 'scale-invariant' in the sense that scaling the function by a fixed amount does not change the shape of the function.

Suppose I have a violent attack with a given level of casualties, or its severity. Assume that events are distributed as a random variable X and events of size x are drawn *iid* from a discrete distribution

$$x = \{1,2,\ldots n\}$$

where $n = x_n$ is the most severe (largest) observation in the data set. Events of size 0 are not admissible because they are logical impossibilities, or non-attacks. In the case where *x* can only take a discrete set of values then I consider the probability distribution

$$\mathrm{p}(x) = \Pr(X = x) = Cx^{-\alpha} \tag{0.2}$$

Where C and α are positive coefficients. The distribution diverges as $x \rightarrow 0$, so the relationship cannot hold for all values of *x*. There must be a lower bound for which *x* > 0 characterizes power-law behavior. This threshold is denoted as x_{min}. Thus, the power-law has an inherent scope condition above a certain value of *x*. I then find that

$$\mathrm{p}(x) = \frac{x^{-\alpha}}{\zeta(\alpha, x_{min})} \tag{0.3}$$

Where $\zeta(\alpha, x_{min})$ is the generalized Riemann zeta function, $\sum_{n=0}^{\infty}(n + x_{min})^{-\alpha}$. The log likelihood function is then

$$\mathcal{L}(\alpha) = -\alpha\left(\sum_{i=1}^{n} ln\, x_i\right) - nln\left(\sum_{n=0}^{\infty}(n + x_{min})^{-\alpha}\right) \tag{0.4}$$

Since the data are discrete in terms of casualties from an attack, the traditional method of analysis for continuous power-law distributions is not appropriate. In other words, there is no exact closed-form expression for a in the discrete case, as opposed to the continuous case described above. However, Clauset, Shalizi and Newman (2009) developed a method of approximation in which true power-law distributed integers are approximated as continuous real numbers rounded to the nearest integer. The result is

$$\alpha \simeq 1 + n\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min} - \frac{1}{2}}\right]^{-1} \tag{0.5}$$

This expression is easier to evaluate the exact discrete maximum likelihood, and the one I use in my own analysis. The size of the bias is less than 1% or better when $x_{min} \geq 6$ (Clauset, Shalizi, and Newman 2009).

To obtain a, I first estimate the x_{min} as the lowest value threshold for the truncation of the data that is hypothesized to fit the power-law. Observed data rarely follow a power-law distribution all values of *x*. The power-law often applies only for values greater than some minimum x_{min}. For these cases, I say the tail of the distribution follows a power-law. Therefore, I need to discard data below this threshold so I am left with only those for which a power-law is valid. I conduct grid-search for each possible value of x_{min}, using the truncated data above the chosen x_{min} to compute two probability distributions: the empirical CDF and the fitted model CDF. I then conduct a Kolmogorov-Smirnov goodness-of-fit test of the absolute value of the difference between each value of the theoretical and empirical distribution values. The Kolmogorov-Smirnov test statistic is

$$\mathrm{D} = \max_{x \geq x_{\min}} \left| S(x) - \mathrm{P(x)} \right| \tag{0.6}$$

where S(x) is the CDF of the data for the observations with value at least x_{min}, and P(x) is the CDF for the power-law model that best fits the data in the region $x \geq x_{min}$. I select the value of *x* that minimizes the KS test statistic and designate it as x_{min}. I then obtain the discrete maximum likelihood estimate of α from equation 1.4, denoted as $\hat{\alpha}$. A discrete maximum likelihood generates unbiased parameter estimates compared to a linear model with a probability density function or cumulative density function (Clauset, Shalizi, and Newman 2009).

The next step computes the confidence intervals for $\hat{\alpha}$ through bootstrapping. I generate a new dataset where each observation is randomly drawn from the empirical distribution given the x_{min}. This draw contains the same number of data points as the number of data points in the original estimated power-law. I repeat this process for 2500 synthetic datasets. Keeping x_{min} fixed, I estimated $\hat{\alpha}$ for each dataset using the same maximum likelihood estimation of equation 1.4 to obtain a distribution of 2500 "bootstrapped" alpha estimates. The limits of the 95% confidence interval are given by the percentiles 2.5 and 97.5 of this distribution, respectively.

After generating parameter estimates for x_{min} and α, the second step determines if the power-law is indeed a plausible fit for the data. The goodness-of-fit test quantifies the plausibility of the hypothesis of a power-law distribution given the observed data. The basic approach samples many synthetic data sets from a true power-law distribution, measures how far they fluctuate from the power-law form, and compares the results with similar measurements on the empirical data (Clauset, Shalizi, and Newman 2009). The KS statistic is one such test that can be adapted for use as a goodness-of-fit test between distributions, though other statistical tests are possible. Note that for each synthetic data set I compute the KS statistic relative to the best-fit power-law for that data set, not relative to the original distribution from which the data set was drawn. Once I have calculated the *p*-value, I must decide whether it is small enough to rule out the power-law hypothesis or whether, conversely, the power-law hypothesis is plausible because I fail to reject the hypothesis. Clauset et al. recommend a $p \leq 0.1$ as a more conservative threshold rather than the more lenient $p \leq 0.05$. In other words, for a *p*-value close to 1 the difference between the empirical data and the model can be attributed to merely statistical fluctuations; but if the *p*-value is below the 0.1 threshold, I can reject the power-law hypothesis as a poor fit for the data.

Simply because the data appear to come from a power-law distribution does not mean it is the best fit. Rare events can be generated from other distributions besides a power-law, including exponential and log-normal distributions. Therefore, in the third step I evaluate the alternative distributions with the same goodness-of-fit tests. This test of alternatives will also be conducted on nested distributions with an x_{min} cutoff. The steps for this process are similar to the process previously described, but for different reference distributions. A high *p*-value for a goodness-of-fit test with the exponential or log-normal distributions indicates I cannot reject the null hypothesis that the empirical data are generated from this reference distribution. If both distributions are a poor fit for the data, the power-law is a reasonable candidate for the underlying data generating process of the observed events.

State-Level Analysis of Violence

Clauset et al.'s method of empirical analysis for power-law relationships advances beyond biased and untrustworthy methods like visual inspection of log-log plots or linear estimation of logarithmically transformed data. However, both data sets on Mexican drug-related violence have weaknesses compared to typical data sets analyzed with this method: small sample size and a level of severity that does not scale several orders of magnitude. Furthermore, the maximum likelihood method becomes intractable when attempting to simultaneously estimate parameters for each of the Mexican state.

Therefore, in the state-level analysis I use Bayesian methods to address the weaknesses in the data, as a robustness check of the maximum likelihood results, and because of its ease in hierarchically modeling disaggregated data.

Clauset et al. (2009) demonstrate that the maximum likelihood method of estimation provides reasonable estimates when $n \cong 50$ with accuracy to about 1%. Both Mexican drug-violence datasets for my analysis have $n \gg 50$. However, the "fat tails" of the distribution have far fewer observations. From maximum likelihood, the tail distribution with $x_{min} \geq 9$ reduces the sample size to $n = 76$ for the PITFWA data set and $n = 62$ in the CSN data set. Both sample sizes are far less than the hundreds or thousands of observations typically observed of natural phenomena when investigating power-law behavior.

A related weakness is that Mexican drug-related violence does not scale several orders of magnitude for casualty severity. Power-law distributions are scale-invariant across multiple orders of magnitude (e.g. earthquakes, casualties of wars, internet hyperlinks, etc.), meaning that the power-law relationship does not change as the "size" of an event increases by a constant factor. The largest single observation is 72 casualties in the PITFWA data set and 39 in the subset of the CSN data set. The goodness-of-fit tests suggest the data are in fact power-law distributed, but inferences remain sensitive when the data only span two orders of magnitude. Repeated Bayesian sampling will help provide greater certainty about the posterior distribution of α.

Bayesian hierarchical models provide a tractable method to explicitly model the geographical variation in violence rather than pooling all the data at the national level. This approach allows us to make inferences about the dynamics of organized criminal violence at the sub-national level. The hierarchical model for disaggregated data accounts for the geographic heterogeneity in organized criminal violence. I examine the distribution of α for each state conditional on the empirical data by using the Markov Chain Monte Carlo (MCMC) method of sampling.

Previous studies show the scaling parameter α captures the overall dynamics of violence during an insurgency or global terrorism in a single measure. Johnson et al. speculate it is a useful measure for asymmetric warfare. Using a Bayesian hierarchical model extends the utility of this measure of asymmetric warfare to the sub-national level. States with an α parameter estimate close to the analytical solution of $\alpha = 2.5$ provide greater support to an inference that organized crime is using asymmetric warfare in that location. For instance, Los Zetas have a presence in over seventeen states (Grayson and Logan 2012), but do not engage in the same level of violence uniformly across all states.

