Terrorist Networks and the Collective Criminal Career: The Relationship between Group Structure and Trajectories

by

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Abstract

Criminology theories have long pointed to criminal groups as playing key roles in shaping offending behaviour. While empirical research has refined this link, showing that individuals’ connectivity to criminal groups shapes their offending patterns, few studies have focused on the group as the main unit of analysis. We know little about the factors that lead criminal groups to emerge and even less about what leads them to evolve and persist over time. Focusing on group trajectories, this dissertation presents three studies that examine the evolution of the networks of terrorist organizations. Drawing from detailed network data derived from self-reports and official sources, this study examines the structural properties associated with 1) turning points in a group’s emergence and transition into violence; 2) network formation before and after a major law enforcement intervention; and 3) repeat offending across terrorist attacks. Collectively, findings showed how a group’s network structure is key for amplifying or attenuating their life cycle. However, group trajectories were found to depend not only on subgroups of densely connected offenders, but also leaders who played key roles in bridging the network and regenerating it over time. These results are used to conceptually develop a typology of group trajectories to explain variations in the life-cycles of terrorist organizations.

Keywords: social network analysis; criminal career; co-offending; group trajectories; terrorism
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Chapter 1.

Introduction

There are few criminal contexts where individual goals are tied so saliently to the group than that of terrorist organizations. Individuals sacrifice their lives in suicide missions, commit acts of violence against random civilians, and risk steep penalties, all on behalf of their commitment to a group cause. Popular explanations of individuals’ willingness to accept these personal costs in favour of a collective cause have traditionally relied on individual differences, such as economic backgrounds or psychological disorders. But the robust finding that little if any appreciable psychopathology or trait differentiate the terrorist from the ordinary person has shifted the focus from the individual to the group in which individuals are embedded, championing the idea that the group is the main motivator for an individual to join an organization. The group context provides opportunities for collective action, while also creating a social milieu that fosters extreme views and solidarity (Johnson & Feldman, 1992; Post, 1987; Post et al., 2003). Yet, little is known about the group-level processes that sustain these behaviours, and allow terrorist groups to emerge and persist over time.

Few dispute the group nature of terrorism; however dominant theories of terrorism have often ignored this context in favour of explanations of political violence at the aggregate level. Popular accounts of terrorism have typically centered on state or regional level differences, such as social disorganization (Huntington, 1968; 1996), economic inequality (Lai, 2007; Piazza, 2011), and regime-types (Eubank & Weinberg, 1994; 1998; Lai, 2004). These studies have found that terrorism is more likely to emerge in areas undergoing rapid economic change (Huntington, 1968; 1998), economic discrimination (Piazza, 2011), and transitions to more repressive regimes (Eubank & Weinberg, 1994; 1998; Lai, 2004), and are often perpetrated by young men in their early twenties (Russell & Miller, 1983; McCauley & Segal, 1987, p. 232-233) who lack social and human capital (Perliger, Koehler-Derrick, & Pedahzur, 2016). Yet, while studies have told us that offenders are more likely to be young adult males, who experience discrimination and live in disadvantaged areas, a basic limit of such approaches is that they don’t account for the group
processes that explain why two individuals seemingly possessing the same risk factors, only one joins a terrorist organization. Furthermore, we know little about the causes of variation within groups who emerge in similar contexts, or cases of terrorism that emerge outside these contexts. That is, we know little about the group-level processes that sustain these behaviours, including the factors that allow terrorist groups to emerge, persist, and evolve into major campaigns.

While dominant paradigms of the terrorist have shifted from the perspective of narcissistic, mentally ill perpetrators, into a multi-causal pathway framework – the methods to research terrorism have been slower to evolve with it. Extensive research on individual traits of terrorism have led to the identification of a host of risk factors; however, there are several areas of disagreement on how these risk factors must converge in order to lead to terrorism. One of the few areas where there does appear to be consensus across scholars is the view that transitions into violent radicalization is a ‘process’ (Neumann, 2013, p. 874). That is, terrorism is not a binary event, where an individual adopts violent extremist beliefs overnight, but rather the result of a series of steps or events that together facilitate transitions into terrorism (Ducol et al., 2015). However, trading in outcome-based approaches in favour of methods that capture these processes has only recently begun to emerge in terrorism studies.

Of the subset of studies that have adopted process-based approaches, they have shown that transitions into terrorism are often associated with the re-structuring of an individual’s immediate social network. Sageman (2004) analyzing the biographies of 172 individuals involved with the Global Salafi Jihad found that terrorist offenders organized into small, densely connected groups. Interactions within these closed groups were suggested to transmit radical ideas, increasing exposure to like-minded individuals, while excluding outside perspectives. Similarly, Nash and Bouchard’s (2015) analysis of a jihadist’s immediate social network, showed how his network evolved over time, with his transition into radicalization associated with a sharp decline in non-radical actor, replacing these individuals with a highly connected group of fellow jihadists. These studies suggest that certain types of interactions, particularly close, dense networks, isolate offenders from external opinions, and facilitate homogeneity, serving as a vehicle for transitions into violent extremism (Wiktorowicz, 2004; Beutel, 2007; Garstein-Ross, & Grossman, 2009). However, we know little about these interactions, and even less about the underlying properties of groups that sustain and promote these interactions over time.
Collective behaviour that emerges only in group contexts requires an understanding of the group-level mechanisms that facilitate it. Recent work has focused on a group's effect on the individual, but has ignored individuals’ effect on the group. This unilateral focus is consistent with criminology theories more generally, which have long pointed to criminal groups as playing key roles in shaping offending behaviours. This research has contributed to our understanding of individual offending patterns, showing that the type and structure of ties moderates criminal behaviour (e.g. Haynie, 2001; 2002; McGloin & Piquero, 2009; 2010; McGloin & Shermer, 2009; Lantz & Hutchison, 2015). Yet, empirical research rarely examines groups as the unit of analysis. Even when studies have included groups as a factor they often treat them as binary variables, ignoring the dynamic and transient nature of criminal groups, while assuming that structural properties extend the same effect across a group’s trajectory. Omitting an understanding of the within-group variation may obscure the mechanisms whereby groups influence behaviour.

To redress this imbalance, this dissertation presents three studies that examine the dynamic interaction between groups and individuals across the lifespan of the group. All studies rely on network methods to examine how a group’s structure influences its trajectory. This process-based approach marks shifts in how we conceive and study terrorism, in that it considers the group not as a static entity, but rather as a dynamic entity that evolves in tandem with group processes and individuals embedded within it.

Assessments of a group’s structure across its trajectory, and its corresponding impact on outcomes, serves two important purposes. First, an understanding of criminal behaviour requires looking at the context in which criminal activities take place. Analyses of groups can help understand the mechanisms that sustain, enhance, or attenuate offending patterns – disentangling the effect of the group from the individual. For instance, studies that examine desistance, can distinguish whether individual desistance patterns are part of larger group-patterns, clarifying group processes and within-individual changes. Second, this sort of inquiry into the causes and correlates of group trajectories (e.g. how they emerge, evolve, and persist over time) can assist in developing effective interdiction strategies. While criminal justice policies are traditionally individual-focused, the groups they belong to often persist beyond the arrest of any members, sustaining group offending patterns. From a deterrence perspective, the arrests of individual members may have minimal impact on crime patterns if the groups they belong to continue to regenerate, recruiting new members into their fold. Hence, develop effective
interdiction strategies requires examinations of the entity as a collective, and the mechanisms that allow it to sustain over time.

The remaining of the introduction is structured as followed: First, I outline a criminal career framework to examine group trajectories. I then turn to the literature on the sociology of small groups, focusing on previous research that has investigated the mechanisms of group dynamics and evolution. This is followed by an overview of network methods and how they may be applied to assess group dynamics. To conclude, a systematic review of the state of the knowledge on terrorist networks is conducted, before presenting the three empirical studies conducted in the dissertation.

1.1. Terrorist Life Cycles and the Collective Criminal Career

Our analysis of the life cycles of terrorist organizations is guided by the criminal career paradigm (Blumstein, Cohen, & Nagin, 1978). Starting in the early 1970s with one of the first large-scale studies of crime, the Philadelphia Birth Cohort Studies (Wolfgang et al., 1972; Tracy et al., 1990), the criminal career paradigm grew in popularity with the publication of the United States’ National Academy of Sciences study (Blumstein, Cohen, Roth, & Visher, 1986). The criminal career can be defined as the longitudinal sequence of offending that characterizes individuals’ offending patterns over their ‘criminal career’. It aims to capture an offender’s onset (begins offending), persistence (continues to offend), escalation (changes in offending patterns over time, such as an increase in seriousness, or specialization), and desistance (decreased rate of offending until the eventual cessation of offences). Although originally designed to assess variation in individual offending patterns, many of the criminal career concepts have been applied to assess variation in group-level offending patterns (e.g. Tremblay et al., 1989; Amirault & Bouchard, 2015; Westlake & Bouchard, 2015).

Consistent with earlier ‘collective criminal career’ scholars, our application of the criminal career paradigm to terrorist groups departs from more traditional individual and outcome-based approaches in two main ways. First, a distinct tradition of criminal career research is the use of individuals rather than groups as the unit of analysis. While an individual-level focus provides a means to capture variation in offending patterns across individuals, scholars have argued that this approach extracts offenders from the setting in which they are carrying out criminal acts. One
of the first departures from an individual to a group-level approach was Tremblay et al.’s (1989) analysis of 62 adult biker gangs. Coining the term ‘collective criminal career’, the authors looked at variation in offending patterns across biker gangs over a fourteen-year period. Different group parameters, including their formation (onset), duration and demise was used to characterize the biker gang landscape in Québec, Canada. The aim was to demonstrate that: 1) the criminal group has its own career, independent of any of the members; and 2) within-individual variation can only be understood within the context of the group’s overall trajectory. The contextual differences afforded by groups influence the opportunities available to offenders embedded within them (e.g. the scope of available co-offenders across cohorts) and the risks associated with continued involvement with the group (Tremblay et al., 1989). This perspective is consistent with criminology research, more generally, that has shown offending pathways are structured by opportunities embedded in peer networks (e.g. McCord & Conway, 2002; McGloin & Piquero, 2010), and terrorism-specific research showing offenders embedded within organizations are more likely to remain committed to the group (Stevenson & Crossley, 2014).

The second point of departure from traditional criminal career research is a shift from an outcome to a process-based approach. Rather than look at variation between individuals using individual attributes as variables, this approach examines the social context in which individuals are embedded. Specifically, network methods are applied to capture the dependency of actors within the group, as opposed to assuming that offenders are independent of one another. From this approach, the group is considered as a set of interdependent interactions with the main variable influencing individual and group processes being the set of interactions. As such, it is assumed that the collective interactions within groups has important implications for understanding a group’s trajectory (Tremblay et al., 1989).

1.2. Group Dynamics and the Sociology of Small Groups

Although groups have long formed a cornerstone of criminology theories, the study of crime has been slow to seize the group as the unit of analysis. However, the idea that group processes play a key role in collective behaviour has a long tradition in the sociology of small groups and social psychology literature. This area of inquiry, often referred to as ‘group dynamics’ has been used to explain why groups emerge and persist over time, and has explicitly merged the two foci of the current dissertation: a group’s evolution and the set of social interactions they
consist of. This approach to understanding groups is highlighted in Lewin’s (1948) conceptualization of the group, one of the earliest scholars to lay the foundations of group dynamics:

The essence of a group is not the similarity or dissimilarity of its members, but their interdependence. A group can be characterized as a ‘dynamical whole’; this means that a change in the state of any subpart changes the state of any other subpart. The degree of interdependence of the subparts of members of the group varies all the way from a loose ‘mass’ to a compact unit (Lewin, 1948, p. 84).

Group dynamics refers to the behaviour, processes, activities, and changes that occur in groups (Lewin, 1943; 1948; 1951). The group is considered a set of interactions that shape its members’ behaviours and actions. How individuals are exposed, interpret information and their corresponding behaviour to this information is influenced by the social environment in which they are embedded. One of the most powerful mechanisms of group dynamics that has emerged in the literature on the social psychology of small groups is cohesion. Cohesion – in network terms, has been operationalized as the degree to which individuals are connected within the group, and conceptually has been referred to capture an attraction to other members of a group, or a ‘we-feeling’ generated by a group – has been found to be a key driver of group dynamics. A group’s cohesion has been associated with its longevity, promoting commitment and attraction to the group (Hogg, 1992). Additionally, cohesion has been found to constrain behaviour, increasing homogeneity among group members. Individuals embedded within cohesive groups are less likely to be exposed to individuals outside, creating an echo-chamber, reinforcing already held perspectives, and fostering the development of an in-group identity (Rice, 2009). Cohesion can also serve as a monitoring mechanism, with high interconnectivity across members meaning that there is little that members can do without others knowing. From this perspective a group’s cohesion mediates group dynamics.

Cohesion has also emerged as a key moderator of the group’s influence on the individual in the terrorism literature, and has been suggested to influence conformity to group norms and more extreme perspectives. Interviews with 35 incarcerated terrorists suggested that cohesion facilitated the development of an in-group norm based influence, defining individuals outside the group as the enemy and finding commonality with others within the group (e.g. Post et al., 2003, p. 176). This has been observed in violent conflict more generally, where members of the group’s actions are influenced by the expectations of the group, and, reciprocally, individual members’ actions influence the group’s standing (Gould, 2003). This creates a collective identity where the
group’s successes/failures become synonymous with the members, creating consequence for individual actions.

Traditionally, group dynamics, or specifically, tests of cohesiveness on group dynamics, have been measured through self-reports or observations of behaviour (e.g. membership turnover, proximity to others, and expressions of belonging) (e.g. Hogg, 1992, p. 41-43). However, these approaches aren’t without their limits, something that has been long expressed in criminology research (e.g. Short & Strodtbeck, 1965). Self-reports are based on the assumption that group members have the ability to accurately perceive and report the cohesiveness of the group, while observation requires direct access to the members. Recently, given that theories of group dynamics are expressed in terms of interactional concepts, there has been a movement towards a network approach to systematically quantify a group’s cohesion as the degree of interconnectivity between members (Papachristos, 2013). This is consistent with early gang research that suggests cohesiveness must involve member interaction (Klein & Crawford, 1967, p. 70), and more recent quantitative analyses of cohesion in the criminology literature (e.g. Haynie, 2001; 2002; McGloin, 2005; 2007; Hughes, 2013). The next section explores the use of network methods to quantify the set of interactions across individuals as a means to understand behaviour.

1.3. The Role of Social Network Analysis in Understanding Small Groups

An understanding of terrorism life cycles as a product of group dynamics requires a methodological shift to network analysis. Network analysis rests on the fundamental premise that individual behaviour is best understood not by studying individual characteristics or attributes, but by examining the network of relations in which individuals are embedded (Wasserman & Faust, 1994). Relationships between individuals are assumed to capture the resources and opportunities that can be accessed through ties to different actors. Differential access to these opportunities and resources in turn can facilitate or constrain behaviour (Wasserman & Faust, 1994). In other words, it is assumed that the web of relations in which individuals are embedded serve as a mechanism whereby actors influence each other’s behaviours. Thus, rather than focus on individuals as the unit of analysis, network methods turn to the relationships between individuals
(or entities) as the unit of analysis. Its main assertion is that actors are all interdependent, and thus cannot be understood without considering the social context in which they are embedded.

The emergence of network analysis can be traced back to the early work of scholars on group dynamics and graph theory. One of the first proponents to quantify a group’s topological structure was Lewin (1951). However, it wasn’t until Cartwright and Zander’s (1953) work on developing graph theory to understand group behaviour and Moreno’s (1953) work on incarcerated adolescent females, would relationships across actors be depicted in a network form. Moreno (1953), a social psychologist, examined ties between incarcerated adolescent women to understand how different sets and patterns of interactions could be used to organize females into housing units that reduced the likelihood of conflict. This resulted in the creation of a ‘graph’, which consisted of a representation of the network, through a set of relations (‘ties’ represented by lines) that connected a set of actors (‘nodes’). This allowed for graph theory, a body of mathematics that captures the properties of the patterns created by these relationships. Graph theory represented a major transition in network analysis, allowing researchers to analyze the overall group structure of all members at the same time versus the structure of the group from the view of a specific person at a time (Scott, 2013).