For the hierarchical model each observation x_{ij} is drawn from the Pareto distribution, where *i* is the individual observation and *j* is the state level random effect. The distribution is as follows

$$x_{ij} \sim \alpha_j c^{\alpha_j} x^{-(\alpha_j+1)} \tag{0.7}$$

where α_j is the parameter describing the distribution for an individual state and *c* is a constant. The distribution from which x_{ij} is drawn must be greater than the constant *c*. The constant *c* is the x_{min} threshold for cutoff of the tail distribution.

The most controversial aspect of Bayesian analysis is its use of prior distributions. The prior distribution includes out-of-sample information such as previous scholarship on organized crime, violence of non-state actors, or the nature of violent competition between multiple organizations. I use a diffuse prior gamma distribution of the α parameter for both the pooled and hierarchical models. For the hierarchical model, instead of holding α constant in the baseline Bayesian model, I allow it to vary as a random effect in every state. Each state level random effect on α has a gamma prior distribution defined by the following

$$\alpha_j \sim \Gamma\left(k_j, \frac{1}{\theta_j}\right) \quad \textbf{(0.8)}$$

where j is the state, k is the shape hyperparameter, and θ is the scale hyperparameter. Again, each state has a diffuse prior distribution. Following the Bayesian estimation, I use the same post-estimation procedure I used for the pooled model at the national level of analysis for α goodness-of-fit tests.

Country-Level Analysis Results

Both measures of drug-related violence—CSN data and PITFWA data—exhibit patterns characteristic of a power-law distribution. The estimated α parameters for each data set are 2.67 and 3.2 respectively. The x_{min} thresholds for both data sets are the identical—9—and similar to threshold estimates for a variety of insurgencies and global terrorism (Clauset, Young, and Gleditsch 2007; Johnson et al. 2006).

The results for each measure are displayed in Table 2. For the PITFWA measure of drug-violence, the estimated α parameter is 2.67 with a bootstrapped 95% confidence interval of 2.48 to 3.38 with an x_{min} threshold of nine. In other words, the tail distribution of attacks with nine casualties or more is well characterized by a power-law. The Mexican government data on drug-related violence has a higher estimated α parameter of

3.2 with a bootstrapped 95% confidence interval of 3.02 to 4.20. It has the same x_{min} threshold of nine.

Table 2. Power-law Estimates with Confidence Intervals

Data Source	α	α Lower Confidence Band	α Upper Confidence Band	x_{min}
PITFWA	2.67	2.48	3.38	9
Mex. Gov.	3.19	3.02	4.20	9

The results of the goodness-of-fit test for plausible alternative distributions are displayed in Table 3. With a *p*-value close to 1 for both data sets, I fail to reject the hypothesis that the empirical data are not power-law distributed. In other words, the power-law distribution is a plausible fit for both data sets. I can reject the hypothesis that the data are exponential or Poisson distributed. However, the goodness-of-fit test for the lognormal distribution provides mixed evidence. On one hand, a *p*-value of ~ 0.67 indicates the lognormal distribution is a plausible fit to the both data sets. On the other hand, when an x_{min} cut-off for the tail distribution is included, the lognormal *p*-value becomes quite small, allowing us to reject the null hypothesis. This mixed evidence, depending on whether an x_{min} threshold is included, suggests small casualty events are driving the results and not the extreme events in the tail of the distribution. In general, it is very difficult to tell the difference between lognormal and power-law behavior. Over realistic ranges of *x* the two distributions are very closely equal, so it unlikely that any test can tell them apart unless the data set is extremely large (Clauset, Shalizi, and Newman 2009). The CSN and PITFWA data sets are too small to make a positive inference that the power-law distribution is the only possible distribution from which the data emerge. Recall that independent-multiplicative systems generate lognormal distributions while interdependent-multiplicative systems generate power-law distributions. Because events are interdependent, power-law distributions have fatter tails—more extreme events—than lognormal distributions. Thus, we can infer that the system of organized criminal violence is a multiplicative system, but whether events are independent or interdependent cannot be ascertained from the given data.

Table 3. Kolmogorov-Smirnov Goodness-of-Fit Test for Multiple Distributions

Distributions	**Data Sources**	
	PITFWA	CSN
Power-Law	.99	.99
Exponential w/ Xmin cutoff	.015	<.001
Exponential	<.001	<.001
Lognormal w/ Xmin cutoff	<.001	<.001
Lognormal	.67	.66
Poisson	<.001	<.001

Bayesian Hierarchical Analysis Results

Calculations for the posterior distribution of α were estimated with WinBUGS called from the software R with a 5,000 iteration burn-in, three MCMC chains with random starting values, and a 50,000 iteration simulation. Visual evidence and r-hat values indicate convergence of the relevant parameter estimates for both the pooled and hierarchical model specifications.

Pooled Model

I conduct an analysis of the Bayesian pooled model for both data sets in order to have a baseline comparison to the estimates generated by the maximum likelihood method. As expected, the Bayesian pooled model supports the results derived from maximum likelihood. The credible intervals are larger than the bootstrapped confidence intervals, suggesting greater uncertainty around the estimated α value due to the small sample size and limited range of *x* in the tail distribution. More specifically, the PITFWA data has a mean $\alpha = 2.8$ with a 95% credible interval [2.4, 3.2] with $x_{min} = 9$. The Mexican government data has a pooled mean of $\alpha = 3.5$ with a 95% credible interval [1.9, 4.2] with $x_{min} = 9$. Again, the x_{min} threshold is determined by the KS goodness-of-fit test. The predicted probabilities against the truncated empirical distribution for the CSN and PITFWA data are displayed in Figure 5 and Figure 6 respectively.

I also conducted a sensitivity analysis to examine the effect of small changes in the prior distribution on the posterior distribution. The posterior density of α falls within a range of 2.66 to 2.92 over a reasonable range of hyperparameters.

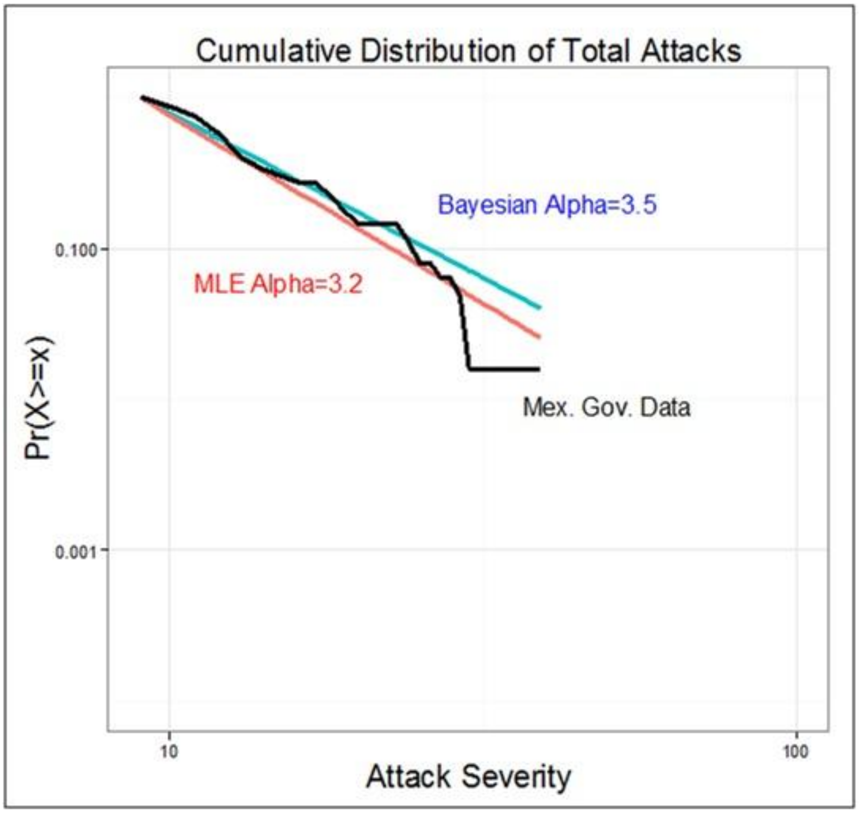

Figure 5. Models for distribution of drug-related attacks in Mexico (CSN).

The figure above displays the actual data of the cumulative distribution of P(X ≥ *x*) in black, the maximum likelihood estimate from the Clauset et al. method in red, and the Bayesian pooled estimate with diffuse priors in blue. Note that the maximum likelihood method and Bayesian method describe the distribution of organized criminal violence with nominally different estimates of α. The data are derived from the CSN database distributed by the Mexican government.

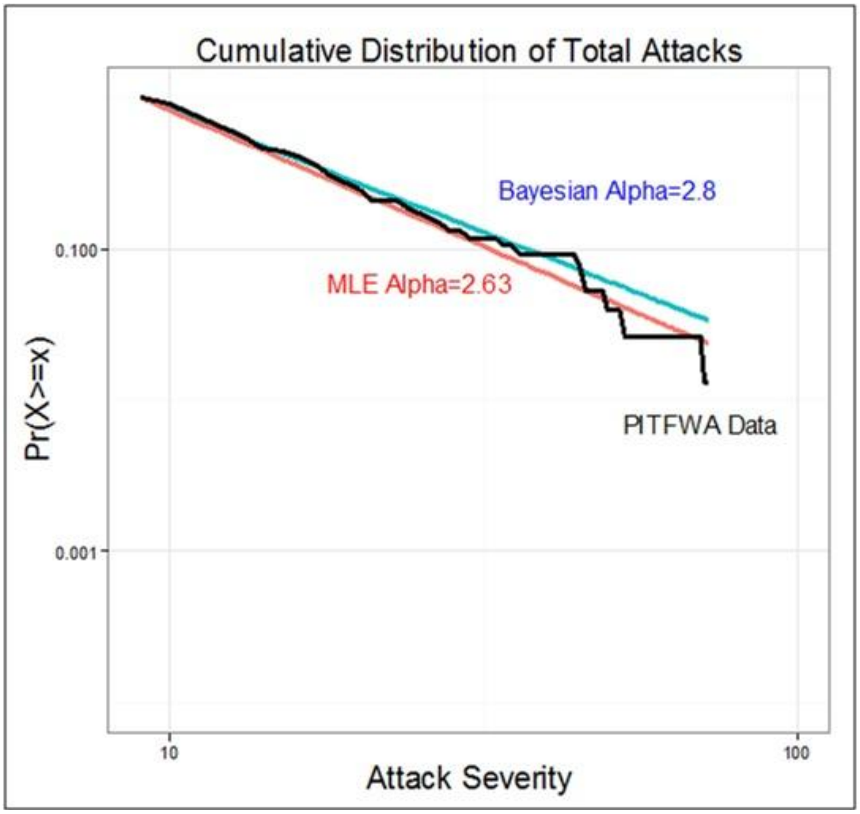

Figure 6. Models for distribution of drug-related attacks in Mexico (PITFWA).

The figure above also displays the actual data of the cumulative distribution of P(X ≥ *x*) in black, the maximum likelihood estimate from the Clauset et al. method in red, and the Bayesian pooled estimate with diffuse priors in blue. Note that the maximum likelihood method and Bayesian method describe the distribution of organized criminal violence with nominally different estimates of α. The data are derived from the PITFWA database distributed by the Penn State University.

Hierarchical Model

The hierarchical model results indicate a range of a scaling parameter values for each state belying the assumption of nation-wide homogeneity. The state-level α estimates are presented in Table 5 in Appendix B. Two features emerge from the results. First, the state-level α estimates cluster together roughly between 2 and 3. The lowest α estimate is 2.2 in the states of Chihuahua and Neuvo León, and the highest α estimate is 3.53 in Tabasco. Note that a lower α estimate indicates a higher likelihood of large scale events.

Second, the KS test shows that the power-law distribution plausibly fits some states better than others. Recall that the null hypothesis is that the sample is drawn from the reference distribution, in this case the power-law distribution with the estimated α parameter. For several states with low *p*-values I can reject the hypothesis that the data conform to the power-law distribution because of small sample size. These states often have only a few observations or organized criminal violence has avoided mass-casualty attacks in those locations. On the other hand, for several states the power-law distribution appears to be a plausible fit for the data. Nineteen states have distributions of organized criminal violence that are plausibly power-law distributed. Figure 7 displays a histogram of those nineteen states by their α estimate. Consider that by removing the states I can reject as not power-law distributed, the mean of the remaining states is $\alpha = 2.53$. From a theoretical perspective, the sub-national variation in violence clusters around the model-derived value.

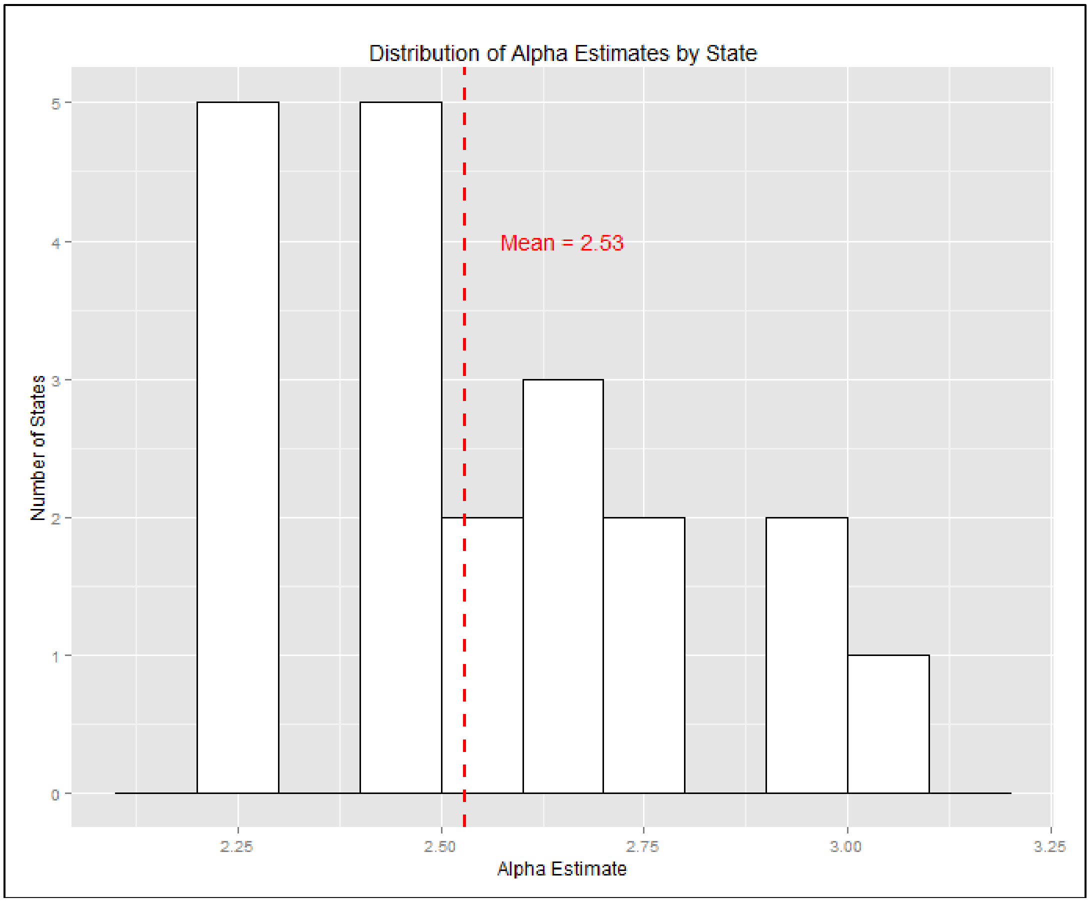

Figure 7. Histogram of state-level α estimates.

The plot above displays a histogram of state-level α estimates, but only of states which passed the KS test of significance. States that do not pass the KS test cannot be well characterized by a power-law distribution, and including those estimates on this plot is misleading. Note that the mean of the state-level α estimates is 2.53, which is close to the analytically derived solution of 2.5 from the model.

Another method of understanding the hierarchical results is by visualizing the data on a map (Figure 8). The map displays each state's α estimate. Lower α values—higher likelihood of a mass-casualty attack—are indicated by red and higher α values—lower likelihood of a mass-casualty attack—are indicated by lighter shades of yellow. States shaded white are ones in which I can reject the null hypothesis that the distribution of attacks conforms to a power-law based on the KS test.