However, network analysis goes beyond the simple collection of dyadic ties between actors, and argues that the:

> flow of information and resources between two people depends not simply on their relationship to each other but on their relationship to everybody else. For example, it matters whether two people who communicate with one another are embedded within a cluster of individuals who also talk to one another, versus embedded within two separate clusters that otherwise do not communicate at all” (Katz et al., 2014, p. 312).

Thus, it provides a means to assess the aggregated features of the network and how different subparts of a group influences other subparts, a key component of group dynamics (Lewin, 1948).

In criminology, network methods have been applied to test many of the direct premises of early theories of crime. For instance, differential association theory argues that criminal behaviour is learned through interactions with delinquent peers. Specifically, that an individual’s relationships provide a means to learn attitudes or ‘definitions’ that are favourable toward the violation of laws (Sutherland, 1947). Social learning theory also emphasizes that an individual’s criminal propensity is linked to their social context, expanding on this and stating that not only exposure to criminal definitions, but the intensity of this exposure is important (Akers, 2009).
These criminal definitions are argued to be diffused across members of the network and reinforced through repeated interactions with others (Felson, 2003). Empirically testing these claims, Haynie’s (2001) study of peer networks found that associating with delinquent peers was more strongly associated with personal delinquency when they were embedded in dense, highly connected networks. In other words, individuals were more likely to behave in ways consistent with the group when these groups were tightly connected.

The structure of criminal networks has also been found to influence offending patterns. McGloin and Piquero (2010) examining the co-offending network of a random sample of arrested youth showed that the structure of an individual’s co-offending network was associated with specialization or versatility. Offenders who were embedded in non-redundant co-offending networks (less cohesive) were found to engage in a diversified set of crime-types. The authors argued that exposure to a range of criminal offenders provided greater access to opportunities and skills that allowed offenders to expand their crime repertoires (McGloin & Piquero, 2010). Other studies have also demonstrated that changes in network properties have a subsequent impact criminal behaviour. Lantz and Hutchison (2015), examining the impact of arresting a ‘central’ member in a co-offending network, showed that arresting brokers – offenders who bridged co-offenders – reduced the number of offences committed by their co-offenders.

These studies also represent one of the main advantages of network analysis: providing a means to treat the group as a dynamic entity. This approach is consistent with criminology research that has found criminal networks evolve over time and across an individual’s life course. As individuals are arrested, killed, or retire from criminal lifestyles, criminal groups may grow, shrink and change in structure over time. This is particularly true in the case of terrorist groups, which have found to have high actor turnover (e.g. Stevenson & Crossley, 2014) and also subject to splintering. For instance, 21 percent of Jones and Libicki’s (2008) sample of 648 groups splintered over the course of their trajectory. Other group dynamics that characterize terrorist life cycles are their tendency to re-structure, form rivalries/compete with one another, forge alliances, and share members (Jones & Libicki, 2008). These organizational characteristics have been suggested to be potent mechanisms in the emergence and eventual demise of groups, terrorist (e.g. Crenshaw, 1991; USIP, 1999; Jones & Libicki, 2008), or otherwise (Klein, 1971). However, the structure of terrorist groups has rarely been examined in tandem with the group’s trajectory.
1.4. Explaining Terrorism from a Network Perspective

Despite the central role of organizational characteristics in early examinations of terrorist organizations (e.g. Crenshaw, 1991) the application of network methods to study terrorist groups is a relatively recent phenomenon. The adoption of network methods in the terrorism literature can be traced back to Valdis Krebs who provided one of the first visualizations of a terrorist network in 2001. Using media sources, Krebs (2001) mapped the internal structure of the 9/11 hijacking network, demonstrating that it went well beyond the hijackers, with a broad range of participants involved in coordinating the operation. Since his well-publicized work, the number of studies using network methods to study terrorist organizations has been steadily increasing. However, there has been little systematic review of these studies, for instance, how data is being collected, the methods that are being applied, and the main findings of this research. The current section provides a systematic review of the academic literature on terrorist networks. The aim is to synthesize what we know about the scope and structure of terrorist networks, and examine the main conclusions that may be drawn on terrorist group dynamics across studies.

Methodology. The review followed the general principles of the Campbell collaboration with the goal of obtaining a comprehensive list of articles for inclusion. The review aimed to capture studies that had mapped out the networks of both individual terrorist offenders and groups, providing a means to compare network properties across studies (a full list of inclusion/exclusion criteria can be found in Appendix A). Focus was placed on peer-reviewed academic papers that had examined the structure of terrorist networks. Other sources, including books, government reports, think tank reports, and university theses/dissertations were also consulted. To locate sources, open source searches on three main websites: Google, LexisNexis, and Google Scholar were conducted, with the search terms being key words common amongst relevant documents. Key words included “terror*”, “extrem*”, “network”, and combinations of. For all acquired sources, a review of all the references cited by each report, as well as any relevant

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1 An exception to this includes Zech and Gabbay’s (2016) review of the literature on terrorist networks. However, the authors review represented “selected publications that are representative of major themes and debates within the literature” (p. 9); where here I intend to provide a systematic review of structural characteristics of terrorist networks across studies.
works that had cited the acquired source were sought out. Finally, the CVs of well-known terrorism network researchers were consulted.²

Acquired sources were then coded based on the studies general objectives, the data sources used to build the network (e.g. open source versus interviews); unit of analysis (individual-level; group-level), whether the network was cross-sectional or longitudinal, the organization’s ideology, network characteristics (e.g. size, density, and clustering coefficient), and, if applicable, the method of statistical analysis, the operationalization of network variables, and the study’s main findings (see Appendix B for full coding scheme).

**Results.** The search strategy resulted in retaining 99 studies that had examined terrorist networks. All studies had been published within a fifteen-year period (from 2001 to 2016). Since the first network study in 2001, its popularity as an analytical technique has been gradually increasing, with most studies of terrorist networks published in the last five years. More than half (65%) of all terrorist network studies have been published from 2012 to 2016. Across studies authors primarily relied on original datasets, using open source data or interviews with law enforcement to map the terrorist networks under study (64 original datasets).³ Across the 64 datasets, many consisted of more than one terrorist network, representing a total of 131 terrorist networks. Most networks mapped the individual-level ties between actors (n=118), with a fraction mapping group-level ties across terrorist organizations (n=13). Sources that mapped the internal structure of terrorist groups (individual-level ties across members) were further divided into attack (n=95), organization (n=13), and ego (n=6) networks.⁴ ‘Attacks’ capture the network of offenders who participated in attacks, ‘organizations’ represent the larger network of offenders involved in the group’s organizational structure, maintaining and sustaining the group, and ‘ego’ networks refer to an individual(s) set of ties to other members within the terrorist organization.

² This included Scott Atran (Director of Research in Anthropology at the CNRS; École Normale Supérieure, Senior Research Fellow, University of Oxford); Victor Asal (University at Albany); Gisela Bichler (California State University); Robert Everton (Naval Postgraduate School); Scott Helfstein (Previously at Combating Terrorism Center); Ami Pedahzur (University of Texas at Austin); and Ari Perliger (United States Military Academy at West Point).

³ Of the 99 studies, 35 relied on publicly available datasets or re-used data from previously published studies. The most popular datasets across these 35 studies included: the Big Allied and Dangerous 1.0 Database (six studies, and also used as a jumping point to expand on for an additional three studies); the John Jay and Artis Transnational Terrorism Database (JJATT) (n=5); Krebs (2001; 2002) (n=6); Koschade (2005) (n=5); and Sageman (2004) (n=4).

⁴ The boundaries of 10 networks were not clearly defined, and therefore classified as ‘unknown’.
Across the 99 studies, analyses of terrorist networks can be broadly classified into two categories: 1) Descriptive, describing the network properties of terrorist organizations; and 2) Analytical, using terrorist network properties to model individual/group behaviour, or examining the factors that predict network properties. The following sections first focus on the scope and structure of terrorist networks across studies; and then turns to studies that conducted statistical analyses, outlining the main findings pertaining to group dynamics across studies.

The scope and structure of terrorist networks. Most studies of terrorist networks tend to be descriptive, examining the structural characteristics of groups: whether the organization adopted covert or efficient network structures and describing how individuals came together and were connected in the periods leading up to, or following an attack. Table 1 reports the structural properties of terrorist networks across studies that disclosed the group’s size, density, and clustering coefficient. These measures were the most popularly reported across all studies, and all provide complementary measures of a network’s degree of connectivity, representing the degree of overall cohesion within a group and compartmentalization into dense subgroups. Density provides insight into the overall degree of connectivity within a network. It is calculated by taking the ratio between the total number of observed ties and total possible number of ties. The clustering coefficient helps tease out the findings of a group’s overall density by measuring the degree of local clusters within the network.

Table 1. Reported Structural Features of Terrorist Networks across Studies

<table>
<thead>
<tr>
<th></th>
<th>Size Mean (SD)</th>
<th>Density Mean (SD)</th>
<th>CC Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attack networks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=95</td>
<td>22.57 (16.31)</td>
<td>.43 (.26)</td>
<td>.45 (.21)</td>
</tr>
<tr>
<td>n=88</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>n=43</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>n=38</td>
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<td></td>
</tr>
<tr>
<td>Organization networks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=13</td>
<td>205.09 (115.27)</td>
<td>.06 (.04)</td>
<td>.52 (.03)</td>
</tr>
<tr>
<td>n=11</td>
<td></td>
<td></td>
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<tr>
<td>n=4</td>
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<td></td>
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<td>n=2</td>
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<td></td>
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<tr>
<td>Ego networks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=6</td>
<td>75.25 (14.99)</td>
<td>.22 (.27)</td>
<td>-</td>
</tr>
<tr>
<td>n=4</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>n=2</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Group networks</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n=13</td>
<td>201.36 (187.66)</td>
<td>.02 (.02)</td>
<td>.54 (.27)</td>
</tr>
<tr>
<td>n=11</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>n=4</td>
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<tr>
<td>n=2</td>
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</tbody>
</table>

Note 1. Not all studies reported the network’s size, density, or clustering coefficient. The n refers to the total number of studies that reported each measure.
Note 2. One outlier was removed (Gill et al., 2014) due to the period of coverage resulted in large-n (n=1384). Network size measures with the outlier included are: mean: 303; SD: 344.02.

The structure of attack, organizational, and ego networks are examined separately, reflecting the different boundaries, and allowing for more accurate comparisons across studies.
Attack networks tended to be relatively small in size, with an average of 22.57 individuals (SD: 16.31) directly or indirectly involved in the attack. Attack networks were moderately well-connected, with 43 percent of all possible ties present between actors, and moderate-levels of clustering (.45). This suggests that attack networks tended to be relatively decentralized but were organized into compartmentalized cells. However, attack networks displayed a wide range of connectivity – even across cells of similar size. For instance, across the 26 offenders involved in the 2002 Al Qaeda Gibraltar attack only 13 percent of all possible ties present. In contrast, the 1995 Aum Shinrikyo Sarin attacks involved 20 offenders, who were all connected.

While attack cells tended to be small, studies of individuals’ ego networks, showed that offenders tended to be connected to an average of 75.25 other individuals within the organization. This high number of ties may be due to the selection of egos, who tend to be chosen for study based on their centrality or an importance in an organization. Surprisingly, ego networks of individuals were relatively sparse, with only 22 percent of all connections of one’s friends connected with one another. This goes against a body of research that finds extremists adopt densely connected networks; however, may be explained by aggregating an individual’s ties over time, rather than at specific intervals. Similarly, organizational networks tended to be much larger, on average consisting of 205.09 members. While attack networks were relatively dense (.43), organizational networks tended to be sparse (.06) with little connectivity across the group. Despite low overall connectivity, organizations had an average clustering coefficient that is over eight times larger than the average density score (.52), suggesting the presence of multiple small, highly connected hubs. This highlights the diversity in density across offenders, with some offenders highly connected to the network, and others with few ties to the organization.

Studies that examined the networks of alliances across groups (e.g. ties across organizations), had an average of 201 organizations in their sample. Groups rarely formed alliances to one another, with two percent of all possible ties present across all groups. However, there was a relatively high degree of clustering (.54), suggesting that of the few groups who created alliances, they formed into highly connected sub-groups.

5 Very few studies mapped changes in the presence or nature of relations over time. Rather studies tended to map relations at a single aggregated point in time. Of the dynamic studies, that captured changes in both the presence of actors and their ties to other actors, they were typically in discrete-time, capturing different periods of activity, or across specific time-intervals (e.g. annual intervals). To facilitate comparison across studies only static network measures are reported.
To determine variation across attack networks, Figure 1 plots the size and density across attacks. A total of 43 studies reported both the attack network’s size and density. Variation in density was found across small groups of 2 to 15 offenders, ranging from almost no connectivity to all members being connected (density of .2 to 1). While larger groups (greater than 15 members – the median group size) had slightly lower variation in measures of density (non-significant). Small groups reported an average density of .46 and larger groups an average density of .37. This is consistent with earlier studies that have shown increases in network size are associated with reduced interconnectivity (Mayhew & Levinger, 1976). However, low density does not always indicate low connectivity with overall measures of interconnectivity masking pockets of cohesion (e.g. Friedkin, 1981). However, few studies reported the clustering coefficient across studies, precluding comparison of local clustering across attack networks.

![Graph showing size and density of attack networks](image)

**Figure 1. Size and Density of Attack Networks**

Note 1. This represents 43 attack networks, representing studies which provided information on both the group’s size and density.

This assessment of the scope and structure of terrorist networks across studies shows that there does not appear to be a monolithic terrorist profile. Rather groups tend to exhibit variation, ranging from small, dispersed networks, to highly connected larger groups. This may be attributed in part to study’s different methods of collecting network data (e.g. relying on interviews versus media sources), and the application of different boundaries (e.g. only those directly involved in the attacks, versus direct involvement and peripheral members). However, even when accounting for methodological differences the results show there are a wide range of network configurations in how terrorist groups organize themselves.
**Group dynamics and terrorist networks.** Despite extensive variation across the network properties of terrorist groups, studies that have examined the impact of these network properties on individual/group outcomes show that there are specific configurations that can help understand the behaviour of groups. This section turns to studies that have conducted statistical analyses of terrorist networks, and can broadly be classified into two categories: 1) studies that use network properties as independent variables to predict outcomes (both group and individual-level outcomes); and 2) studies that use network properties as a dependent variable, as something to be predicted.

Many of these analyses are guided by the core assumptions that networks organize themselves around efficiency and security. While security is optimized in decentralized network structures, minimizing exposure to outside enforcement, efficiency is facilitated in networks with higher connectivity, providing the necessary communication chains to coordinate complex crimes. A key component of terrorist network analysis has been to test these assumptions. That is, which network structures are more predictive of security or efficiency? To measure these concepts, studies have used the longevity of an organization to measure its security (ability to avoid detection) and productivity to measure efficiency (number, or lethality of attacks). These studies have led to three key findings:

i. **Groups that adopt elements of centralization and decentralization are more likely to survive longer.** Perliger (2014) examining the networks of 18 terrorist attacks (consisting of 479 offenders) found that there was no one terrorist profile. Findings from ANOVA tests found that there found no significant relationship between a group’s duration (measured in months) and their structural characteristics (density and centralization). While there was a tendency for groups who lasted longer periods to have a lower density, these were not statistically associated with their longevity. In contrast, groups who survived for a greater duration, were more likely to adopt clique based structures, with resilient groups adopting a high number of small densely connected groups. This led to the main conclusion that a balance between densely connected clusters and a decentralized overall network is more likely to increase a group’s survival over time.

ii. **Groups who have a higher number of alliances to other organizations are more likely to survive longer.** At the group-level, studies have shown that the number of alliances a group has with other terrorist organizations extends their life span (Acosta, 2014; Phillips, 2014; Pearson et al., 2015). This finding has been reproduced across data sets and has been maintained even
when controlling for other factors, such as regime type, group ideology, group size, and economic factors.

***The number and structure of alliances to other terrorist organizations influences groups’ lethality:** Studies have also found that alliances with other terrorist organizations increases a group’s own lethality. However, two sets of findings have characterized the literature on the impact of alliances on a group’s lethality. Looking across 310 militant organizations active between 1980 to 2013, Acosta (2016) found that the number of ties an organization had to other groups increased the number of suicide attacks they perpetrated. Consistent with these findings, Asal and Rethemeyer (2008a; 2008b) examining 395 terrorist organizations from 1998 to 2005, demonstrated that highly connected groups not only conducted more attacks, but were also more likely to inflict a greater number of fatalities. A finding that was maintained even when excluding one of the most fatal and connected groups – Al Qaeda. In contrast, Pearson et al.’s (2015) examination of 149 terrorist groups active during 1987 to 2005 found that the number of alliances did not impact the lethality of group, when controlling for the structure of these alliances. Controlling for a group’s eigenvector centrality, showed that groups who had alliances with groups who were well connected, increased the likelihood of launching fatal attacks, while a group’s own connectivity had no impact on fatalities. In contrast, Horowitz (2014), who mapped the relations between terrorist organizations using data derived from the Terrorist Knowledge Base (TKB) (also used to create the BAAD dataset used by Asal and Rethemeyer (2008a; 2008b), examined 431 terrorist organizations active between 1998 to 2008 and found that the number and structure of a group’s alliances (using eigenvector centrality) were both associated with a group’s lethality. This discrepancy in findings may stem from two scenarios. One, earlier studies failure to control for the structure of alliance ties when predicting a group's lethality. Or, alternatively, it may be related to Pearson et al.'s (2015) truncated sample, only examining 149 of the 395 groups examined in Asal and Rethemeyer’s (2008a; 2008b) studies.

A second body of research has focused on the relationship between the organization’s structure and an individual’s involvement with the terrorist group. These studies have found that the degree to which an individual is connected to the group influences their commitment to the group; yet once members become connected to the group there is a saturation point in their connectivity, with few new relationships being formed after a certain number of connections have been established.
i. Offenders’ connectivity to a terrorist organization influences the length of their involvement. Stevenson and Crossley (2014) examining the networks of 249 leaders of a terrorist organization found that leaders with high degree and closeness centrality remained with the group for longer periods. These findings suggested that joining a group and becoming a central member helps promote integration and sustains their commitment over time (Stevenson & Crossley, 2014, p. 83). In contrast, Bichler and Bush (2016), examining the ego networks of 41 of the most central actors of Al Qaeda, found that actors who had fewer connections to the network were more likely to survive longer (not be arrested or killed). However, they did find that individuals who did remain with the group for longer periods had fewer non-redundant contacts, showing that many of the people they knew also knew each other. This suggested that it wasn’t an individual’s overall number of ties, but rather the degree of closure that may explain why offenders stay with terrorist organizations for prolonged periods.

ii. Embeddedness in the group reaches a saturation point. Individuals who join terrorist networks tend to increase their contacts over time as they become more involved. However, at a certain point – even though the overall network is still growing – individuals already embedded in the network stop forming new connections (Helfstein, 2012). Examining the longitudinal progression of tie formation across offenders involved in six al Qaeda terrorist attacks, Helfstein (2012) showed “that the predicted number of new relationships per period, approximately one year, increases to a maximum of two and half just beyond the halfway point in cell longevity. Once reaching the maximum, the predicted number of new links per period declines rapidly despite the fact that the cells continue to add new members in an approximately linear fashion until the attack” (p. 43-44). Thus, while individuals are likely to create new relationships to other terrorist offenders upon entering the network, the tendency to make new ties drops over time. The author suggests that these patterns may be explained by offenders’ search for external validation. While offenders seek external validation in the early stages of joining the group, this effect decreases as they “progress through the stages of radicalization” (p. 44). This study represents one of the few systematic analyses of the intersection between the group and the offender’s network over time, looking at patterns in tie formation as the group evolves.

A third body of research has examined the factors that predict terrorist network structure. These studies have shown that terrorist groups tend to organize themselves in specific patterns: i) becoming more centralized over time; and ii) structuring themselves into compartmentalized cells.
i. **Terrorist networks become increasingly cohesive over time.** Terrorist organizations are not stable across their life spans. Previous studies have found that groups become more connected in the immediate stages leading up to an attack (Helfstein & Wright, 2011a; Everton, 2013a; Everton, 2015). Looking across attack networks, Helfstein & Wright (2011a) showed that groups adopted more centralized structures with individuals forming more ties to one another in the period prior to executing an attack. These findings are consistent with Everton’s (2013a) analysis of Jemaah Islamiyah who found that, regardless of whether the network consisted of operational ties between actors directly involved in executing the attack or more peripheral members, it became more centralized over time. Bush and Bichler (2015) using SIENA models, also found a tendency for individuals to increase their connectivity to the overall network. Specifically, they found that members of the organization who sent messages “indirectly through an intermediary to receive messages back directly”. Similarly, Cunningham, Everton, and Murphy (2015) also found that offenders in the terrorist network were more likely to form ties with the friend of a friend over time. In particular, they found that the tendency for local clusters to form in terrorist networks was even stronger than the tendency of individuals to form ties with others in the network who had a high number of ties.

ii. **Terrorist offenders are more likely to form ties with individuals who share similar characteristics, and organize themselves into densely connected clusters.** Using data on 161 members of Jemaah Islamiyah, Cunningham et al. (2015), found that individuals who were affiliated with the same mosque or school were more likely to form ties. Similarly, Perliger et al. (2016), relying on 331 offenders who participated in attacks across the globe, found that individuals who were from the same area in which the attack was perpetrated were more likely to have a high number of contacts and be connected to offenders with a high number of contacts. In contrast, Gill et al. (2014), examining 1,384 members of the Provisional Irish Republican Army, did not find homophily between members. Members who had a similar demography or status were no more, no less likely to form ties between one another. However, the authors did find a tendency for members to form ties with others in the network who had similar tasks or roles within the organization. This is consistent with Zech (2010) who found that individuals with the same roles were more likely to collaborate together in the 2004 Madrid bombing network.

The formation of alliances across groups also appears to be determined by logistical factors. Groups that have similar ideological motivations, organizational duration, share a common enemy, and are from the same region are more likely to form alliances with one another.
(Asal et al., 2016). The latter finding is consistent with Bapat and Bond (2012) who found that groups who both operate in areas with weak governmental control are more likely to form alliances. Building on these findings, Asal et al. (2016) represents one of the few studies to control for structural effects when examining the predictors of alliances across terrorist organizations. Findings showed that alliances were not only more likely to form between organizations that shared the same ideology, common enemy, were from the same country, or had been active for a similar duration, but also found a tendency for organizations to form alliances within cliques or subgroups.

Assessment of the terrorism network literature. A review of the literature shows that there is no monolithic profile of terrorist organizations. On average attack networks tend to be relatively small in size, have few connections across members, and a high number of densely connected small groups; however, there is great variation across organizations. While some groups are relatively small with few connections across members, others are large with high connectivity across members. Statistical analysis of terrorist groups shows that the degree of connectivity to other organizations influences their productivity (measured by number and lethality of attacks) as well as the length of their life span. Furthermore, groups tend to become increasingly centralized over time, as they lead up to action stages, and are often structured into cliques or densely connected subgroups.

This review also allows us to identify a few gaps in the literature. A first gap extends from the boundaries of groups. Most studies are only able to study the action component of the network; however, going beyond the ‘action’ boundary and looking at the members who played indirect roles shows how attack networks are embedded in a larger set of relations. Of the few studies that have gone beyond the attack network, they have demonstrated the importance of including these peripheral members. Krebs’ (2001; 2002) analysis of the 9/11 hijacking network illustrated the advantages of applying broad boundaries for examining a group’s network structure, showing that members, beyond the hijackers, were important in bridging the action segment together, allowing the group to adopt a more efficient network structure. This is consistent with Rodríguez (2005) whose examination of the 2004 Madrid train bombing network led to the claim that “this larger network does not act, but it makes action possible”. While these studies have shown that terrorist organizations depend on a larger set of members beyond those directly implicated in the conspiracy, few studies have systematically examined how the larger set of interactions influence the evolution of terrorist groups.
Second, most studies have followed trends in structure across groups, with few studies looking at variation in structure within groups. Studies tend to be static in nature, only looking at a group’s structure at a single point in time. However, criminal groups, terrorists or otherwise, are rarely fixed entities. The recruitment of new members, interdictions, disengagement, and internal conflicts, are a few of the processes that impact the structure of illicit organizations. While dynamic tendencies are characteristic of group processes, much of the research on terrorist networks have classified structural properties into bounded categories. Restricting networks to static interpretations, assumes that structural properties extend the same effect across a group’s trajectory. An assumption that has been challenged by research on the impact of offending networks across dimensions of the criminal career (e.g. McGloin & Piquero, 2010; Lantz & Hutchison, 2015; Thomas, 2016). Changes to an offender’s network can create subsequent impacts on a group’s offending pathways. Terrorism research has not been blind to the dynamic tendencies of organizations (e.g. Xu, Hu, & Chen, 2009; Helstein & Wright, 2011a; Bush & Bichler, 2015; Cunningham et al., 2015; Bichler & Bush, 2016); however, few studies look at the interaction between a group’s evolving network properties and their trajectories. A focus on dynamic group processes can help disentangle whether structural properties influence individuals’ and groups’ trajectories, or whether they are simply a result of these processes.

1.5. Research Contributions

It is well accepted that the nature of relations in which offenders are embedded influences offending pathways. Yet, few studies have examined the intersection between a group’s network structure and group behaviour. If a group’s network structure is important for understanding terrorist organizations we would expect certain structural properties to be associated with key turning points in a group’s evolution. Furthermore, if the group plays a role in structuring behaviour, then we should see an effect of the group on individuals’ actions above and beyond any individual attribute. This dissertation aims to examine the intersection between a group’s structure and its trajectory, by presenting three independent, but related empirical studies that examine the role of criminal groups in shaping offending behaviour at both the individual and group-level. The first study examines the structural features associated with a terrorist organization’s emergence; the second study looks at the factors that lead individuals to collaborate within terrorist organizations; and the third study focuses on the correlates of repeat offending within a group over time. Across all studies we examine the role of an organization’s
structural features, as well as other theoretically relevant variables - as potential confounders in predicting a group’s dynamics.

1.5.1. Study 1. Group Boundaries and the Emergence of the ‘Toronto 18’ Network

The first study examines the network properties of a terrorist organization from the time it emerged until its demise, to assess how structural features influenced key turning points across the group’s trajectory. Most studies assess the ‘action’ component of the network, only including actors who were detected and charged with an offence. But ignoring sets of actors can cut off the social influence mechanisms that an offender is embedded in and lead to presentations of groups as static, rather than reflect the dynamic and transient nature of group-offending. The aim is to look at how the full scope of affiliates, who interacted with the group, but were not charged, influenced the group’s structural evolution in a major terrorist conspiracy.

Data obtained from interviews with an individual formerly embedded in the Toronto 18 – a terrorist organization widely stated to consist of 18 members – and court documents provided a rare opportunity to see the full scope of the group across its trajectory. Network methods are first applied to examine how the non-charged affiliates fit into the original group structure. Following this, longitudinal community detection methods are applied to see how their set of interactions influenced the group’s evolution over time. We examine the distribution of non-charged affiliates into communities, and how the structure of these communities evolved over time. These analyses allow for both empirical and theoretical contributions. At an empirical level, this allows us to compare group boundaries across official sources and self-report data, and how this influences our assessments of the emergence and evolution of illicit groups. At a more theoretical level it serves as an examination of the group-level processes of radicalization, allowing us to examine the structural features associated with a group’s emergence and transition into an organization willing, and capable to commit violence.

1.5.2. Study 2. Criminal Collaboration and Risk: The Drivers of Al Qaeda’s Network Structure before and after 9/11

The second study examines the correlates of co-offending in terrorist networks. We know that criminal groups are more likely to adopt sparse, decentralized networks to minimize exposure to law enforcement (Baker & Faulkner, 1993; Morselli, Giguère, & Petit, 2007). But despite long
standing theoretical links between a network’s aggregate structure and the degree of risk, empirical research has rarely examined the drivers of tie formation at the individual-level. That is, little is known about the factors that lead individuals to collaborate, and co-offend in criminal groups. Using data on 118 terrorist offenders across six attacks we test whether individual decisions to collaborate are influenced by variation in law enforcement activity.

Al Qaeda who faced two different levels of law enforcement activity pre/post-9/11 provides an opportunity to examine individual decisions to collaborate across periods of increased risk. Network data on 118 offenders who were involved in attacks are mapped from open sources, including court documents, government reports, and media sources. Our empirical focus is the patterning of connections between co-offenders in terrorist attacks, and how this varies under more intense law enforcement pressure. To examine the factors that lead two offenders to develop a co-offending tie we use Exponential Random Graph Models (ERGMs). As a class of statistical models, ERGMs assess the probability of a tie between two actors existing, using properties of the network as well as actor attributes as predictors (Lusher, Koskinen, & Robins 2013). ERGMs consider a binary relationship as the dependent variable: the presence or absence of a tie between two co-offenders. Our main predictor is triad closure – the tendency for a tie to exist between offenders who have a co-offending tie in common – to capture whether local network closure is moderated by external risk. The study also considers an offender’s leadership position, as well as their role in the attack as potential confounders in predicting the formation of ties.

1.5.3. Study 3. Terror on Repeat: Criminal Social Capital and Participation in Multiple Attacks

The third study examines the predictors of repeat offending within terrorist groups. Terrorist groups often depend on repeat offenders to maintain their longevity. Yet, little is known about the individual offenders who perpetrate multiple attacks on behalf of a group. This study relies on data for 118 offenders involved across eight attacks perpetrated by Jemaah Islamiyah. The series of attacks provides us with a unique opportunity to study patterns in selecting terrorist co-offenders. A majority of the JI members were only selected once, but some were involved in as many as six or seven attacks. The question at the heart of this study is whether there are clear differences between the single attack and the repeat terrorist offenders. We posit that criminal social capital – here measured by an offender’s co-offending ties – is likely to be a predictor of participation in multiple attacks.
Data on the 118 offenders is obtained from the John Jay and Artis Transnational Terrorism Database (Atran et al., 2008) a public online database that provides network and attribute data, and open sources, including think tank reports, news media and peer-reviewed articles. The individual network of each terrorist offender in the overall network is constructed, to examine their structural position within the group. Poisson regression models are used to model the number of attacks an individual is involved in. The hypothesis that the size and structure of an offender’s network facilitates selection and willingness to be involved in multiple attacks can be tested. The study also considers competence in the form of human capital – highest level of education – along with criminal capital – occupying a leadership position and experience as a militant – as potential confounders in predicting repeat terrorist offenders.

Summary. While individually each study taps into a specific outcome (e.g. group-level radicalization; formation of co-offending ties; and repeat offending), together these studies aim to address two of the main limitations on the literature of terrorist organizations: 1) the implications of obscuring the wider periphery of participants who interact with the group; and 2) how within-group variation of structural properties influences group dynamics. Although these limitations were identified through a review of terrorism research, they also extend to the study of criminal groups more generally.

Further, all analyses aim to be complementary, capturing three different groups at different points in their trajectory. The first study captures a terrorist group whose trajectory was cut-short, with group members arrested prior to the execution of the attack. In contrast, the second and third studies capture terrorist organizations who survived over extended periods, conducting multiple attacks, despite large-scale law enforcement interdictions. These latter groups allow us to examine the progression of interactions across attacks, from the group’s earliest attacks until the beginning of their demise – as interdictions began to hinder the organization – spanning close to a decade of the groups’ operations. Further, these latter groups allow us to examine an organization who operated transnationally, and an organization who was primarily active in a single country. A focus on across these groups, and the individuals embedded within them, provides a means to capture variation in context, longevity, and importantly organizational structure. Together these studies aim to contribute to the development of a collective criminal career framework that may be applied to further our understanding of group trajectories.
Chapter 2.