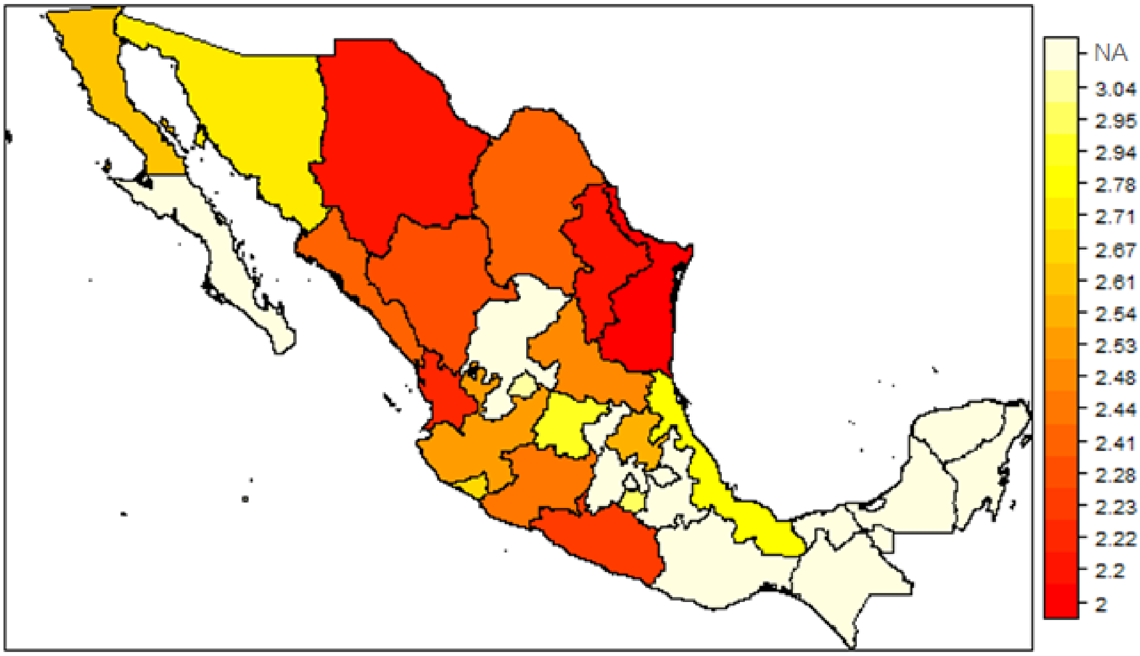

Figure 8. Geographical representation of state-level α estimates.

The lower the α estimate value, the higher the likelihood of mass-casualty attacks. These areas are denoted in red. States denoted in yellow have a lower likelihood of mass-casualty attacks, but they are still power-law distributed which indicates a non-zero probability of a mass-casualty attack. States denoted in white failed the KS statistical test of significance; they are areas where we can reject the null hypothesis that organized criminal violence is power-law distributed. These areas are better depicted by a normal distribution with an average level of violence and standard deviation.

Several features emerge from the data when analyzed geographically. First, a geographic representation of model estimates demonstrates patterns of criminal violence vary throughout Mexico: organized criminal violence is not entirely homogenous. In some areas, criminal violence reveals a strikingly similar pattern to α estimates of terrorism and insurgencies while others lack any resemblance to a power-law distribution and can be better characterized by a normal distribution. From this perspective, organized crime is more flexible in its use of violence to achieve its profit-motivated ends: it can generate a pattern of violence like an insurgency or remain at the level of petty street crime. The difference depends on the organizational dynamics of organized crime. Thus, the data support the contention that organizational dynamics are driving the violent behavior of organized criminal groups.

Second, Mexican states with strategic value to the transportation and distribution of illicit goods by organized criminal groups are more likely to be well-characterized by a power-law distributed pattern of violence. These are states in which organized crime uses numerous strategies of violence to compete with each other and the state over control of lucrative drug distribution *plazas*. Furthermore, these states of strategic value—on the U.S. border and Pacific coast—have α estimates close to the theoretically-derived value of 2.5. Therefore, I infer that an organizational model of organized crime derived from the behavior of terrorist groups and insurgencies has an important scope condition: it only applies in areas where organized criminal groups compete with each other and the government for control over territory. Areas where a criminal organization has monopolistic control over a territory will not exhibit this pattern. Qualitative analysis on organized criminal groups in these strategic locations has shown that they behave in similar ways to insurgencies and terrorist groups. The data provides empirical support to the contention that plazas of strategic value for drug distribution are the areas where organized criminal groups are most likely to behave like insurgencies and terrorist groups.

Third, states with the lowest α estimates (red) have a significantly higher likelihood of mass-casualty attacks than states with higher α estimates (light yellow). States like Tamaulipas and Chihuahua on the northern border with the United States, with violent cities like Nuevo Laredo and Ciudad Juarez respectively, have the greatest likelihood of a mass casualty attack. Under an assumption of a normal distribution, the predicted probability of a mass-casualty attack (40 casualties) in Tamaulipas is so vanishingly small it is essentially 0%. Under an assumption of a power-law distribution, Tamaulipas—with the lowest α estimate of any Mexican state at α = 2.0 (as shown in Table 4)—has a predicted probability of a mass-casualty event is 0.4%. This may not appear to be a significant difference at first, but since we know that such rare events do occur indicates that the power-law distribution is a more reasonable assumption for future research on organized criminal violence. Furthermore, the predicted probabilities for mass-casualty attacks vary by an order of magnitude between states that well-characterized by a power-law distribution. The predicted probability for a large casualty event is twice as large in Tamaulipas as it is in as in Jalisco (0.4% vs. 0.2%) and twenty times as large as it is in Aguascalientes (0.4% vs. 0.02%). Thus, the power-law distribution can provide more information than simply that violence exhibits a macro-level pattern like insurgencies or terrorist groups. It provides a method to evaluate the potential for rare events like mass-casualty attacks by geographic location.

Table 4. Predicted Probabilities for Selected Mexican States

State	α	x_{min}	Severity (Number of Casualties)		
			10	20	40
Tamaulipas	2.0	7	7%	2%	0.4%
Jalisco	2.53	6	7%	1%	0.2%
Aguascalientes	3.04	3	2%	0.2%	0.02%

It is important to note that the power-law scaling parameter, or asymmetric warfare measure, does not describe merely a trivial relationship. The scaling parameter does not indicate the raw level of violence as measured by total number of casualties or total number of attacks. Rather, it captures the pattern of violence generated by dynamically evolving organized criminal groups within a larger system. Clearly, states with low levels of violence, such as Yucatán, do not exhibit a power-law distribution of violence because they have fewer observations from which to draw a valid α estimate. The Bayesian analysis generates an α estimate for minimally violent states like Yucatán, but the estimate is determined to be invalid when subjected to the KS test.

Discussion

The evidence presented suggests the macro-level pattern of organized criminal violence in Mexico is well-characterized by a power-law at both the national level and at state level where asymmetric warfare is the most prevalent. Furthermore, the scaling exponent approximates the theoretically-derived value of $\alpha = 2.5$ at the national level by two data sets and state level by the available data from 2006 to 2010.

This study provides quantitative evidence to support an inference the organized criminal groups are part of the same set of violent non-state actors that include terrorists and insurgents. In other words, groups in this higher-level class of organization generate similar patterns of violence due to organizational dynamics rather than a motivation for profit or politics. First, qualitative analysis of Mexican organized crime, specifically Los Zetas and La Familia Michoacána, demonstrates the use asymmetric warfare as an operational characteristic (Campbell 2010; Manwaring 2009; Sullivan and Elkus 2010; Turbiville 2010). The quantitative evidence I have provided also supports this argument and the inference that asymmetric warfare is not limited to only those two criminal organizations.

Second, the evidence also supports the contention by Johnson et al. (2006) that power-laws emerge within any modern asymmetric war fought by loosely organized groups prone to violence. Figure 9 indicates the similarity in power-law scaling exponents between global terrorism, insurgencies, and organized criminal violence. This figure plots the power-law scaling exponents from both data sources of organized criminal violence in Mexico I used onto a scale created by Bohorquez et al. (2009) for their study on empirical similarities between terrorism and insurgency. Note that both scaling exponents cluster around the analytically-derived and empirical value of 2.5 (depicted as yellow circles). Johnson et al. and Bohorquez et al. find similarities in organizational violence independent of politics, ideology, religion or geography. Using the same analytical approach to organizational violence I find the behavior is independent of profit-motivation in addition to other factors.

Third, the evidence also support Richardson's Law (Clauset, Young, and Gleditsch 2007) that scale invariance is *a generic feature* of the severity distribution of all deadly human conflicts. In other words, the differences in the type of conflict—insurgency or criminal war—determine the particular scaling behavior. More broadly, the power-law scaling parameter can be a useful measure to examine macro-level patterns for a variety of conflicts.