Group Boundaries and the Emergence of the ‘Toronto 18’ Network

2.1. Introduction

Where illicit groups begin and end presents a major challenge in the study of covert networks. Defining group boundaries – who is considered part of an illicit group – is among the first steps in designing a network study. Yet, who to include, or exclude, is often made independent of researchers’ assessments, with criminal networks frequently restricted to the set of offenders and relations reported in official crime data. Limited by the available evidence, the individuals present at the operational stages, and those who are actually detected, criminal justice sources force boundaries on groups that are much more fluid and dynamic than they seem. However, despite representing a well-known missing data problem, there has been little cross-validation across network data collected from official records and self-reports of individuals involved in criminal events.

The limitations of official data sources are well known. Official sources underreport the number of offences and offenders involved in carrying out these crimes. Studies that examine the convergence of official and self-report data have tended to focus on the extent to which the scope of criminal activity diverges across sources (e.g. Kirk, 2016; Payne & Piquero, 2016). However, little systematic research exists on how missing data impacts our understanding of the offenders who come together to commit these crimes. The missing data inherent in official sources creates two main issues for the study of criminal groups: 1) groups are much larger than they appear in official data; and 2) groups are often treated as static entities in official data.

The dynamic and transient nature of criminal groups have led to an increase in the application of network methods to study them. Network analysis rests on the fundamental premise that individual behaviour is best understood not by studying individual characteristics or

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6 This is based on a search of the number of network articles in major criminology journals (Criminology, Journal of Research in Crime and Delinquency, and Journal of Quantitative Criminology) using the search term "network*" for the years 2011 to 2015. (2011: n=41; 2012: n=46; 2013: n=40; 2014: n=39; 2015: n=55).
attributes, but by examining the network of relations in which individuals are embedded (Wasserman & Faust, 1994). This is consistent with a body of research that emphasizes that an understanding of offending pathways requires examinations of the full set of actors in an offender’s network (e.g. Paternoster, 1989; Akers & Lee, 1999). However, a reliance on official sources has restricted most studies to the ‘action’ component of the network – those who are detected and charged with a criminal offence. Ignoring sets of actors can cut off the social influence mechanisms that an offender is embedded in, and thus bias our understanding of offending pathways. Further, non-criminal (or non-charged) actors have been shown to be generally necessary for a crime event to occur, providing licit services, or serving broker functions to bridge offender’s together (e.g. Tremblay, 1993; Warr, 1996; Bouchard, 2007; Morselli, 2009). Excluding these actors can lead to presentations of groups as static, rather than reflect the dynamic nature of group-offending, carrying implications for our understanding of criminal networks (Bouchard & Morselli, 2014; McGloin & Nguyen, 2014).

Despite an increase in the use of network methods in criminology, studies have yet to examine how excluding non-criminal facilitators influences assessments of illicit networks. This study examines this missing data issue by looking at the role of non-criminal facilitators in the emergence and evolution of a terrorist organization. Interviews with an individual formerly embedded within a terrorist organization and court documents covering over two years of court proceedings, provide us with a network perspective generally inaccessible to researchers. These sources allow us capture the full scope of the ‘Toronto 18’ – a group widely stated to consist of 18 members – going beyond the offenders charged as part of the conspiracy, to examine how their sets of interactions changed over time. Community detection methods designed for longitudinal network data (Palla, Barabási, & Vicsek, 2007) allow us to examine how the non-charged affiliates influenced the group’s formation, evolution, and eventual split into two independent factions, accelerating the steps toward an attack.

### 2.2. The Problem of Boundary Specification for Crime Groups

The problem of boundary specification extends beyond the purview of criminology, and can be broadly classified into two perspectives: 1) boundaries exist independently of the group structure (i.e. individual attributes are used to identify group boundaries); and 2) boundaries are dependent on the group’s structure (i.e. patterns of ties and social interactions can be used to identify relevant actors). Both approaches are not mutually exclusive, but rather represent
complementary methods to assess the scope of groups. Elements of both of these strategies are found within Laumann et al.’s (1983) seminal research on boundary specification. According to this work, group boundaries can be approached through a realist strategy, in which group parameters are based on the perspective of members themselves, or a nominalist approach, where boundaries are specified according to the analytical framework proposed by the researcher. As identified by Laumann et al. (1983), the realist strategy is limited to the extent that it requires members have a shared conception of the group and are aware of the full extent of the group’s composition or operations, relying on the implicit assumption that a ‘natural’ boundary exists – two conditions that are hard to find in criminal contexts. In contrast, the nominalist approach uses the theoretical questions being examined by the researcher to create group boundaries. Providing guidelines to apply the latter approach, Laumann et al. (1983), proposes that relations, the frequency or role of social interactions, can be used as one of the methods to set group boundaries.

That social ties can assist in defining group boundaries, aligns with a network approach to boundary specification. A network approach elaborates on Laumann et al.’s (1983) strategy of using an actor’s set of social ties, by stating that the structural properties of the networks themselves can assist in defining the scope of the group (e.g. Morselli et al., 2007). Rather than define boundaries using actor attributes, the fluidity and flexibility of illicit groups suggests that network methods allow researchers to systematically map the relations within the group instead of assuming a single, homogenous entity are best tailored to capture these dynamics. This was demonstrated by Bouchard and Konarski (2014) who constructed the full co-offending network of a criminal gang to identify its core members. Their findings showed that 1) core members went beyond those originally designated by police; and 2) some of the core members identified by police, only played peripheral roles in the criminal network. Thus, a network approach advocates using the overall set of interactions with members to define boundaries, providing empirical measures to identify key actors, and a more comprehensive picture of all the relational elements that go into carrying out criminal offences (Morselli, 2009; Campana, 2011; Papachristos, 2011; Campana & Varese, 2012; Bouchard & Konarski, 2014).

2.3. **Group Boundaries: Going Beyond the Crime Event**

In covert contexts a network approach to define boundaries provides a method to capture the larger set of individuals that were necessary for a crime event to occur. Previous research has
suggested that criminal groups consist of more than the general pool of accomplices at the time of the offence (Tremblay, 1993). Limiting networks to the actors involved at the time of event, misses the range of social interactions that led to the criminal act, including licit actors, such as legitimate businesses, and the brokers, including family and friends that may have been necessary to bring the group together to conduct operations.

Providing a clear demonstration of the need to extend boundaries beyond the pure operational-segment, is one of the earliest mappings of a terrorist network, that of 9/11 by Valdis Krebs. In his study, Krebs (2001) made a convincing case of demonstrating that studying the operational network alone was enlightening, but insufficient for a full understanding of the processes leading to a terrorist event. Assessing the operational segment of the network (i.e. the hijackers) independently, Krebs (2001) found that the network was highly decentralized with few connections between members, suggesting a very covert structure. However, integrating the operational segment with 18 complementary participants, (actors who were not directly involved in the attack, but provided financial support, skills or knowledge) substantially increased the network’s efficiency, with connectivity across members increasing by 40 percent. Furthermore, accounting for facilitators provided a more nuanced view of core members’ structural positions. Analyses of the full network showed that suitable co-offenders were selected through trusted ties that connected them to the overall operation.

That group evolution, in particular its formation, requires adopting broader views of the organization is also consistent with Marc Sageman’s (2004) pioneering work on the global Salafi jihad led by Al Qaeda. Data on the biographies of 172 terrorist operatives affiliated to the global Salafi jihad were collected with the aim of examining terrorist networks across the world. One of the main conclusions from this work was that members’ social circles, including friends and family; are key to explaining individuals’ transitions into violent groups (2004, pp. 112-113). An exclusive focus on the participants directly involved in attacks would have ignored the individuals who played a key role in members’ entry into terrorist groups (also see Nash & Bouchard, 2015).

Inclusion of these broader members, thus, has important implications for understanding the emergence and evolution of groups; however, access to these affiliates is often limited. Many of the key members involved in facilitating group processes may not be among those directly implicated in the criminal event, highlighting how a reliance on prosecution and enforcement data can bias group boundaries. These challenges extend to law enforcement investigative data, such as wiretaps, that may only represent specific relations to secure convictions or be confined to the
networks of targeted offenders deemed priorities (Campana & Varese, 2012). This was demonstrated by Morselli (2009) who found that reliance on a single investigation misconstrued the extent of a drug trafficking network. Merging three independent law enforcement investigations, the authors showed that the drug trafficking network consisted of a single unit, rather than three separate organizations. When the network was examined as a single unit, it demonstrated that many of the core participants were non-gang members, showing the challenges of focusing on actor attributes to define boundaries. Complementary sources that provide information on the full set of network actors and relations can assist in capturing the dynamic interactions that comprise criminal events.

This also has important implications when testing social influence mechanisms central to many criminology theories, such as learning and opportunity perspectives (Sutherland, 1947; Akers et al., 1979). Central to these theories are the notion that it’s not just exposure to delinquent peers that facilitate offending, but the intensity of exposure and ratio of delinquent to non-delinquent peers that influence offending pathways. This was empirically demonstrated by Haynie (2002) who examined 2,606 respondents in the National Longitudinal Study of Adolescent Health to study the impact of peer networks on their delinquency. Finding showed it was the ratio of delinquent peers in an individual’s network which most strongly predicted their delinquency, more than the total number of delinquent peers, the absolute degree of peers’ delinquency, or the average degree of peers’ delinquency. Thus, the mechanisms that mediate an offender’s delinquency (or that of the group’s) may require an examination of their entire network, rather than just the criminal elements. Thus, focusing on the criminal elements derived from official crime data such as arrest/conviction records can extract offenders from the larger set of relations that influence the adoption of criminal norms and definitions favourable towards crime.

2.4. Current Study

The purpose of this study is two-fold: 1) to examine the impact of excluding non-charged actors on assessments of criminal groups’ evolution; and 2) and how these actors influence groups’ transitions into violence. Criminal groups, terrorists or otherwise, are rarely fixed entities. Consisting of a range of participants from the time they form until their criminal act(s), only a subset of actors and their interactions are detected. The fluidity and transient nature of criminal groups has been observed across terrorist organizations, gangs, and drug trafficking networks (e.g. Decker & Pyrooz, 2015). To examine the impact of restricting networks to the charged
elements, the current study examines the emergence and evolution of a major Canadian terrorist conspiracy – the Toronto 18. The organization, infiltrated by a police agent in the early stages of the group’s formation, provides a rare opportunity to see a group unfold from the early beginnings until its demise. Similar to other scholars relying on unique case studies before us (e.g. Natarajan, 2006), we capitalize on an opportunity to access some of the inner workings/interactions within a group in order to reflect on the larger implications of the social structure in which criminal groups are embedded. Our examination of the group is guided two primary objectives: 1) how do the complementary (non-charged) actors fit into the original 18-member group structure? and 2) how do these actors influence the group’s emergence and evolution?

The Toronto 18 represents the first jihadist-motivated organization prosecuted in Canada following 9/11. Our data extend over a six-month period, from the time a police agent first infiltrated the group until the arrest of 18 members. Although already on law enforcement radar when the police agent first entered the group, the organization had taken few steps toward planning their attacks, and it was during this period that new members were still being recruited. This early stage of the group’s trajectory facilitated the agent’s entry, and also that of others who shared similar extremist beliefs, but who were still testing the waters. Further, the group’s movement into an organized terrorist conspiracy did not evolve in a linear fashion, with the group splitting into two factions only a few months before their arrest. While the two leaders appeared to have complementary leadership styles, an ideological leader - who had charismatic traits to attract and maintain new recruits - and an operational leader - who coordinated the logistics of the attack - their approaches to violent, radical ideas and managing the network created friction. Our network data allows us to assess key turning points in the group’s evolution from the early stages of the group’s formation to the final stages of preparation to conduct an attack.

2.5. Data and Methods

2.5.1. Mapping the ‘Toronto 18’ Network

To map the longitudinal network of the Toronto 18, information about the broader set of affiliated actors required direct access to the organization. A police agent formerly embedded within the group over a six-month period, provided a perspective of the group’s internal dynamics, that of one of the members (albeit ‘pseudo-member’ in this case). Three semi-structured interviews - each approximately two hours in length - were conducted over a one-month period.
Interviews were guided through a series of open-ended questions that tracked the agent’s and group’s interactions during the six-month infiltration of the organization. Questions were asked of the agent regarding each encounter with the organization (a process which was facilitated by notes that the agent had taken at the time of the event). And, for each encounter, the agent was asked about the members’ present, the context of the encounter, the location of the encounter, and a characterization of the relationship between the individuals present.

Despite unique access to an ‘insider’, this data source also presented its own unique limits. The network was constructed primarily from the agent’s perspective and is contingent on the agent becoming aware of their presence. This limit may be mitigated by the extended duration the agent had with the network (over six-months) and the embedded nature of the interactions (the agent was directly accepted into the organization, forming direct links with the leaders, attended training camps, group outings, and the recruiting of members). However, given that the group split into two factions in the months leading up to their arrest, the agent’s involvement at this stage was limited to the one faction, meaning there was little exposure to developments in the break-away faction. To mitigate this limitation, complementary network data acquired from Canadian court documents were obtained to supplement and, where applicable, cross-reference the interview data.

Court documents, which have been cited as the ‘gold standard’ in terrorism studies given that they are generally subject to cross-examination (Sageman, 2004; Freilich et al., 2014), were obtained through two strategies. First, a systematic search of the Canadian court database, www.CanLii.org, using the accused’s names and variations of to acquire available relevant documents was conducted. Second, an information request provided access to documents not openly available through the CanLii website. Together these strategies provided access to 65 court documents totaling approximately 2,290 pages (average: 36.9; SD: 24.3 pages per document). These documents included transcripts of the proceedings, indictments, agreed statement of facts, rulings, reasons for judgment, sentencing, and court of appeal proceedings.

All actors identified in the interviews and court documents were included in the network. This included all individuals who socially interacted with, or were integrated into the group, attending training camps, group outings (e.g. dinners), or were being recruited to join the organization. One exception were the spouses of the members. While there is evidence that some of the group members’ significant others espoused extremist beliefs, they did not attend meetings with group members and were excluded from conversations when members met. However, this
does include the two police agents who infiltrated the network. While these individuals were not officially members the decision to incorporate them extends from their extensive involvement in the group, and their acceptance by the group as members.

### 2.5.2. Measures

Our analyses proceeds in two steps, each relying on a different set of measures that first capture the static, and then the dynamic network properties of the group. The first set of measures — *density, clustering coefficient, and degree centralization* — serve to operationalize the aggregated structural features of the group. These measures represent different features of the group’s cohesion, allowing us to see how the larger set of actors fit into the original 18-member group structure. The second analysis relies on longitudinal community detection methods, to examine how the dynamic set of interactions, and specifically clusters of cohesive subgroups evolved over time.

#### i. Static measures of network cohesion

*Density.* Density calculates the degree to which actors are connected, by taking the total number of ties present between members and dividing it by the total number of possible ties (Wasserman & Faust, 1994). Scores of high density suggest a well-connected network and low scores implies low-connectivity between members. Density has been used to measure a group’s overall cohesion, with higher scores indicating greater cohesion (e.g. Haynie, 2001; 2002; McGloin, 2007), as well as a group’s ability to remain covert, with lower scores indicating a greater ability to elude detection (Morselli et al., 2007).

*Clustering coefficient.* While density captures the overall connectivity of a group, the clustering coefficient assesses the distribution of density across actors. It does this by taking the density of each actor’s personal network (the degree to which their ties are connected between one another) and averaging this across the network (Watts & Strogatz, 1998). Thus, this latter coefficient measures the extent to which actors’ contacts are connected amongst themselves, identifying localized clustering that is not captured by an overall density score. A lower score suggests a low degree of local clustering, while a higher score represents a network with a high degree of local clustering.
Degree centralization. Degree centralization measures whether connectivity within a network is clustered around a single or limited number of nodes, with low degree centralization (0%) representing cliques, where are nodes are well connected, and high degree centralization (100%) indicating that connections exist only between one actor and all other nodes (Freeman, 1979). High degree centralization may suggest more formal organizational structures, with a few key nodes directing other more peripheral members (e.g. Morselli, 2009).

ii. Dynamic network measures

Newman community detection. Community detection methods provide a means to detect cohesive subgroups present in the network and track them over time. This method partitions the network into densely connected subgroups who have a high number of connections to one another, and few connections across subgroups. We apply the Newman community detection method in the ORA software suite (Carley et al., 2013). In this method, an agglomerative hierarchical clustering procedure is used, where each node starts as its own group, proceeding to combine groups in a hierarchical manner until only a single group remains (Clauset, Newman, & Moore, 2004).  

To examine the longitudinal progression of communities within the network, we divide the network into eight time periods. While our data extends over a one year period, from March 2005 – when members of the group first met with other extremists from the US and UK – and ends with the arrests of 18 Canadian members in the summer of 2006, detailed information on the social interactions of members were only available from late November to the end of May – reflecting the time the agent infiltrated the group. Rather than exclude the pre-November network data, we aggregate these interactions as a single time period (pre-November). For November to May, the data allows us to divide the time span into month intervals, creating a total of eight time points. For each time period we apply the Newman community method to detect groupings of offenders. Communities detected in the network across time periods are matched with the preceding time period to see how they evolve, in particular whether the communities split, merge, form, or

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7 This study applied a variety of community network detection algorithms, including Girvan-Newman (Girvan & Newman, 2002), Louvain (Blondel et al., 2008) and the Clique Percolation Method (Palla et al., 2005), selecting the Newman community detection method as it provided the highest modularity score and greatest face validity with our data.
dissolve. Matching is done by examining the degree of relative actor overlap across communities in consecutive time steps in descending order (Palla et al., 2007).\(^8\)

After applying the community detection method across each time period, I first examine how the non-charged affiliates are distributed within these communities over time. Second, to examine how the structure of communities influence the network’s evolution, I apply Palla et al’s (2007) measures of network stability over time. The authors, examining the evolution of communities in a collaboration (co-authorship) and communication (phone-call) network over time, demonstrated that network evolution is a function of interconnectivity across communities. Specifically, they showed that the degree to which actors are connected within their respective community, to the degree they share connections with other communities predicts whether two sub-groups will merge or split (Palla et al., 2007). Modelling our analysis off of Palla et al. (2007) I take the total number of a member’s connections (a proxy measure for how much a member is committed to this group) to outside of their community \(w_{out}\) as well as the degree of connections an actor has to their community \(w_{in}\). I then adopt Palla et al’s (2007) calculation of the probability that the member will leave the community as a function of the following ratio \(w_{out}/(w_{in} + w_{out})\). Higher values reflect individuals who have greater commitment to individuals outside the community, which has been demonstrated to show an increased likelihood of leaving the group (Palla et al., 2007, p. 667). Lower scores show greater commitment to the group and thus greater stability. These group processes can help us understand why individuals might remain with violent factions of a group, while others may leave.

2.6. Results

2.6.1. The 40 Members of the ‘Toronto 18’ Network

Originally labelled the ‘Toronto 18’ by media sources,\(^9\) various government reports and publications continue to refer to the group by this designation, capturing the 18 individuals within

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\(^8\) This diverges with the approach used by Palla et al. (2007) who looked at relative link overlap between communities; however, our approach was suitable for the current sample given the small group size and relative stability in community membership across periods.

\(^9\) For example, see Toronto Star “Toronto 18” http://www3.thestar.com/static/toronto18/index.html which profiles each member of the originally charged 18.
Canada who were charged with participating in the conspiracy. Court documents coupled with interviews with the police agent, led to the identification of 22 other individuals affiliated with the Toronto Group, increasing its size by 122 percent.

Of the additional 22 actors, six were exclusively obtained from the interviews and ten were exclusively obtained from the court documents. The six remaining actors were mentioned in both interviews and court documents. The ten individuals obtained from court documents primarily captures individuals who were recruited after the group’s split (two-months before their arrest) - with both factions continuing to independently advance plans towards an attack, attracting new recruits. While the court documents provided extensive data on the scope of the network, the interviews provided us with detailed data for the dates of tie formation and dissolution between actors.

Who are these 22 affiliates? Some of these affiliates were charged as part of other terrorist conspiracies in the UK (n=1) and in the US (n=2). However, most affiliates included individuals who interacted with the group, shared their extremist views, but were not taking active steps toward the group’s terrorist objectives (n=13). It also includes individuals who did not hold extremist beliefs, but participated with the group by providing information about financial scams, or other tactical knowledge that could facilitate the groups aims (n=4). This study does not argue that these additional individuals should have been included in the court case, rather it highlights their role in bringing together the network and influencing its evolution. Much like Krebs (2001) deconstructed the Hamburg cell to highlight the peripheral members who were necessary to bring together the operational segments, this study looks at these affiliated members to examine how they linked and influenced the overall network.

Figure 2 illustrates the extent to which the larger pool of affiliates fit into the Toronto 18 network. The 18 charged members are represented by black nodes and the 22 non-charged affiliates are depicted by grey nodes. Actors’ placement within the network is done using the multi-dimensional scaling feature in ORA software suite (Carley et al., 2013), which positions actors according to similar patterns of relations. Individuals who share the same set of relations are placed in proximity to one another, while actors who are different in regard to their set of relations

are positioned at greater distances from one another. An examination of how these complementary actors fit into the Toronto 18 network, shows that many of the non-charged affiliates occupied peripheral positions. Most affiliates only interacted with one to five other members of the network. However, some affiliates were central to the network, connected to upwards of 20 other actors, many of these key players, including the two ringleaders. In contrast, the majority of the 18 charged members form a relatively dense core in the network, connected to other charged members. However, similar to the affiliates, a subset of the charged members are spread across the periphery of the network, with only a few ties connecting them to the group.

Figure 2. The 40 Members in the Toronto 18 Network
Note 1. Black nodes represent the 18 charged members and grey nodes identify the 22 non charged affiliates.

The impact of non-charged actors on group structure. To examine how excluding the non-charged affiliates can influence assessments of group structure this study looks at the network’s density and clustering coefficient, that provide complementary measures of the degree of connectivity and clustering of social ties within the network. Table 2 demonstrates that the 18 charged members formed a relatively cohesive network, with 52 percent of all possible ties present. However, increasing group parameters to include the additional 22 actors (accounting for the full 40-member network) decreased the density from 52 percent to 25 percent. Given that density is dependent on network size, it is not surprising that expanding group parameters to include a wider range of actors results in lower connectivity across all actors. However, this same trend is captured with the clustering coefficient, with the Toronto 18 initially presenting a tightly knit group, with a high degree of interconnectivity between actors’ contacts. Again, when including
the ‘affiliated’ actors this measure decreased from 74 to 54 percent. These findings suggest that the Toronto Group is a much less dense and clustered network than initially presented.

Table 2. Structural Features across Boundaries of the Toronto Group

<table>
<thead>
<tr>
<th></th>
<th>‘Toronto 18’</th>
<th>‘Toronto 40’</th>
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</thead>
<tbody>
<tr>
<td>Density</td>
<td>52%</td>
<td>25%</td>
</tr>
<tr>
<td>Clustering coeff.</td>
<td>74%</td>
<td>54%</td>
</tr>
<tr>
<td>Degree centralization</td>
<td>41%</td>
<td>63%</td>
</tr>
</tbody>
</table>

Differences also emerge in the degree to which ties are concentrated around a few select members. A degree centralization of 41 percent suggests that the number of ties appear to be distributed relatively equally across members. However, degree centralization increases to 63 percent when the full group of 40 is considered. This increase is to be expected, with the addition of any actors to a network likely to increase the overall centrality of already central actors. However, an examination of individuals’ degree centrality shows that these affiliates are primarily connected to the ideological leader. Degree centrality, which measures the number of contacts an individual has within the network, shows this. The ideological leader’s centrality score was barely influenced when considering the full 40-member network, only dropping four percentage points, from 88 to 84 percent, suggesting he knew many of the additional 22 members. In contrast, changes in boundaries from the 18 to 40 member network most significantly impacted the operational leader, whose centrality score dropped from 82 to 46 percent when all 40-members were included, suggesting he knew relatively few members beyond the charged 18.

These static assessments show members’ aggregated contacts over the group’s duration; however, it masks the temporality of tie formation. Whether the entry of new actors, and the departure of old ones are distributed across time or concentrated around key points, have important implications for understanding the group’s evolution. Hence, the second analysis aims to quantify the longitudinal emergence of the Toronto 18 group, and the role of the affiliates from the group’s early stages of formation to their interdiction.

2.6.2. The Structural Evolution of the ‘Toronto 18’

Community detection methods are used to examine how the affiliated members fit into the Toronto 18 network, and how densely connected subgroups evolved over time. Across each time period I look at how the non-charged affiliates are positioned within communities, and how cohesiveness within communities changes over time. Figure 3 shows that the Toronto Group did
not represent a single, static entity, rather it evolved time, recruiting and excluding actors at different stages in the process. The group consisted of two to four communities of densely connected actors at any one point in time. The 18 charged actors (black nodes), and the 22 non-charged affiliates (grey nodes) are distributed across the four communities, with charged and non-charged members found within the same communities.

Figure 3.  Evolution of the ‘Toronto 18’ Network
Note 1. Black nodes represent the 18 charged members and grey nodes identify the 22 non charged affiliates.
Note 2. The square node represents the ideological leader, and the diamond node the operational leader. Note 3. Nodes are positioned using MDS scaling, which positions actors with similar patterns of ties in proximity to one another.

Both the operational and ideological communities are notable for their duration throughout the entirety of the Toronto 18’s operation. From the beginning of the group’s formation both the operational and ideological ringleaders formed two distinct communities, absorbing the two other smaller communities over time. The communities with shorter life spans consisted of the international affiliates – representing primarily a group of extremists based in Atlanta and the UK, who visited and interacted with the group, even facilitating overseas training – and the youth – primarily capturing members under 18 who were recruited and charged as part of the conspiracy. Both were integrated into the operational and ideological ringleaders’ respective communities. However, the youth community is distinct, as the group re-emerges as its own distinct community – separating from the operational community – in Time 6.
The distinct structure of the two leaders’ respective communities reflect their distinct styles to managing the network. Table 3 shows the composition (the ratio of charged to non-charged actors within each community) and the stability scores (the degree of outgoing to ingoing connections within the community) across communities over time. The network stability scores show that higher values were often associated with corresponding changes to communities in the following time periods. This is particularly evident for the international affiliates – whose high score (42%) was reflected in their short survival, quickly being integrated into the ideological community in Time 3. However, perfect correspondence between stability scores and community evolution are not always observed. For instance, the youth community survives despite high volatility scores in Time 6. This suggests that the stability scores, while helpful for indicating network processes should be interpreted in tandem with group processes.

Table 3. Composition and Stability of Communities over Time

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<th>T1</th>
<th>T2</th>
<th>T3</th>
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<th>T7</th>
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<tbody>
<tr>
<td><strong>Ratio Charged/Non-charged (%)</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Ideological</td>
<td>63</td>
<td>57</td>
<td>33</td>
<td>33</td>
<td>30</td>
<td>44</td>
<td>27</td>
<td>42</td>
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<tr>
<td>Operational</td>
<td>100</td>
<td>100</td>
<td>75</td>
<td>85</td>
<td>85</td>
<td>100</td>
<td>78</td>
<td>70</td>
</tr>
<tr>
<td>Youth</td>
<td>100</td>
<td>80</td>
<td>100</td>
<td>-</td>
<td>-</td>
<td>38</td>
<td>63</td>
<td>18</td>
</tr>
<tr>
<td>Intl affiliates</td>
<td>25</td>
<td>25</td>
<td>-</td>
<td>-</td>
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<tr>
<td><strong>Community stability (%)</strong></td>
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<td>15</td>
<td>20</td>
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<td>Intl affiliates</td>
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Note 1. Higher ratios indicate a higher proportion of charged members within the community.
Note 2. Higher percentages indicate volatility, while lower percentages indicate more stability in the community.

An examination of the community structure over time suggests that changes in the group’s internal density and the distribution of non-charged affiliates, served as a precursor of the split between groups. While both the ideological and operational communities showed relative degrees of stability over time, with slight peaks of volatility in Time 3 and Time 6 for the ideological community – reflecting the lead-up to the split – differences primarily emerge in terms of the composition of the community. Table 3 shows that the operational community consisted almost exclusively of charged offenders from the early stages of the group’s formation until their arrest, ranging from 70 to 100 percent of charged members over time. This is in contrast to the ideological community that primarily consists of non-charged members, ranging from 27 to 63 percent of charged members. The operational leader’s priorities rested on securing a stable set of individuals committed to taking steps towards conducting the attack. Across all time periods the composition of the operational ringleader’s network is almost exclusively charged members, with two to three
non-charged affiliates brought into the community at different time points. In contrast, the *ideological* leader, actively pursuing new recruits, had a much higher actor turnover in his network. This is reflected in the increase in non-charged members brought into his community over time.

These differing recruiting practices across the leaders, while complementary, created friction over time, leading to the split of the two groups in Time 6. In the early stages of the group's formation (Time 1 to Time 5), the two leaders are able to keep these two communities distinct, with the *operational* leader primarily managing the more serious, charged members, and the *ideological* leader dealing with the wider set of recruits and affiliates. However, these two approaches to the network start to conflict in Time 6. The group's shift to a less cohesive network structure, which primarily influenced the *ideological* ringleader's contacts, also creates security concerns for the *operational* leader. Non-charged affiliates who were brought into communities with core members challenged the security and direction of the group, causing disenfranchisement among the more action-oriented members. The *operational* leader, whose contacts remained stable across time periods, maintaining social ties primarily to the 18 charged members reacts by making corresponding shifts to his own network. Departing from his normal network behaviour, the *operational* leader introduces a new member into the group, isolating him from the *ideological* community and introducing this new individual to a few key *operational* members.

This causes the *operational* group to breakaway, forming two independent communities in Time 7. Clear differences emerge between these two groups, with each exhibiting different structural properties, reflecting their group's objectives. The *ideological* leader, faced with the loss of a cohort of recruits, is primarily focused on building up his followers rather than take concrete steps toward an attack. To do this, he continues to reach out to new affiliates, holding a second training camp. In contrast, the *operational* leader eager to accelerate steps towards an attack, takes on a notably different network structure confining his group primarily to the charged members. By splitting from the *ideological* group, the *operational* community creates a smaller, more efficient network among the charged members, while keeping new actors on the periphery.

2.7. Discussion

Moving from a cohesive to a fragmented and disconnected group highlights the challenges of maintaining a stable group of extremists over time. This process requires consensus among
group members that is challenged when peripheral members become part of the process. The evolution of the Toronto Group was characterized by transient membership; with a series of arrests leading to the forcible removal of members, and new recruits continuously filling this gap, joining across time periods. However, not all of these recruits were among the charged 18, taking on peripheral roles, and were not directly implicated in the attack.

This study shows how restricting groups to boundaries defined by criminal justice sources can limit our understanding of group evolution. Only a minority of participants interacting with the group were charged for a crime. Yet the majority had an impact on the evolution of the group. Looking across the 18-members charged as part of the conspiracy and the full 40-member network, showed how the group evolved not as a single unit, but was rather structured around four communities. These subgroups highlighted the ringleaders’ distinct ways of managing the network, serving as precursors of the group’s eventual split into two independent factions, and its emergence into a major terrorist conspiracy. Neglecting these affiliates masks changes within the network and leads to presentations of the group as a static, cohesive community.

These findings confirm Tremblay’s (1993) suggestion that the search for suitable co-offenders goes beyond the pure action segment. When we go broader – beyond the actors directly implicated in the crime – we find the real sequence of events, and the full set of actors that contribute to this sequence. Criminal groups don’t discriminate between members and non-members based on a set of criminal justice criteria. Rather belonging to a group consists of more than the degree of criminal acts one directly participates in. Individuals in a criminal group may consist of the direct participants, but also the wider social circle that interacts and shares criminal norms. This wider periphery who affiliates with the group plays an important role in the group’s evolution influencing and structuring the other subparts. Previous scholars have argued that this periphery is often necessary to sustain the continuity of groups, serving as potential co-offenders over time (Bouchard & Morselli, 2014). However, consistent with the current study’s findings, affiliates also have the potential to facilitate organizational breakdown, creating conflict and discord between the more ‘criminal’ elements. Applying wider boundaries to the study of criminal groups can help enhance our understanding of the processes that lead some affiliates, but not others to transition into co-offenders.