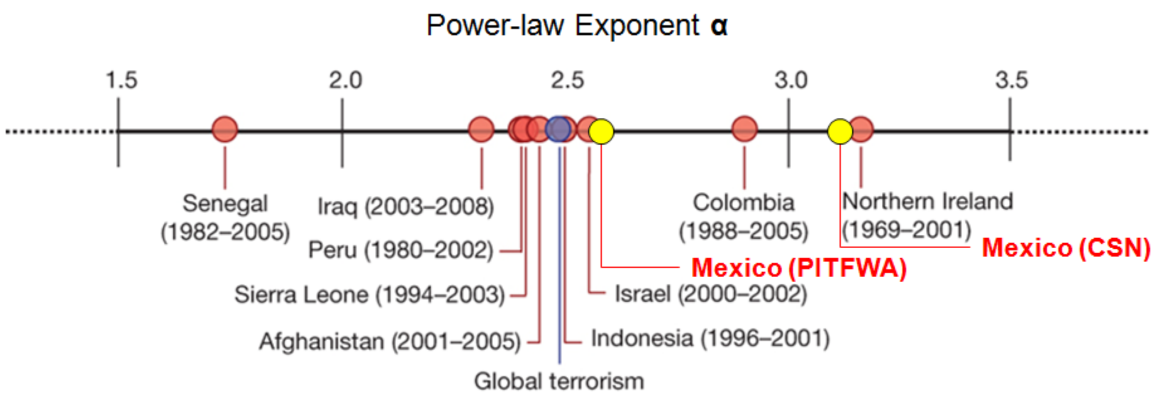

Figure 9. Power-law Scaling Exponent for Violent Non-State Actors

The figure above is from Bohorquez et al. (2009) represents the power-law scaling exponents for a variety of insurgencies and global terrorism from 1968-2007. I have added two additional data points (coded as yellow circles) that mark the scaling exponents of the two data sets of organized criminal violence in Mexico. Bohorquez et al. show that global terrorism and multiple insurgencies empirically cluster around a value of α = 2.5. Both the CSN and PITFWA data of organized criminal violence cluster around the same value.

Critics will argue that this power-law relationship is simply a statement of the obvious: rare events such as mass casualty attacks occur less frequently than skirmishes with only a few casualties. But the power-law describes a particular *kind* of way in which the probability of an event declines as the event gets more extreme. There is no *a priori* reason to suspect that as size of an event doubles, its probability will diminish by some constant factor. That is exactly what the scaling parameter conveys. Furthermore, the scaling parameter parsimoniously describes a relationship between the severity of violence and its frequency.

Organized criminal violence is also well characterized by a power-law at the sub-national level, conditional on its location and strategic value to organized crime. Variation between states further supports my argument that organized criminal groups exhibit characteristics of asymmetric warfare in areas where they are intensely engaged with their competitors and government forces. Conservatively stated, the entire country of Mexico is not under siege from organized crime wielding forms of warfare, but rather smaller geographic areas shaded red and orange in Figure 8. It is these areas that are comparable to other insurgencies around the world. The power-law pattern is not only helpful in establishing that organized crime can exhibit similar patterns of violence to other violent non-state actors, but also in demonstrating its use as an indicator of asymmetric warfare at the sub-national level.

Conclusion

This study has sought to leverage the study of macro-level patterns of human conflict to answer a question in the literature on the nature of the similarity between crime and terror, and more broadly between violent non-state actors. This approach follows Findley and Young (2012) encouragement of conflict scholars to “engage the ambiguities” between forms of violence. My approach is to understand any overlap between warfare and organized criminal violence through the quantitative analysis of power-law distributions. That both forms of conflict generate similar empirical patterns of violence supports the argument organized criminal groups, insurgencies and terrorist groups are not as distinct as many believe. Shelley’s remark about “antiquated concepts” seems particularly apt.

Part of the reason the literature on intrastate conflict has neglected organized crime is because it is considered a law enforcement problem. Yet, research on intra-state conflict could benefit from including organized crime in the analysis. First, criminal organizations continue to generate instability and threaten human security across Central and South America, particularly in El Salvador, Guatemala, and Honduras. The era of Latin American civil wars may be receding only to be replaced by the era of Latin American "criminal wars." Second, belligerents in war often turn to organized crime in the post-conflict environment, utilizing the same skills for profit instead of politics. Disarmament, demobilization, and reintegration (DDR) policies will have to become sensitive to the incentives and dynamics of organized crime. For example, in 2012 political leaders in El Salvador negotiated a public truce between Mara Salvatrucha (MS-13) and Barrio 18 with "peace zones," confidence building measures, and limited disarmament. Third, organized criminal groups may be legitimate actors in an analysis of veto players for war termination or peace duration. In smaller countries they may have the resources to compete with any of the politically-motivated veto players on which intrastate scholars typically focus.

I conclude by speculating on a few implications from this empirical finding. First, organized criminal groups can be classified in the same class of violent non-state actor as insurgencies and terrorist groups based on equivalent patterns of violence. This finding requires a new unifying conceptual and theoretical framework that integrates them. Organizational dynamics of complex systems can provide one starting point for the study of violent non-state actors. The aggregation-disaggregation model of violence travels surprisingly well beyond the phenomena for which it was derived. These systems have many interdependent units and nonlinear feedback pathways that make a systems analysis potentially fruitful. On the other hand, not all organized criminal activity is violent. Scholars need to better understand the conditions under which criminal organizations choose to behave as a firm providing illicit goods versus one that destabilizes society through violence. Social Network Analysis could also provide a useful framework for the behavioral by this class of organization. Networks provide links for learning, coordination, and resource gathering. For instance, the FARC is a node on both the IRA network of organizations that have received training in the use of explosives (Bloom and Horgan 1990) and a network for drug distribution to Mexican organized crime.

Second, scholars must be cautious in using analytical tools that underestimate the probability of rare mass-casualty events, whether it is by profit-motivated or politically-motivated groups. Many quantitative studies of conflict assume normal distributions for their data and implicitly within their models. Yet, these assumptions may drastically underestimate the likelihood of the exact type of events the analysis is trying to explain or predict. While quantitative models relying on central tendencies and standard deviations may be able to explain, or even predict, behavior most of the time, the problem is that the extreme outcome at the end of the tail may only occur once and have a disproportionate impact on adjacent systems.

Third, power-law analysis provides a potent framework to evaluate social phenomena. Outliers, rare events, and extreme values populate the data landscape of complex interdependent systems in the domain of inter- and intra-state conflict. This approach equips scholars to incorporate ‘black swan’ events into theories and models instead of dismissing them in favor of the less extreme and more frequent events. Extreme events are not outliers that defy scientific generalization and therefore require event-specific, contextual explanations. Rather, extreme events are merely part of a pattern understudied in the social sciences.

References

Adriani, Pierpaolo, and Bill Mckelvey. 2011. "Managing in a Pareto World Calls for New Thinking." *M@n@gement* 14(2): 89–118.

Albanese, Jay S. 2000. "The Causes of Organized Crime." *Journal of Contemporary Criminal Justice* 16(4): 409–23.

Alfarano, Simone, and Thomas Lux. 2010. "Extreme Value Theory as a Theoretical Background for Power Law Behavior."

American Public Media. 2008. "Gangster Confidential."

Astorga, Luis, and David A Shirk. 2010. Working Pa Center for U.S.-Mexico Studies (San Diego) *Drug Trafficking Organizations and Counter-Drug Strategies in the U.S.-Mexican Context*.

Bailey, John, and Matthew M Taylor. 2009. "Evade, Corrupt, or Confront? Organized Crime and the State in Brazil and Mexico." *Journal of Politics in Latin America* 1(2): 3–29.

Bak, Per, Chao Tang, and Kurt Wiesenfeld. 1987. "Self-Organized Criticality: An Explanation of the 1/f Noise." *Physical Review Letters* 59(4): 381–84.

Ball, Philip. 2004. *Critical Mass: How One Thing Leads to Another*. New York: Farrar, Straus and Giroux.

Ballina, Santiago. 2011. "The Crime–terror Continuum Revisited: a Model for the Study of Hybrid Criminal Organisations." *Journal of Policing, Intelligence and Counter Terrorism* 6(2): 121–36.

Beckett, Ian F.W. 2001. *Encyclopedia of Guerrilla Warfare*. New York: Checkmark Books.

Beittel, June S. 2011. Security *Mexico's Drug Trafficking Organizations : Source and Scope of the Rising Violence*.

Berman, Eli. 2009. *Radical, Religious, and Violent: The New Economics of Terrorism*. Cambridge, MA: MIT Press.

Berman, Eli, and David D Laitin. 2008. "Religion, Terrorism, and Public Goods: Testing the Club Model." *Journal of Public Economics* 92: 1942–67.

Bernstein, Lisa. 1992. "Opting Out of the Legal System: Extralegal Contractual Relations in the Diamond Industry." *Journal of Legal Studies* 21(1): 115–57.

Bloom, Mia, and John Horgan. 1990. “Missing Their Mark : The IRA ’ s Proxy Bomb Campaign.” *Social Research* 75(2): 579–614.

Bohorquez, Juan Camilo, Sean Gourley, Alexander R Dixon, Michael Spagat, and Neil F Johnson. 2009. “Common Ecology Quantifies Human Insurgency.” *Nature* 462(7275): 911–14.

Brands, Hal. 2009. “Los Zetas: Inside Mexico’s Most Dangerous Drug Gang.” *Air & Space Power Journal* October.

Bremmer, Ian, and Preston Keat. 2009. *The Fat Tail: The Power of Political Knowledge for Strategic Investing*. Oxford University Press.

Bruneau, Thomas C. 2005. “The Maras and National Security in Central America.”