Although groups have long formed a cornerstone of criminology theories, empirical studies of crime have been slow to seize the group as the unit of analysis. Research has tended to focus on the impact of the group on individual offending pathways, but not the impact of individuals on
the group trajectory. Although crime is often characterized by co-offending (Reiss, 1998; Andresen & Felson, 2012a; 2012b), when the group is considered, it is typically only to examine its effect on individual offending pathways. This research has contributed to our understanding of criminal patterns, showing that the type and structure of ties to criminal groups moderates their impact on offending patterns (e.g. Haynie, 2001; 2002; McGloin & Piquero, 2009; 2010; McGloin & Shermer, 2009; Lantz & Hutchison, 2015). However, omitting an understanding of the group itself may obscure the processes that lead to this interaction between groups and offending pathways. This raises questions about the intersection between individual offending pathways and the group’s overall trajectories, creating challenges in disentangling the effect of individual pathways from the group trajectory. Future studies require examinations of both the individual and the group across cases to further our understanding the interaction between group and individual dynamics.

Furthermore, including the broader environment in which co-offenders are embedded may have important implications for understanding criminal pathways. For instance, studies that examine the impact of groups on individual offending trajectories have shown that arresting individuals who are central to their co-offending network decreases the offending rates of their immediate co-offenders (Lantz & Hutchison, 2015). Future studies may investigate how the broader set of affiliates to which offenders are embedded – and from which they select co-offenders (e.g. Warr, 1996) – structure these relationships, and the types of crimes from which offenders desist. Examinations of this relationship could help explain how affiliates turn into co-offenders and sustain larger group patterns. Co-offending literature, primarily based on official sources, misses the larger periphery from which offenders are drawn, and thus the wider opportunities that may be available to them.

*Limitations.* Case studies of groups are useful for detailed understandings of the internal dynamics of group processes, but are not without their limitations. For one, focusing on a single case raises issues of generalizability. At the same time, it also offers the opportunity to examine in detail how peripheral players influence group structure. A second limitation of the study is that while it aimed to expand boundaries beyond the 18 charged members it cannot claim to have captured every member involved in the network. While multiple sources allowed us to minimize this risk, the network relied heavily on accounts made during interviews with the police agent who was principally positioned within the *ideological* community. Thus, the agent was not as familiar with the *operational* context, particularly following the split, when he too was broken off from this.
group. This leads to the third limitation, the impact of police agents on group formation. Although from the group’s perspective, members are unaware of the individuals’ enforcement roles; the agents’ behaviour is likely not to be that of a typical member. For example, the agents’ roles in acquiring evidence on members can lead to the creation of ties to a high number of members. This may have unintended effects on the group, such as bridging unconnected others and increasing overall group cohesiveness. Law enforcement shapes the network when planting new individuals with the objective of gathering information. The emergence of the group thus cannot be ignored from the context of introducing a key government player.

*Modelling missing data.* Access to key participants in covert contexts is rare, and reliance on open source material including court documents, or newspapers are often the primary or sole methods to map illicit networks. While the results highlight that individuals extracted from court documents overlapped with police agent interviews, these documents are limited to presenting individuals that helped secure convictions and are not representative of the wider social context in which illicit actors operate. For research that does not have full access to the entire set of relations, a frequent occurrence in criminal settings, sampling techniques, including snowball sampling, and alter-driven surveys have been shown to be able to capture accurate representations of the network (Heckathorn, 1997; Salganik & Heckathorn, 2004). Other studies have turned to biographies of former offenders, providing a means to map key players in individuals’ ego networks; however this may miss the full set of group relations.

Recent developments in the modelling of missing data may assist in capturing the full scope of covert networks. For instance, Handcock and Gile (2007) developed a maximum likelihood estimator to generate representations of the complete network. The estimator takes the observed segments of the network to guide the sampling using covariate information derived directly from the matrix to guide the maximum likelihood estimation method. While the size of the current network, and distribution of actors and ties, precluded us from applying this method in the current study, it has been applied elsewhere. For example, Young (2011) used this approach to model missing data in the nomination of ties across friendship networks from the National Longitudinal Survey of Adolescent Health. However, this represented a large sample and data was assumed to be missing at random. If the assumptions inherent in official sources can be identified, it may allow for the modelling of these patterns.
2.8. Conclusion

The process of establishing network boundaries is often among the first steps in the research design; however, this fundamental stage is often reduced to delimiting boundaries to actor attributes, and ignores the larger subset of actors that were involved. Expanding the network beyond those charged, more closely reflects the reality in which offenders, and would-be offenders are embedded – carrying important implications for analyses of group processes. This is particularly relevant in network approaches that are designed to capture the complex set of relations that allow a crime event to occur, mapping the interdependency between actors and the patterns of these dynamic interactions on outcomes. For the Toronto Group, taking into account the larger pool of affiliates, and how they were integrated into the core, shows inconsistencies between the leaders’ management styles of the network, consequently influencing network evolution. This extends to other criminal behaviour that emphasizes the social processes that are central to understanding delinquent behaviour, including learning and opportunity perspectives, (Sutherland, 1947; Akers et al., 1979). Restricting actors to those with specific attributes, may neglect the wider subset of actors that were integral to illicit events, and thus may present biased assessments of the influence of an illicit actor’s network. This perspective is particularly relevant when studying covert groups, who are in fact a set of dynamic actors that interact and are influenced by a larger social context that criminologists should aim to capture.
Chapter 3.

Criminal Collaboration and Risk: The Drivers of Al Qaeda’s Network Structure before and after 9/11

3.1. Introduction

There is extensive variation across groups and their ability to survive over time. Much of this variation is moderated by a group’s resilience; that is, their ability to continue functioning despite external shocks (Holling et al., 1995; Masten & Reed, 2002). Criminal groups, who are continuously challenged by external and, often unexpected, disruptions, vary in their ability to withstand these shocks (Dujin, Kashirin, & Sloot, 2014; Bright, 2015). While law enforcement interventions completely dismantle some groups, others manage to continue illicit operations despite the removal of key players (Ayling, 2009). Much of this variation has been attributed to groups’ network structure. Groups who adopt more decentralized structures have been found to be more resilient, while centralized networks are less robust and more prone to failure (Albert, Joeng, & Barabasi, 2000; Bouchard, 2007). Thus, under conditions of greater risk, criminal networks are more prone to self-organizing into sparse, decentralized networks, so as to minimize exposure to law enforcement, and maximize internal security (Baker & Faulkner, 1993; Morselli et al, 2007).

This research has contributed to our understanding of the link between network structure and resilience, but despite long standing theoretical links between a network’s aggregate structure and the degree of risk, empirical research has rarely examined the drivers of tie formation at the individual-level. Assessing structure primarily through group measures can obscure the local, internal dynamics that generate these structures (Kalish & Robins, 2006). To consider the processes that drive covert structure, the current study aims to assess: what drives individuals to collaborate when faced with greater risk? To do so this study examines the factors that lead individuals to collaborate across six Al Qaeda attacks over a period of increased law enforcement targeting. This provides an opportunity to examine how variation in external risk influenced
individual decisions to collaborate. Our main predictor, triad closure, allows us to see whether network processes, such as local density – typically measured at the group-level – also drives individual decisions to collaborate.

3.2. The Link between Network Structure and Risk

Extant literature has argued that network disruption and network resilience are directly related. Groups who adopt more secure, decentralized structures have been cited to last longer, while more efficient, centralized groups are found to be less resilient to the removal of key players. For instance, decentralized groups such as the Front de Libération du Québec – one of the longest running terrorist campaigns in Canadian history – have been used as evidence of resilience, with cellular structures allowing independent cells to emerge despite large scale arrests (Charters, 2008). In contrast, the demise of groups such as the Front de Liberation National – an Algerian terrorist organization – have been claimed to be linked to the networks centralization and dependence on key actors (Kilberg, 2012). This structural variation across covert groups, has been found to stem from considerations of both security and efficiency (Baker & Faulkner, 1993; Morselli et al., 2007). While security is optimized in decentralized network structures, minimizing exposure to outside enforcement, efficiency is facilitated in networks with higher connectivity, providing the necessary communication chains to coordinate complex crimes.

These network structures have primarily been observed at the group-level; however, research has also suggested that these same factors drive the formation of network ties at the individual-level. In his seminal research on selecting suitable co-offenders, Tremblay (1993) advanced the idea that considerations of both trust and competency drive offender’s selection of criminal collaborators. Offenders must balance the need to work with trusted accomplices – to ensure security – while also connecting to contacts who have the skills to effectively commit a crime. That instrumental processes guide the selection of co-offenders has also been suggested to drive offending patterns. For instance, the propensity for offenders to adopt stable co-offending patterns (i.e. re-use the same contacts) has been suggested to be tied to individual’s specialized skill sets and access to criminal opportunities (McGloin et al., 2008). Co-offending patterns have also been linked to the availability of offenders. Stolzenberg and D’Alessio (2008) suggest that drops in co-offending rates after the age of 18, are driven by the lack of opportunity, with offenders having fewer peer relationships to co-offend with due to movement out of school settings and other life-course transitions.
Most co-offending studies have tended to focus on the impact of collaboration on individual offending pathways (e.g. Reiss, 1988; McCarthy & Hagan, 1995; Piquero, Farrington, & Blumstein, 2007; McGloin et al., 2008; Andresen & Felson, 2012a; 2012b). However, a subset of co-offending studies have begun to empirically examine the processes that drive offenders to collaborate (e.g. Thomas & Grund, 2012; 2015). Findings have shown that the selection of co-offenders has been tied to endogenous network effects and homophily. Examining 48 gang members over a three-year period, Grund and Densley (2015) found that offenders from the same ethnicity have a higher tendency to co-offend with one another, while also demonstrating that this tendency becomes more pronounced when individuals of a similar ethnicity are embedded in triad closure. That offenders tend to affiliate with others who are similar to themselves, is consistent with studies that found homophily among co-offenders. van Mastright and Carrington (2014), using official records, demonstrated that groups exhibited age and sex homophily across more than 10,000 crime events, even when controlling for crime type. A finding that has been reproduced across studies (e.g. Reiss & Farrington, 1991; Warr, 1996). Thus, we know that conceptually co-offending is driven by a combination of an offender’s trust and skill level, while empirical tests have shown other factors including homophily influence the formation of co-offending ties.

3.3. Current Study

Previous research suggests that co-offending exhibits unique properties; however, little is known about how these traits are influenced by different contexts. The current study aims to fill this gap by examining how decisions to collaborate is influenced by the degree of risk. Focusing on an organization that has remained resilient despite major intervention efforts – Al Qaeda – provides an opportunity to examine how, and whether, the drivers of collaboration vary across periods of increased law enforcement intervention. This approach allows us to assess one of the key concepts – network structure – using the group as its own reference category to examine the different mechanisms through which the decision to collaborate may be influenced by contextual factors. If network considerations of security and efficiency are present at the group-level, I would expect to see these same network effects influencing individual decisions to collaborate. This study hypothesizes that considerations of security, measured by a reduction in exposure through lower connectivity, should be observed. Examining the drivers of collaboration can provide us with a more nuanced understanding of network mechanisms that dictate groups’ resilience and survival over time.
3.4. Data and Methods

3.4.1. Mapping the Al Qaeda Attack Network

Offenders who were involved in at least one of six Al Qaeda attacks from 1998 to 2005 form the core of the analysis. The attacks in this study represent some of Al Qaeda’s most substantial operations (The 9/11 Commission Report, 2004; Hoffman & Reinares, 2014) and were also selected due to having sufficient open source information to map the networks of offenders involved in the attack, having resulted in public commissions, or criminal trials. These attacks include the 1998 US Embassy bombings in Kenya and Tanzania, the 2000 USS Cole bombings, the 9/11 plane hijackings, the July 7, 2005 London transit bombings, the July 21, 2005 London subway plots, and the August 2006 airline plot (described below).

Network data for offenders involved in the six attacks were collected through two main strategies. First, court record databases were searched for transcripts, indictments, and sentencing memorandums for all accused offenders. This resulted in obtaining over 8,000 pages of trial transcripts for three of the six attacks: the 1998 US Embassy bombing, the 2005 July 21 London Plot, and the 2006 UK Airline Plot. Second a systematic search for government/think tank reports, news media and scholarly articles was conducted, using two web-based search engines, Lexis Nexis and Google. Searches were conducted using logical combinations of keywords, including the names of the accused and characteristics of the attack (e.g. date, event type, location). These searches allowed for detailed information on the attacks, in particular the 9/11 Commission Report, and the Report of the Official Account of the Bombings in London on 7th July 2005. These sources were also supplemented by information derived from the United National Security Council Al Qaeda Consolidated List, and the New York Times Guantanamo Docket. For all of the acquired sources, all relevant documents cited by the report were acquired, as well as any that cited the report.

The networks included all offenders listed as being involved either directly, or indirectly in at least one of the six attacks. This included individuals who had direct roles, such as those who planned or executed the operation, and individuals with indirect roles, including those who

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11 Provided detailed information on the 1998 US Embassy Bombings, the 2000 USS Cole attack, the 9/11 hijackings, the 2005 July 7 London Bombing, and the 2005 21 July London Plot
13 http://projects.nytimes.com/guantanamo
provided safe houses to the offenders. Network ties between offenders were coded as present if there was any recorded interaction between two individuals. This consisted of in-person meetings, phone calls, emails, letters, and/or faxes. Ties were also coded as present if both individuals were listed as being present at the same location for the same event. For instance, individuals who were both present at the bomb building location, at the same training camp, or attended the same meeting were coded as having a network tie. Thus, the operationalization of co-offending ties diverges from previous research, which defines a tie between two offenders according to their participation in the same crime event (e.g. McGloin & Piquero, 2009; 2010; Andresen & Felson, 2012a; 2012b; Lantz & Hutchison, 2015). Rather, the current study operationalizes a co-offending tie as a recorded interaction between two offenders who also participated in the same event (i.e. attack). Given the scale and scope of terrorist attacks, requiring a range of offenders directly involved in executing and attack, and others indirectly in its coordination, means that many of the individuals participating in the same event are not directly connected, or even aware of other co-participants.

3.4.2. Measures

Information on an offender’s role, whether they occupied a leadership position, and age at the time of first attack was also collected. An individual’s role reflected their primary function in carrying out the attack. Roles were classified into three categories: individuals who were involved in executing the attack (e.g. bombers, hijackers), the logistics of preparing for the attack (e.g. surveillance, bomb-makers), and the management of the attack (e.g. approving and coordinating operations). The creation of these categories was based on the testimony of a former Al Qaeda member who listed these three roles (executors, logisticians, and managers) as the primary duties of individuals involved in attacks (US v. Bin Laden, 2000 S.D.N.Y. Aug 17, 2000, p. 2). For offenders who were involved in more than one attack, only one adopted a different role in the subsequent attack. In this case, the individual first assisted with the logistics for the 1998 US Embassy Bombing, and then transitioned into management, coordinating the 2000 USS Cole operation. For this case I took the highest achieved role, coding the offender as occupying a management position.