Bunker, Robert J. 2011. Epoch *Criminal (Cartel & Gang) Insurgencies in Mexico and the Americas : What You Need to Know , Not What You Want to Hear*.

Campbell, Lisa J. 2010. “Los Zetas: Operational Assessment.” *Small Wars & Insurgencies* 21(1): 55–80.

Cederman, L.E. 2003. “Modeling the Size of Wars: From Billiard Balls to Sandpiles.” *American Political Science Review* 97(1): 135–50.

Cederman, L.E., T. Camber Warren, and Didier Sornette. 2011. “Testing Clausewitz: Nationalism, Mass Mobilization, and the Severity of War.” *International Organization* 65(04): 605–38.

Chepesiuk, Ron. 2003. *The Bullet or the Bribe: Taking Down Colombia’s Cali Drug Cartel*. Westport, CT: Praeger Press.

Clauset, Aaron, and Kristian Skrede Gleditsch. 2011. “The Developmental Dynamics of Terrorist Organizations.” *arXiv Preprint*: 1–21.

Clauset, Aaron, Cosma Rohilla Shalizi, and Mark EJ Newman. 2009. “Power-Law Distributions in Empirical Data.” *SIAM Review* 51(4): 661–703.

Clauset, Aaron, and Frederik W Wiegel. 2010. “A Generalized Aggregation-Disintegration Model for the Frequency of Severe Terrorist Attacks.” *Journal of Conflict Resolution* 54(1): 179–97.

Clauset, Aaron, and Maxwell Young. 2005. “Scale Invariance in Global Terrorism.” *arXiv Preprint*: 1–6.

Clauset, Aaron, Maxwell Young, and Kristian Skrede Gleditsch. 2007. “On the Frequency of Severe Terrorist Events.” *Journal of Conflict Resolution* 51(1): 58–88.

Cornell, Svante E. 2007. "Narcotics and Armed Conflict: Interaction and Implications." *Studies in Conflict & Terrorism* 30(3): 207–27.

CSN. 2011. "Base de Datos de Homicidios Presuntamente Relacionados Con La Delincuencia Organizada." *Presidencia de la República*.

Dishman, Chris. 2001. "Terrorism , Crime , and Transformation." *Studies in Conflict & Terrorism* 24: 43–58.

———. 2005. "The Leaderless Nexus: When Crime and Terror Converge." *Studies in Conflict & Terrorism* 28(3): 237–52.

Dobias, Peter. 2009. "SELF-ORGANIZED CRITICALITY IN ASYMMETRIC WARFARE." *Fractals* 17(1): 91–97.

Fearon, James D, and David D Laitin. 2003. "Ethnicity, Insurgency, and Civil War." *American Political Science Review* 97(01): 75–90.

Findley, Michael G., and Joseph K. Young. 2012. "Terrorism and Civil War: A Spatial and Temporal Approach to a Conceptual Problem." *Perspectives on Politics* 10(2): 285–305.

Finnegan, William. 2010. "Silver or Lead."

Gambetta, Diego. 1996. *The Sicilian Mafia: The Business of Private Protection*. Harvard University Press.

Ghattas, Kim. 2010. "Clinton Says Mexico Drug Crime Like An Insurgency." *BBC*.

Graham, Dave. 2013. "Prominent Mexicans Urge Government to Decriminalize Marijuana." *Reuters*.

Grayson, George W. 2010. *La Familia Drug Cartel: Implications for U.S.-Mexican Security*. Carlisle, PA.

———. 2011. *Mexico: Narco-Violence and a Failed State?* New Brunswick, NJ: Transaction Publishers.

Grayson, George W, and Samuel Logan. 2012. *The Executioner's Men: Los Zetas, Rogue Soldiers, Criminal Entrepreneurs, and the Shadow State They Created*. New Brunswick, NJ: Transaction Publishers.

Grillo, Ioan. 2011. *El Narco: Inside Mexico's Criminal Insurgency*. Bloomsbury Press. New York.

Grinberg, Emanuella, and Monica Trevino. 2009. "Mexican Police, Soldiers Killed in Multicity Attacks by Drug Gang." *CNN World Online*.

Hill, Peter B. 2006. *The Japanese Mafia: Yakuza, Law and the State*. New York: Oxford University Press.

Hoffman, Bruce. 2006. *Inside Terrorism*. Revised an. New York: Columbia University Press.

Humphreys, M. 2005. "Natural Resources, Conflict, and Conflict Resolution: Uncovering the Mechanisms." *Journal of Conflict Resolution* 49(4): 508–37.

Hutchinson, Steven, and Pat O'malley. 2007. "A Crime-Terror Nexus? Thinking on Some of the Links Between Terrorism and Criminality." *Studies in Conflict & Terrorism* 30(12): 1095–1107.

Johnson, N, M Spagat, J Restrepo, J Bohórquez, N Suárez, and E Restrepo. 2005. "From Old Wars to New Wars and Global Terrorism." *Iraq*.

Johnson, N., Mike Spagat, Jorge A Restrepo, Oscar Becerra, Juan Camilo Bohorquez, Nicolas Suárez, Elvira Maria Restrepo, and Roberto Zarama. 2006. "Universal Patterns Underlying Ongoing Wars and Terrorism." *arXiv Preprint*: 1–69.

Kahler, Miles. 2009. "Networked Politics: Agency, Power, and Governance." In *Networked Politics: Agency, Power, and Governance*, ed. Miles Kahler. Ithaca: Cornell University Press, 1–20.

Kalyvas, Stathis N. 2003. "The Ontology of 'Political Violence': Action and Identity in Civil Wars." *Perspectives on Politics* 1: 475–94.

Kenney, Michael. 2007. "The Architecture of Drug Trafficking: Network Forms of Organisation in the Colombian Cocaine Trade." *Global Crime* 8(3): 233–59.

———. 2009. "Turning to the 'Dark Side': Coordination, Exchange, and Learning in Criminal Networks." In *Networked Politics: Agency, Power, and Governance*, ed. Miles Kahler. Ithaca: Cornell University Press, 79–102.

Kilcullen, David. 2006. "Counterinsurgency Redux." *Survival: Global Politics and Strategy* 48(4): 111–30.

Landa, Janet T. 1981. "A Theory of the Ethnically Homogenous Middleman Group: An Institutional Alternative to Contract Law." *Journal of Legal Studies* 10(2): 349–62.

Lessing, Benjamin. 2012. "The Logic of Violence in Criminal War: Cartel-State Conflict in Mexico, Colombia, and Brazil." University of California, Berkeley.

Makarenko, Tamara. 2005. Security "The Crime-Terror Continuum: Modelling 21st Century Security Dynamics." University of Wales, Aberystwyth.

Malkin, Victoria. 2001. "Narcotrafficking, Migration, and Modernity in Rural Mexico." *Latin American Perspectives* 28(4, Mexico in the 1990s: Economic Crisis, Social Polarization, and Class Struggle, Part 2): 101–28.

Mandel, Robert. 2011. *Dark Logic: Transnational Criminal Tactics and Global Security*. Stanford, CA: Stanford University Press.

Manwaring, Max G. 2008. *Insurgency, Terrorism & Crime*. Norman, OK: University of Oklahoma Press.

———. 2009. *A New Dynamic in the Western Hemisphere Security Environment: The Mexican Zetas and Other Private Armies*. Carlisle, PA: Strategic Studies Institute, Army War College.

Martin, Carlos. 2012. "Categorization of Narcomessages in Mexico: An Appraisal of the Attempts to Influence Public Perception and Policy Actions." *Studies in Conflict & Terrorism* 35(1): 76–93.

Metz, Steven. 2007. *Rethinking Insurgency*. Carlisle, PA: Strategic Studies Institute, Army War College.

Oehme, Chester G. 2008. "Terrorists, Insurgents, and Criminals—Growing Nexus?" *Studies in Conflict & Terrorism* 31(1): 80–93.

Olson, Mancur. 1993. "Dictatorship, Democracy, and Development." *American Political Science Review* 87(3): 567–76.

Penn State University. 2012. "Political Instability Task Force Worldwide Atrocities Dataset." http://eventdata.psu.edu/data.dir/atrocities.html (December 7, 2012).

Pickands, James III. 1975. "Statistical Inference Using Extreme Order Statistics." *The Annals of Statistics* 3(1): 119–31.

Podolny, Joel M., and Karen L. Page. 1998. "Network Forms of Organization." *Annual Review of Sociology* 24: 57–76.

Powell, Walter W. 1990. "Neither Market Nor Hierarchy--Network Forms of Organization." *Research on Organizational Behavior* 12: 295–336.

Ramsey, Geoffrey. 2012. "Is El Salvador Negotiating with Street Gangs?" *Insight Crime*.

Richardson, Lewis F. 1948. "Variation of the Frequency of Fatal Quarrels with Magnitude." *Journal of the American Statistical Association* 43: 523–46.