To capture individuals who held leadership positions in the group, two binary variables were created that captured both Al Qaeda central staff and local leaders. Al Qaeda central staff included all the individuals who belonged to the Al Qaeda core (i.e. directly living in Afghanistan,
or Pakistan), and served on an Al Qaeda committee (e.g. the military committee) or were in direct contact with individuals on these committees. Given that all the attacks in this study occurred in countries outside of Afghanistan/Pakistan, this study also coded for local leaders who operated within the target countries. Local leaders were typically involved in recruiting and coordinating the execution team, while some were involved in logistics or even in executing the attack. Three members from Al Qaeda central were also local leaders, consisting of individuals who relocated to the operations site to assist in recruiting and coordinating for the attack. Our final variable, age, was coded by taking the difference between the year of the offender’s first attack and the offender’s year of birth.\(^{14}\)

*The Exponential Random Graph Model.* Our empirical focus is the patterning of connections between co-offenders in terrorist attacks, and how this varies under more intense law enforcement pressure. To examine the processes that lead to the presence of network ties, this study adopts Exponential Random Graph Models (ERGMs). As a class of statistical models, ERGMs assesses the probability of a tie between two actors existing, using properties of the network as well as actor attributes as predictors (Lusher et al., 2013). ERGMs consider a binary relationship as the dependent variable: the presence or absence of a tie between two co-offenders. In other words, the outcome of interest is the presence of a co-offending tie. Two models are run, to capture the factors that lead to the presence of a tie before a major intervention and during the intervention. The attacks are divided across the two periods using the War on Terror as the cut-point. This cut-point was selected due to the nature and intensity of the intervention, but also theoretically, the international anti-terrorism response that targeted Al Qaeda core members following the 9/11 attacks has created substantial debate on how interdictions have influenced the organization’s structural features (e.g. Sageman, 2008; Hoffman, 2008). Terrorism scholars have been divided on whether the group has transitioned into autonomous cells or retains a hierarchical structure. Despite extensive dispute, assessments have yet to use network data to empirically observe the group’s structure over time. Dividing the attacks across these two periods allows us to empirically assess if, and how, structure has evolved.

\(^{14}\) As there were missing values for an offender’s year of birth for 13 individuals (16%) we imputed these values using the median year of birth. For offenders involved in the attacks pre-US War on Terror (median age: 29) and during the War on Terror (median age: 25).
To examine the drivers of co-offending across the pre-War on Terror and War on Terror periods three classes of predictors are used: 1) individual attributes (e.g. role; Al Qaeda Central Staff; Local leader); 2) homophily (ties formed between offenders who share the same attribute, e.g. same role in the attack); and 3) triad closure, an endogenous structural effect, that captures whether offenders are more or less likely to complete triads. An additional variable that accounts for which attack an offender participated in is added, to control for the fact that offenders who participated in attacks with a larger number of accomplices may have a greater opportunity to form more ties. This variable also controls for the fact that offenders are more likely to form ties with others with whom they participated in the same attack.

To model endogenous structural effects that could explain the presence of a tie between offenders, a term to control for triad closure is included. Triads consist of any set of three persons, with triad closure referring to the process whereby triads containing two ties between actors will likely form the third, creating a triangle whereby all three actors are tied. In other words, capturing whether ties are more likely to exist between offenders who have a co-offending tie in common. The geometrically weighted edgewise-shared partner distribution (GWESP) is used to examine the likelihood of triad closure on the presence of a tie (Goodreau, 2007; Robins et al., 2007; Hunter, Goodreau, & Handcock, 2008). The GWESP term provides a means to capture whether ties are more likely to exist due to transitive triads. To do so, it also captures that fact that co-offending ties between two offenders can ‘close’ multiple triads at the same, accounting for the number of ‘triangles’ any offender could close (Hunter & Handcock, 2006; Hunter, 2007). Thus, rather than consisting of a count of the number of triangles an offender closes, it provides a “parametric form of the count distribution that gives each additional shared partner a declining positive impact on the probability of two persons forming a tie” (Goodreau, Kitts, & Morris, 2009, p. 110-111).

For both dyadic dependence models the Markov Chain Monte Carlo (MCMC) estimation to approximate the likelihood is used (Snijders, 2002). To assess goodness-of-fit measures of the spectral goodness-of-fit are used (Shore & Lubin, 2015), and compared the observed network parameters with the simulated networks (presented in Appendix C) (Hunter et al., 2008). The spectral goodness-of-fit (SGOF) captures the “percent improvement a network model makes over a null model in explaining the structure in the observed data” – varying between 0 and 1 (Shore & Lubin, 2015, p. 26). For the SGOF, 1,000 simulations were used. For the MCMC estimation,
the sample size was set at 10,000 and the interval between samples at 5,000. All analyses were conducted in the statnet package for R (http://www.statnetproject.org).

3.5. Results

First the global structural characteristics of the attack networks across the pre-War on Terror and War on Terror periods are examined, before turning to the drivers of network structure – at the local level – to examine the predictors of co-offending.

Across the six attacks 118 offenders were either directly or indirectly involved in their execution. As shown in Figure 4, none of the offenders in the pre-War on Terror period were active in the War on Terror period – creating two distinct networks. However, within the two time periods (pre-War on Terror/War on Terror), repeat offenders’ (n=13) bridge the attacks, capturing the dependency between operations. Figure 4 demonstrates that most of the repeat offenders (white nodes) are positioned as bridges, connecting different segments of the attack networks. However, some repeat offenders are also found among the periphery, representing a few, isolated ties across the attacks.

![Figure 4. The Al Qaeda Attack Network](https://example.com/figure4.png)

**Figure 4.** The Al Qaeda Attack Network

Note 1. Grey nodes represent repeat offenders who were involved in more than one attack in the pre- or post- War on Terror period and black nodes represent offenders who were only involved in one attack.
Measures of the networks’ properties shows how the overall pattern of ties were structured across the two periods (Table 4). The scale and scope of attacks plotted during the War on Terror period, are substantially smaller, which is reflected in the size of the attack networks, with only 35 actors active across the three attacks, compared to 83 actors across the three attacks in the pre-War on Terror period. Not surprisingly, given the larger group size, actors in the pre-War on Terror period have a higher average number of ties to other offenders (Pre-War on Terror: Average Degree: 11; War on Terror: Average Degree: 5.3). Both attack networks share similarity in their patterns of connectivity. This is reflected by the measures of density, capturing the number of observed ties by the maximum number of possible ties (.13 and .16, respectively) and clustering coefficients, capturing the degree of local clustering in the network (.42 and .48, respectively). While the War on Terror networks were slightly more cohesive, these results show that the patterning of connectivity within the attacks appear to have similar patterns, despite operating on much different scales.

**Table 4. Structural Features across Al Qaeda Attacks**

<table>
<thead>
<tr>
<th></th>
<th>Pre-War on Terror</th>
<th>War on Terror</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>83</td>
<td>35</td>
</tr>
<tr>
<td>Density</td>
<td>.13</td>
<td>.16</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>.42</td>
<td>.48</td>
</tr>
<tr>
<td>Average Degree</td>
<td>11.0</td>
<td>5.3</td>
</tr>
</tbody>
</table>

In addition, few differences exist between the networks’ composition across the two periods. Bivariate analyses presented in Table 5 show that no significant differences emerge across offenders over the two periods in regard to the distribution of offender roles, leadership roles, and Al Qaeda central staff. One difference across the two periods, was that offenders active in the pre-War on Terror period were significantly older (median: 29; SD: 7.1) than offenders who participated in post-9/11 attacks (median: 25; SD: 7.2). No significant differences in offender centrality emerges across the two periods. Offenders’ had similar degree centrality (number of connections to other offenders) and betweenness centrality (the degree to which actors serve as bridges between unconnected others), regardless of whether they participated in the pre-War on Terror or War on Terror period.
Table 5. Offender Characteristics across Al Qaeda Attacks

<table>
<thead>
<tr>
<th>Role</th>
<th>Pre-War on Terror</th>
<th>War on Terror</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% Frequency (n)</td>
<td>% Frequency (n)</td>
</tr>
<tr>
<td>Management</td>
<td>8 7</td>
<td>9 3</td>
</tr>
<tr>
<td>Logistics</td>
<td>60 50</td>
<td>54 19</td>
</tr>
<tr>
<td>Execution</td>
<td>31 26</td>
<td>37 13</td>
</tr>
<tr>
<td>Local leader</td>
<td>7 6</td>
<td>17 6</td>
</tr>
<tr>
<td>Al Qaeda Central</td>
<td>22 18</td>
<td>17 6</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age - first attack*</td>
<td>29.9 7.1</td>
<td>27.1 7.2</td>
</tr>
<tr>
<td>Network measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>.30 3.2</td>
<td>.12 0.9</td>
</tr>
<tr>
<td>Betweenness</td>
<td>.12 10.4</td>
<td>.15 1.0</td>
</tr>
<tr>
<td>N=</td>
<td>100 83</td>
<td>100 35</td>
</tr>
</tbody>
</table>

***p<.001; **p<.01; *p<.05

Note 1. Chi-square and t-tests were run to test for differences in offender characteristics across the pre-War on Terror and War on Terror periods. For the two network measures, t-tests were run in UCINet 6 to account for violations of the assumption of independence.

3.5.1. The Drivers of Collaboration

To examine whether consideration of risk influences offenders’ decisions to collaborate, two exponential random graph models were run. The first model examines the predictors of collaboration among offenders involved in attacks prior to the War on Terror campaign, while the second model examines the predictors of collaboration among offenders involved in attacks during the War on Terror. Table 6 presents the ERGM results for the two models. The parameters can be interpreted in the same fashion as logistic regression coefficients. They represent the log-odds that a tie between two offenders will exist if the formation of the tie increases the corresponding network statistic, conditional on the rest of the network (Goodreau et al., 2009). The edge statistic is similar to the intercept in standard regression, providing an indication of the baseline probability of ties forming.
Table 6. Exponential Random Graph Models Predicting Collaboration across Al Qaeda Attacks

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-War on Terror</th>
<th>War on Terror</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
</tr>
<tr>
<td>Edges</td>
<td>-4.29***</td>
<td>.66</td>
</tr>
<tr>
<td>Ties</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logistics&lt;sup&gt;1&lt;/sup&gt;</td>
<td>-1.61***</td>
<td>.21</td>
</tr>
<tr>
<td>Execution&lt;sup&gt;1&lt;/sup&gt;</td>
<td>-.03</td>
<td>.19</td>
</tr>
<tr>
<td>Local leader</td>
<td>-.08</td>
<td>.34</td>
</tr>
<tr>
<td>AQ Central</td>
<td>.82***</td>
<td>.12</td>
</tr>
<tr>
<td>Participated in 2&lt;sup&gt;nd&lt;/sup&gt; attack in series&lt;sup&gt;2&lt;/sup&gt;</td>
<td>.22</td>
<td>.12</td>
</tr>
<tr>
<td>Participated in 3&lt;sup&gt;rd&lt;/sup&gt; attack in series&lt;sup&gt;2&lt;/sup&gt;</td>
<td>-.02</td>
<td>.09</td>
</tr>
<tr>
<td>Homophily</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management</td>
<td>-.91</td>
<td>.56</td>
</tr>
<tr>
<td>Logistics</td>
<td>1.43***</td>
<td>.27</td>
</tr>
<tr>
<td>Execution</td>
<td>-.85**</td>
<td>.30</td>
</tr>
<tr>
<td>Local leader</td>
<td>-.27</td>
<td>.37</td>
</tr>
<tr>
<td>AQ Central</td>
<td>.24</td>
<td>.14</td>
</tr>
<tr>
<td>Participated in the same attack</td>
<td>1.55***</td>
<td>.12</td>
</tr>
<tr>
<td>Triad closure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GWESP</td>
<td>2.47***</td>
<td>.45</td>
</tr>
</tbody>
</table>

**AIC** 2203 318.3  
**SGOF** .48 (.33-.62) .45 (.22-.64)

***p<.001; **p<.01; *p<.05

Note 1. ‘Management’ represents the reference category for an offender’s role in the attack.

Note 2. The first attack in the series (Pre-War on Terror: 1998 US Embassy Bombings; War on Terror: July 7, 2005 London Bombings) represents the reference category for the attack an offender participated in.

Results from the pre-War on Terror period indicate that offenders who took on logistical roles were more likely to connect with their own (b: -1.61; SE: .21; p<.001), but less likely to form ties with others (b: 1.43; SE: .27; p<.001), suggesting a degree of role compartmentalization. A finding that has been demonstrated across terrorist organizations (Gill et al., 2014). In contrast, during the War on Terror period, being a logistician had no effect on the presence of ties. Rather, in the War on Terror period, individuals with an execution role, such as bombers, were less likely to form ties with others (b: -2.19; SE: .68; p<.01), but no more or less likely to form ties with one another. One similarity between the two periods, was the impact of being an Al Qaeda Central Staff on the presence of ties. Regardless of whether the attack occurred in the pre-War on Terror (b: .82; SE: .12; p<.001) or War on Terror period (b: 1.57; SE: .53; p<.001), being an Al Qaeda central staff member increased the likelihood of ties to other offenders. However, only in the War on Terror period were Al Qaeda central staff more likely to have a tie with other central staff members (b: 2.44; SE: .62; p<.001), with no significant homophily found among Al Qaeda central staff in the pre-War on Terror period. In contrast, only in the War on Terror period, did local
leaders, who operated and actively recruited in the target country, have an increased odds of a tie existing with other offenders \( (b: 1.90; \text{SE: .39; } p<.001) \). Lastly, differences between the two networks also emerged in regard to endogenous structural effects. In the pre-War on Terror period, the GWESP term indicates that co-offenders were more likely to form ties that complete transitive triads \( (b: 2.47; \text{SE: .45; } p<.001) \). However, this same effect did not occur in the War on Terror period. Rather, triad closure does not appear to have an effect on the presence of ties when attacks were conducted during the War on Terror.

3.6. Discussion

As law enforcement shift their interdiction strategies, so do the illicit networks they target. Faced with increased risks, criminal groups adjust to more covert structures. This flexibility that provides criminal groups with the resilience to survive over time also influences individual-level decisions to collaborate. Only under periods of less intense law enforcement scrutiny were offenders more likely to collaborate when they had a co-offending tie in common. Thus, an increase in external risk influenced whether individuals created closure within their accomplice network. This finding links the drivers of local-level interactions that produce the macro-structural features associated with security and efficiency.

Local closure as a predictor of collaboration is consistent with previous co-offending studies (Grund & Densley, 2012; 2015). The tendency for offenders to form ties based on shared co-offenders may suggest an instrumental process, whereby offenders maximize their network efficiency when external shocks are at a minimum. Offenders are better able to pass on information and organize complex illicit operations when in direct contact with their accomplices. Triad closure has also been found to be more likely to occur in contexts where individuals share strong, close ties (Granovetter, 1973). That is, individuals are more likely to introduce close friends, or in this case, co-offenders, when they share strong relationships. The local pockets of triad closure, suggests the possibility of strong ties, a feature that has been deemed key for successfully operating in hostile criminal contexts (e.g. Tremblay, 1993). However, the true test of the presence of strong ties would be through self-reports, or on information on the nature of the relationship prior to the offender’s involvement in the attack network.

The drivers of criminal collaboration has important implications for targeting covert networks. A tendency for local closure not to influence collaboration under periods of greater law
enforcement activity may open up possibilities for fracturing or exploiting a lack of trust between members. The absence of clustering may have the effect of creating more decentralized processes at the local level, whereby offenders do not know, or at the very least, do not interact with the connections of their co-offenders. This not only decreases the transmission of information, but also direct monitoring of other actors, and potentially compliant, or non-compliant behaviour.

However, interestingly, looking at the aggregate network structures across the two periods, showed that the War on Terror attack networks exhibited greater overall connectivity (as measured by density and the clustering coefficient) relative to attacks in the pre-War on Terror period. This is consistent with previous studies, that have found interdictions can have the effect of increasing a network’s connectivity, and thereby its efficiency (e.g. Dujin et al., 2014; Bright, 2015). However, the finding that closure does not influence collaboration at the local-level suggests that while aggregate processes increase connectivity overall, these ties are not falling into patterns of localized close structures. This could help resolve this discrepancy in the literature that states networks are more likely to adopt decentralized structures under increased risk, and empirical research that has demonstrated interdictions can increase a network’s connectivity. Fewer pockets of clustering could make attack networks harder to target. While the overall rate of information flow is increased, the local closure to facilitate communication between network segments is no longer present. Thus, showing that even though overall connectivity in a group might increase after heightened risk, individual’s still organize according to principles of security, minimizing their opportunity for exposure. Enforcement may only be exposed to partial segments of the network, but not the full set of actors on which it may rely on to carry out operations.