———. 1960. *Statistics of Deadly Quarrels*. Chicago: Quadrangle Books.

Rios, Viridiana. 2012. "Why Did Mexico Become so Violent? A Self-Reinforcing Violent Equilibrium Caused by Competition and Enforcement." *Trends in Organized Crime* August.

Rios, Viridiana, and David A Shirk. 2011. "Drug Violence in Mexico: Data and Analysis Through 2010."

Robb, John. 2007. *Brave New War: The Next Stage of Terrorism and the End of Globalization*. Hoboken, NJ: John Wiley and Sons Inc.

Roberts, David C., and Donald L. Turcotte. 1998. "Fractality and Self-Organized Criticality of Wars." *Fractals* 6(4): 351–57.

Rosenthal, Justine a. 2008. "For-Profit Terrorism: The Rise of Armed Entrepreneurs." *Studies in Conflict & Terrorism* 31(6): 481–98.

Ross, Michael L. 2004. "How Do Natural Resources Influence Civil War? Evidence from Thirteen Cases." *International Organization* 58(01): 35–67.

Safire, William. 2009. "On Language: Fat Tail." *New York Times*.

Sambanis, N. 2004. "What Is Civil War?: Conceptual and Empirical Complexities of an Operational Definition." *Journal of Conflict Resolution* 48(6): 814–58.

Sanderson, Thomas M. 2004. "Transnational Terror and Organized Crime: Blurring the Lines." *SAIS Review* 24(1): 49–61.

Schelling, Thomas C. 1967. "Economic Analysis of Organized Crime." 114–26.

Shelley, Louise I. 2006. "The Globalization of Crime and Terrorism." *E-Journal USA*. http://www.america.gov/st/business-english/2006/February/20080608103639xjyrreP4. 218692e-02.html.

Shelley, Louise I, and John T Picarelli. 2005. "Methods and Motives: Exploring Links Between Transnational Organized Crime and International Terrorism." *Intelligence* 9(2): 52–68.

Shelley, Louise I., and John T. Picarelli. 2002. "Methods Not Motives: Implications of the Convergence of International Organized Crime and Terrorism." *Police Practice and Research* 3(4): 305–18.

Skarbek, David. 2011. "Governance and Prison Gangs." *American Political Science Review* 105(04): 702–16.

Smith, Richard L. 1987. “Estimating Tails of Probability Distributions.” *The Annals of Statistics* 15(3): 174–207.

Snyder, R. 2006. “Does Lootable Wealth Breed Disorder?: A Political Economy of Extraction Framework.” *Comparative Political Studies* 39(8): 943–68.

Sornette, Didier. 2006. *Critical Phenomena in Natural Sciences. Chaos, Fractals, Self-Organization and Disorder: Concepts and Tools*. 2nd Ed. Berlin: Springer.

Sullivan, John P, and Adam Elkus. 2010. “Cartel V. Cartel: Mexico’s Criminal Insurgency.” *Small Wars Journal*.

Sullivan, John P., and Adam Elkus. 2008. “State of Siege: Mexico’s Criminal Insurgency.” *Small Wars Journal*.

———. 2011. “Open Veins of Mexico: The Strategic Logic of Cartel Resource Extraction and Petro-Targeting.” *Small Wars Journal*: 1–8.

Tarrow, Sidney T. 2007. “Inside Insurgencies: Politics and Violence in an Age of Civil War.” *Perspectives on Politics* 5(3): 587–600.

Tilly, Charles. 1985. “War Making and State Making as Organized Crime.” In *Bringing the State Back In*, eds. Peter Evans, Dietrich Rueschmeyer, and Theda Skocpol. Cambridge: Cambridge Uniersity Press.

Turbiville, Graham H. 2010. “Firefights, Raids, and Assassinations: Tactical Forms of Cartel Violence and Their Underpinnings.” *Small Wars & Insurgencies* 21(1): 123–44.

U.S. Department of State. 2003. *Patterns of Global Terrorism*.

Varese, Federico. 2005. *The Russian Mafia: Private Protection in a New Market Economy*. Oxford: Oxford University Press.

Weinstein, J. M. 2005. “Resources and the Information Problem in Rebel Recruitment.” *Journal of Conflict Resolution* 49(4): 598–624.

Williams, Phil. 2007. “Strategy for a New World: Combating Terrorism and Transnational Organized Crime.” In *Strategy in the Contemporary World*, eds. John Baylis, James L. Wirtz, Colin S. Gray, and Eliot Cohen. New York: Oxford University Press, 192–208.

Young, Joseph K., and Michael G. Findley. 2011. “Promise and Pitfalls of Terrorism Research.” *International Studies Review* 13(3): 411–31.

Zanini, Michele, and Sean J.A. Edwards. 2001. "The Networking of Terror in the Information Age." In *Networks and Netwars: The Future of Terror, Crime, and Militancy*, eds. John Arquilla and Ron Ronfeldt. Santa Monica, CA: RAND, 29–60.

Appendix A: Model Derivation for the Distribution of Organized Criminal Violence

I replicate Clauset and Wiegel's (2010) model solution on the steady-state behavior of terrorist violence by replacing two of the assumptions. First, I relax assumption 1 to postulate a pool of criminals tending towards violence. Second, I relax assumption 2 to postulate that criminals can form cells of varying sizes. The model is based on five assumptions about the interaction of cells that make up the modern organized criminal group. I make no other assumptions about the relationships between these criminal cells, their motivation, the mode of attack, the tactic that the attackers uses, or that this model represents the behavior of a hierarchical organized criminal group.

While I have not yet tested the assumptions against empirical data, the model is worthwhile to study because it provides a prediction—a power-law distribution in the frequency and severity of events—that agrees with a wide variety of other studies on human conflict (Bohorquez et al. 2009; Clauset, Young, and Gleditsch 2007; Clauset and Young 2005; Johnson et al. 2006). This model allows for an exploration of quantitative predictions and critical assumptions of organized criminal group behavior.

Assumptions

1. There is a "pool" of organized criminals likely towards violence. I assume $N \gg 1$ and constant in time. The assumption that N is constant implies that criminals who are eliminated by arrest, extradition, inter- or intra-cell conflict, alternative preferences, or in the course of an attack are replaced immediately by an equal number of radicalized individuals.

2. These criminals can form cells of size 1,2,3… Let n_k denote the number of cells consisting of k = 1,2,3… individuals.

3. Cells grow by a process of "aggregation," in which any pair of cells merge to form a larger cell. More specifically I assume that any pair of cells consisting of k and ℓ individuals respectively has a probability $A_0\left(k\ell\right)^a$ per unit time to combine into a cell of size $k+\ell$. Here $A_0 > 0$ and $a \geq 0$ are parameters of the model and I analyze the model for general a. To be realistic when comparing with the data, however, I choose a $\cong$ 1 to represent the fact that the number of possible human relations between members of the two cells $k\ell$, i.e. it scales linearly with the product of the cell sizes.

4. Cells fall apart or "disintegrate" spontaneously into single individuals. Let $b(k)$ denote the probability per unit time that a given cell of k individuals will disintegrate spontaneously into k cells of size one, and where $b(1) = 0$. The explicit form of the function $b(k)$ is not needed to calculate the equilibrium distribution of cell size, provided one studies the asymptotic region $N \gg 1$.

5. At any time, any cell can launch an attack. For simplicity, I assume that the attack occurs with probability (per unit time) that is independent of the cell's size, its "age", the number of attacks it has previously launched, etc. and that the severity *v(k)* of an attack is roughly proportional to the cell's size *k*, i.e., $v(k) \propto k$, for $1 \ll k \ll N$.

To be precise, the number of possible pairings of a k-cell with a ℓ-cell, i.e. the number of potential combinations between some cell of size k and some cell of size ℓ, equals $n_k n_\ell$ for k ≠ ℓ, and $\frac{1}{2} n_k \left(n_k - 1\right)$ for k = ℓ. However, if $N \gg 1$, I find that all $n_k \gg 1$; in this case I can approximate $\frac{1}{2} n_k \left(n_k - 1\right) \cong \frac{1}{2} n_k^2$, which simplifies the mathematics considerably but does not fundamentally alter the results.

The analysis of this model will show that the steady-state distribution of the sizes of the organized criminal group cells follows a power-law distribution with exponent α = 2.5. By assumption 5, that the severity of an attack is proportional to the size of the attacking cell, this then implies that the distribution of the event severities follows a power-law distribution with the same exponent.

From the five assumptions discussed above, I can write down the equation for how *nk(t)* changes with time for k = 2,3,…

$$\frac{dn_k}{dt} = \frac{1}{2} A_0 {\sum_{i,j=1}^{\infty}}' i^a j^a n_i n_j - A_0 k^a n_k \sum_{j=1}^{\infty} j^a n_j - b(k) n_k \ , \qquad \textbf{(0.9)}$$

where $\sum{}'$ denotes a summation over all natural numbers i and j such that

$$i + j = k \qquad \textbf{(0.10)}$$

The equation for *dn1/dt* is not needed in the analysis. In words, the first term on the right-hand size of equation (0.9) represents the increase of the number of cells of size k because of the aggregation of two smaller cells, the second term measures the decrease of this number because such a cell can itself merge with another cell, and the third term represents the loss of these cells because of spontaneous disintegration.

As I am interested mainly in the steady-state behavior of this model, I denote $\lim_{t\to\infty} n_k\left(t\right)$ by n_k^*, where * is not an exponent but a label that denotes the attached variable being in its steady-state limit. Equation (0.9) now simplifies to

$$\frac{1}{2}A_0\sum_{i,j=1}^{\infty}{}' i^a j^a n_i^* n_j^* = A_0 k^a n_k^* \sum_{j=1}^{\infty} j^a n_j^* + b(k) n_k^* \qquad \textbf{(0.11)}$$

for k = 2,3,… As a technical detail, I point out that the term with the *j=k* in the second summation in the right hand side of equations (0.9) and (0.11) come from the fact that the number of pairs *k*, *k* equals $\frac{1}{2}n_k^2$, but as each combination of two such cells leads to the decrease of n_k by two, the loss term is proportional to $2\cdot\frac{1}{2}n_k^2 = n_k^2$.

A simple way of solving the set of equations given in equation (0.11) is by introducing the generating functions

$$f(z) \equiv \sum_{k=1}^{\infty} k^a n_k^* z^k \qquad \textbf{(0.12)}$$

$$g(z) \equiv \sum_{k=1}^{\infty} b(k) n_k^* z^k \qquad \textbf{(0.13)}$$

That is, I multiply equation (0.11) by z^k and then sum over k from 2 to ∞. This reduces the system of equations to

$$\frac{1}{2}A_0 f(z) f(z) = A_0 f(1)\left\{ f(z) - n_1^* z\right\} + g(z) \qquad \textbf{(0.14)}$$

where I used the fact that b(1) = 0 because a cell of one individual cannot disintegrate into single individuals.

Although the solution of equation (0.14) is difficult for general *z* and *N*, it is much simpler in this case where *z* is fixed and the limit $N \to \infty$ is studied. For $N \gg 1$, the equilibrium frequencies n_k^* will be proportional to *N* (for *k* smaller than some cut-off k_0 which I need not calculate explicitly). Hence the leading orders of magnitude (in N) of the various terms in equation (0.14) are

$$f(z) \sim N \qquad \textbf{(0.15)}$$

$$g(z) \sim N \qquad \textbf{(0.16)}$$

$$\frac{1}{2} A_0 f(z) f(z) \sim N^2 \qquad \textbf{(0.17)}$$

$$A_0 f(1)\left\{ f(z) - n_1^* z \right\} \sim N^2 \qquad \textbf{(0.18)}$$

This means that for z fixed and $N \gg 1$, equation (0.14) can be replaced by

$$\frac{1}{2} f^2(z) - f(1) f(z) + f(1) n_1^* z = 0 \qquad \textbf{(0.19)}$$

which has the solution

$$f(z) = f(1) - \sqrt{f^2(1) - 2 f(1) n_1^* z} \qquad \textbf{(0.20)}$$

Substituting *z* = 1 shows

$$f(1) = 2 n_1^* \qquad \textbf{(0.21)}$$

And gives

$$f(z) = 2 n_1^* \left\{ 1 - \sqrt{1 - z} \right\}. \qquad \textbf{(0.22)}$$

The definition of *f(z)* given in equation (0.12) shows that the term $k^a n_k^* z^k$ can now be found as the coefficient of z^k in the power series expansion of equation (0.22). For small values of *k* these coefficients can be calculated by hand from the series

$$f(z) = 2 n_1^* \left(\frac{1}{2} z + \frac{1}{2} \cdot \frac{1}{4} z^2 + \frac{1}{2} \cdot \frac{1}{4} \cdot \frac{3}{6} z^3 + \frac{1}{2} \cdot \frac{1}{4} \cdot \frac{3}{6} \cdot \frac{5}{8} z^4 + \ldots \right). \qquad \textbf{(0.23)}$$

For example, the first four terms are

$$2^a n_2^* = \frac{1}{4} n_1^* \ , \tag{0.24}$$

$$3^a n_3^* = \frac{1}{8} n_1^* \tag{0.25}$$

$$4^a n_4^* = \frac{5}{64} n_1^* \tag{0.26}$$

$$5^a n_5^* = \frac{7}{128} n_1^* \tag{0.27}$$

To obtain the coefficients for $k \gg 1$, one can use Cauchy's theorem, which gives the contour integral

$$k^a n_k^* = \iota \frac{n_1^*}{\pi} \oint_C z^{-k-1} \sqrt{1-z}\, dz \ , \tag{0.28}$$

where the contour C encircles the origin of the complex z-plane once in the counter-clockwise direction. This contour can be deformed into a contour C' which encircles the branch cut $1 \leq z < \infty$ once in clockwise direction. For z near to the branch point at $z = 1$, it is convenient to first write

$$z = 1 + \zeta \tag{0.29}$$

$$z^{-k-1} \cong e^{-(k+1)\zeta} \tag{0.30}$$

When ζ has a small positive imaginary part, one can writes $\sqrt{-\zeta} = -\iota\sqrt{|\zeta|}$; when ζ has a small negative imaginary part, one writes $\sqrt{-\zeta} = +\iota\sqrt{|\zeta|}$. Hence I find the asymptotic result

$$\begin{aligned} k^a n_k^* &\cong \frac{2}{\pi} n_1^* \int_0^\infty \sqrt{\zeta} e^{-(k+1)\zeta} d\zeta \\ &= \frac{1}{\sqrt{\pi}} n_1^* (k+1)^{-3/2} \end{aligned} \tag{0.31}$$

for $k \gg 1$. For k as small as 5, the last equation gives reasonably close approximations of the true values, e.g., for $5^a n_5^*$ the value of 0.038, where as the exact value from equation (0.27) is 0.055.

This analysis thus shows that the number of cells consisting of k organized criminal group members, at equilibrium, is given by the power law

$$n_k^* \cong \frac{1}{\sqrt{\pi}} n_1^* k^{-a-3/2} \quad \textbf{(0.32)}$$

for $k \gg 1$. Hence, because of model assumption 5, that the severity of an event is proportional to the size of the attacking cell, the probability p_k that an organized criminal group attack will claim k victims will also have a power law distribution is

$$p_k \propto k^{-\alpha} \quad \textbf{(0.33)}$$

for $k \gg 1$, with an exponent

$$\alpha = a + \frac{3}{2} \quad \textbf{(0.34)}$$

As mentioned before, I assume that a ≅ 1, which leads to the prediction,

$$\alpha = \frac{5}{2} \quad \textbf{(0.35)}$$

In fact, for a = 1 and b(k) ∝ k, this model can be solved exactly, i.e. with no approximations, and doing so recovers the results of other formal models (Johnson et al. 2005, 2006).

Appendix B. Hierarchical Model Results

Table 5. Hierarchical Model Results by State

State	$\hat{\alpha}$	Std. Dev.	KS-Test *p*-value
Aguascalientes	3.04	0.43	0.90
Baja California	2.61	0.23	0.98
Baja California Sur	2.91	0.65	<.01
Campeche	3.03	0.61	<.01
Chiapas	2.91	0.36	<.01
Chihuahua	2.2	0.11	0.96
Coahuila	2.41	0.21	0.99
Colima	2.67	0.42	0.90
Distrito Federal	2.57	0.37	< .01
Durango	2.28	0.13	0.90
Guanajuato	2.94	0.35	0.90
Guerrero	2.23	0.12	0.99
Hidalgo	2.54	0.38	0.96
Jalisco	2.53	0.2	0.98
México	3.15	0.3	<.01
Michoacán	2.44	0.15	0.98
Morelos	2.95	0.33	0.96
Nayarit	2.22	0.2	0.99
Nuevo León	2.2	0.12	0.95
Oaxaca	3.38	0.44	<.01
Puebla	2.88	0.45	<.01
Querétaro	3.09	0.67	<.01
Quintana Roo	2.81	0.57	<.01
San Luis Potosí	2.48	0.29	0.90
Sinaloa	2.41	0.14	0.99
Sonora	2.71	0.21	0.99
Tabasco	3.53	0.57	<.01
Tamaulipas	2.6	0.07	0.90
Tlaxcala	3.1	0.69	<.01
Veracruz	2.78	0.27	0.90
Yucatán	2.69	0.59	< .01
Zacatecas	2.45	0.26	< .01