Results also demonstrate that network effects were not the only factors to have an impact on individual decisions to collaborate. The role of Al Qaeda Central Staff in bringing the network together remained prominent across periods, but Central Staff members shared responsibilities with local leaders in forming ties in the War on Terror period. This finding bridges a debate on the evolution of Al Qaeda’s structure following 9/11. Claims that a decentralized Al Qaeda threat has superseded a centralized one, are contrasted with assertions that core Al Qaeda members continue to maintain operational oversight over attacks. Sustaining the debate is research which has supported both perspectives (e.g. Sageman, 2008; Hoffman & Reinares, 2014; Stollenwerk, Dörfler, & Schibberges, 2015). While some findings suggest that the Al Qaeda threat is fuelled by multiple, autonomous cells, others point to a central entity. The current finding merges both
perspectives, finding that the Al Qaeda threat has evolved into autonomous, self-radicalized groups (e.g. Sageman, 2008), but that key Al Qaeda members continue to provide assistance to local cells operating within target countries (Hoffman, 2008; Hoffman & Reinaires, 2014). That local leaders were only important for bridging the network in the War on Terror period may be attributed to the US interdiction strategy that focused on increased border targeting, hindering the likelihood of Al Qaeda central staff members travelling to target countries, and thereby placing greater pressure on local leaders.

This analysis contributes to the limited work on the drivers of criminal collaboration, yet it isn’t without its limitations that may inform future research. First, given that the two periods (pre-War on Terror and War on Terror) capture two distinct cohorts of offenders, the extent to which these processes are driven purely by distinct characteristics of the new offenders versus variation in the law enforcement activity is unknown. On one hand, the very fact that three major Al Qaeda attacks were perpetrated during the War on Terror by a distinct set of actors allows us to see how the group was able to maintain itself and regenerate over time. However, the manner in which offenders organize themselves in the War on Terror period may be related to offender characteristics. While bivariate analyses between the two cohorts of offenders found few differences for the variables tested, additional factors such as the skill-level and competency of offenders may have influenced whether offenders decide to collaborate. This is particularly relevant in periods of increased interdictions, where there may be fewer specialized or skilled offenders from which to select from.

Relatedly, the larger social context from which the offenders were selected across the two periods may vary. Our data only allows us to assess the network at the time of the attack. Thus, it is not known how individuals joined the network, and whether these co-offending ties are based on pre-existing relationships. Previous research has demonstrated that individuals often join organizations in small groups (Sageman, 2004, p. 112). Thus, it may be that prior to an increase in law enforcement activity (i.e. Pre-War on Terror) that triadic closure was related to these processes. That is, two or three individuals would join the terrorist organization at the same time thereby creating this closure. However, in the War on Terror period, with greater interdictions, there was a smaller pool from which to select potential accomplices. Thus, rather than small groups of co-offenders being recruited, individuals were recruited as lone actors at a time, reducing the likelihood of connectivity. This has important implications for understanding how individuals become radicalized, and how terrorist networks are able to regenerate. Access to the
larger social context in which terrorist networks operate and are drawn from may further our understanding of how and why offenders choose to collaborate with one another. This social capital upon which a terrorist organization depends, and from which it emerges, may have important implications for how a group develops and is reproduced over time.

An additional limitation extends from our selection of six Al Qaeda attacks, split across the pre-War on Terror and War on Terror periods. These six incidents represent only a subset of all attacks that were perpetrated on behalf of Al Qaeda over this time. Lacking data on the full scope of all Al Qaeda attacks, our sample is limited to only the attacks for which there was access to sufficient network data. This captured major Al Qaeda attacks that were perpetrated across the two periods; however omits smaller-scale attacks. These attacks may involve fewer individuals, or individuals not directly tied to Al Qaeda leadership, and thereby influence how members are organized. Smaller networks may take on denser network structures, emerging from groups of small closed ties. Further, local attack networks inspired by Al Qaeda but lack direct involvement of Central Staff may exhibit greater tendencies of closure, as offenders may not have to communicate with individuals across borders. Future research that looks across variation in networks necessary to conduct attacks of different scales may further our understanding of the network properties to effectively conduct operations.

Relatedly, another avenue of research is to examine how network properties of groups evolve over time – from the lead up to the attack, and in the stages following its commission. The current study examined the aggregated network ties at the time of the attack. However, network ties are not formed in a uniform pattern, but rather are concentrated around the period immediately leading up to the attack (Helfstein & Wright, 2011a; Everton, 2015). Future research may examine how the distribution of network ties over time influences the resilience of an organization. For instance, study may examine how patterns of tie formation influence the time to recovery. The type of processes by which a system reacts to and absorbs or adapts to shock may have important explanatory power for furthering our understanding of resilience (Holling et al., 1995).

3.7. Conclusion

Extant literature has argued that network structure conditions the impact of external shocks on a group’s resilience. This research contributed to our knowledge about variation in network properties at the group-level; however, was limited by a lack of understanding of the
individual-level factors that led groups to adopt these structures. In light of understanding the mechanisms that produce these network properties, the current study examined the local processes that drive collaboration between offenders across periods of varying degrees of risk. The analyses suggest that the security context in which offenders are embedded influences the degree to which individuals maximize or minimize connections. Connectivity was maximized in periods of decreased law enforcement activity, with offenders more likely to collaborate with others in dense, local groups. Following an increase in law enforcement interdiction, triad closure had no impact on collaboration, and the organization relied more heavily on local leaders to bridge the network. That these same processes can be captured across both the aggregate and individual level suggests a link between the macro-level structures and the micro-interactions that produce them. Co-offending tie formation appears to be subjected to a set of stable underlying processes that are supplemented by other, harder to predict mechanisms embedded within the specific context in which they operate.
Chapter 4.

Terror on Repeat: Criminal Social Capital and Participation in Multiple Attacks

4.1. Introduction

An offender’s illicit network has been identified as an important factor for understanding offending patterns across the criminal career. Offenders with higher numbers of co-offenders tend to re-offend more and persist for longer in their individual offending career, a finding that has been demonstrated across crime-types (Piquero, Farrington, & Blumstein, 2007) and age groups (Lantz & Hutchison, 2015). However, studies have yet to examine how co-offending ties impact offenders’ continued involvement with a criminal organization. Social ties are not distributed equally across group members. Some offenders are more embedded within an organization, having a greater number of ties to other group members, while others are located on the periphery, having few connections to the overall group. Previous research has suggested that individuals who occupy more peripheral positions in illicit groups may be at a greater likelihood of desistance (e.g. McGloin, 2005). While individuals embedded in the group have been suggested to be more likely to remain, having greater exposure to criminal norms and access to illicit opportunities embedded in social ties (McCarthy & Hagan, 1995), while reducing access to legitimate ones. In this sense, the group context matters, because offenders are dependent on not simply their willingness to be involved in future offences, but also an opportunity to be recruited for a future offence. Although research has advanced our understanding of the structure of criminal network on offending pathways, the extent to which a person’s structural position influences their likelihood of committing multiple offences on behalf of the group is unknown. An examination of the factors that allow members to be selected to commit offences over time can provide additional insight into group processes, while also informing the potential for strategic interventions of the most prolific offenders.
To examine repeat offending in a group context this study focuses on to a terrorist organization who conducted eight consecutive attacks over a six year period. Continuity in membership across the attacks provided an opportunity to assess repeat offenders. Building on previous research, this study focuses on variation in offenders’ co-offending ties, and their structural position within the organization as predictors of repeat offending. The question at the heart of the study is whether individuals who come into their first attack already more socially embedded into the organization end up being the repeat offenders that help sustain future attacks. This approach is consistent with earlier studies that have demonstrated highly connected terrorist offenders are better able to access resources (Pedahzur & Perliger, 2006), and remain committed to collective objectives (Stevenson & Crossley, 2014) both factors in a group’s sustained operations.

4.2. Factors Associated with Participation in Terrorist Attacks

What could be the factors involved in the selection of specific individuals to carry out an attack? As is the case with the successful coordination of many high stakes crimes (Cornish & Clarke, 2002; Lacoste & Tremblay, 2003; Steffensmeier & Ulmer, 2005; Morselli, 2005; 2009; Bouchard & Nguyen, 2011; Malm & Bichler, 2011; McCuish, Bouchard, & Corrado, 2015), we would look for a combination of trust factors and specific types of skills needed to carry out the attack. While previous research has primarily examined the selection of suitable co-offenders for a criminal event; for the purposes of this study, an important distinction needs to be made between an individual’s selection into their first participation in a terrorist attack, and the possibility of being selected again for one or more attacks. The factors that are associated with first participation may differ from those associated with the second attack, after the individual had a chance to prove herself or himself. In other words, one’s performance during the first attack would be a key predictor of being provided with additional opportunities within a terrorist organization. Prior to the first attack, however, here it is posited that opportunities and resources provided through an offender’s social ties to an organization – who you know – and the perception of competence to carry out one’s role in the attack are some of the building blocks predicting participation.

Perception of competence has been shown to be an important factor in criminology to characterize offenders’ self-efficacy (e.g. Brezina & Topalli, 2012), but not necessarily in the context of recruitment of co-offenders, the way it is used here. Perception of competence is
important in a terrorism context because organizing attacks and maintaining operations over time requires a range of skills and competencies for all the steps required in the crime commission process (Newman & Clarke, 2006; Shapiro, 2013). Terrorist attacks require skilled offenders not only at the time of the attack, but also a range of actors beyond the incident, from those involved pre-event (e.g. bomb-makers), to those that are required post-event (e.g. providers of safe houses) (Koschade, 2006). Perception of competence may be appraised within informal arenas that provide an opportunity to demonstrate or acquire these skills, such as training camps. The typically longer preparation prior to terrorist attacks of the type conducted by resilient organizations may provide an opportunity to project one’s abilities to perform their roles.

However, performance during the actual offence provides for more accurate assessments of these factors. From this perspective, an offender’s first attack provides a legitimate forum to display their skill-level and ability to contribute to an organization’s aims. An offender’s ability to perform under high-risk, high-stress contexts may weigh heavily in whether they are recruited for future attacks. Performing a task successfully highlights competency and trust, both highly valued in illicit contexts (Tremblay, 1993). Further, being selected multiple times also reflects an offender’s ability to avoid being detected and detained by law enforcement. Demonstration of these skills allows groups to organize themselves more effectively, recruiting or excluding members based on demonstrated experience, or lack thereof. These crime-specific skills are generally transmitted through social ties, as formal mechanisms to improve criminal skills are not available (Tremblay, 1993; Tremblay & Morselli, 2000; McCarthy & Hagan, 2001; Steffensmeier & Ulmer, 2005). Thus, it may be expected that repeat offenders are strategically positioned in their network to acquire this knowledge through fellow offenders. Connections may also serve a dual purpose, providing access to additional opportunities and connecting offenders to the individuals responsible for organizing future attacks. In a terrorism context, trusted ties provide both security and resilience, allowing groups to minimize the number of interactions between members while still maintaining cohesiveness (Krebs, 2002; Sageman, 2004; Roberts & Everton, 2011; Shapiro, 2013). Criminal social capital – the ability to use one’s social network for criminal outcomes – is expected to be a key predictor of selection in terrorist attacks. Below I further develop on criminal social capital as a predictor of participation in multiple attacks.
4.3. Repeat Offenders and Criminal Social Capital

The repeat terrorist offenders considered in this study do not have perfect comparison points in more traditional criminological research. Yet, research on career criminals and the factors associated with persistence provide a useful guide in approaching this type of inquiry. Individuals who have been recruited to a terrorist organization, become a member, and participate in multiple attacks across many years as adults qualify under the terrorist career umbrella (e.g. Amirault & Bouchard, 2015). Previous research on repeat offenders and career criminals has identified co-offending ties as important factors in explaining offending patterns. Piquero, Farrington, and Blumstein (2007), identified a high number of criminal contacts as being associated with increases in both the frequency and duration of offending. Criminal contacts serve as a proxy measure of an offender’s criminal social capital. The number of available co-offenders may increase the number of illicit opportunities, providing a larger pool of accomplices to select or be selected from. Further, these same contacts may increase proficiency at crime, serving as social resources to transmit and receive criminal knowledge (McCarthy & Hagan 1995; 2001; Morselli, Tremblay, & McCarthy 2006; Bouchard & Nguyen 2011; Launtz & Ruback, 2015).

Previous co-offending research has found that it is rare for offenders to re-use criminal contacts for future offences (McGloin et al., 2008). In the few instances where offenders do develop stable co-offending patterns (re-using the same contacts), these patterns have been argued to be associated with an offender’s skill set, including access to resources or opportunities that make them a valued asset (Morselli, 2001; McGloin et al., 2008). Lantz and Ruback (2016) recently demonstrated this tendency for co-offending contacts to share opportunities, finding that repeated targeting of the same burglary location, when not involving the same offender, often involved their connected co-offenders. Moreover, research has also demonstrated that access to more non-redundant criminal contacts (individuals who are not all directly connected) also increases one’s crime repertoire (McGloin & Piquero, 2008). The finding that individuals tend to be more diversified in their crime types when they co-offend has also been observed across aggregate data (Andresen & Felson, 2012a; 2012b).

The idea that criminal social capital facilitates offending by providing access to criminal opportunities is rooted in social learning theories of crime, such as Sutherland’s (1947) differential association theory. These theories align with Coleman’s (1988) more general argument that an individual’s structural position (i.e. how they are connected to others within their network) provides
them with differential access to resources and opportunities embedded in social ties. While Coleman (1988) was referring to conventional social capital – licit opportunities embedded in social ties – criminal social capital refers to its illicit counterpart – illicit opportunities accessed through criminal contacts. The difference being conventional social capital inhibits offending (Sampson & Laub, 1993), and criminal social capital facilitates it (McCarthy & Hagan, 1995). Criminologists who tested the hypothesis that criminal social capital engenders beneficial criminal outcomes have focused either on access to lucrative crime opportunities (Morselli & Tremblay, 2004; Descormiers, Bouchard, & Corrado, 2011), or on detection avoidance (Bouchard & Nguyen, 2010). For instance, in market crimes Morselli (2001) found that serving as a broker, bridging disconnected players along the illicit trafficking chain, provided access to more profitable transactions and hands-off roles that protected individuals from detection by law enforcement.

While brokerage can shape a criminal career, by providing access to lucrative opportunities, in high-risk violent crimes the sum of social ties may play an important factor in continuity. Making the decision to adopt violent measures to promote a political cause has been consistently linked to an individual’s social ties (Della Porta, 1988; Sageman, 2004). Social ties not only provide access to additional opportunities, but have also been suggested to reinforce radical views, diffuse accountability for violence, and increase the costs of not engaging in violent behaviour through social exclusion (McCauley & Segal, 1987). Hence, ties to other offenders may play a salient role in offending, cementing radical beliefs, while providing additional opportunities for action. However, despite serving a number of practical purposes for terrorist organizations, high connectivity may also create risks for offenders. Previous studies have found that high connectivity within illicit networks increases an individual’s exposure and risk of detection (Baker & Faulkner, 1993; Morselli, 2010). Individuals with a high number of connections to a group may have greater commitment and opportunities that could facilitate continued involvement; however these same connections come at a cost, potentially increasing the risk of detection.

4.4. Current Study

To examine the role of criminal social capital in explaining variation across individual’s selection for future attacks, this study analyzes 118 offenders across eight attacks perpetrated by Jemaah Islamiyah (JI), a jihadist-inspired terrorist organization that operates in Indonesia. The series of attacks provide us with a unique opportunity to study patterns in selecting terrorist co-
offenders. A majority of the JI members were only selected once, but some were involved in as many as six or seven attacks. The question at the heart of this study is whether there are clear differences between the single attack and the repeat terrorist offenders. It is posited that criminal social capital – here measured by an offender’s co-offending ties – is likely to be a predictor of participation in multiple attacks. The availability of network data allows us to systematically analyze the structural position of each terrorist offender in the overall network. The hypothesis that an offender’s network size facilitates selection and willingness to be involved in multiple attacks can be tested. The study also considers competence in the form of human capital – highest level of education – along with criminal capital – occupying a leadership position and experience as a militant – as potential confounders in predicting repeat terrorist offenders.

4.5. Data and Methods

4.5.1. Mapping the Jemaah Islamiyah Attack Network

To measure the impact of criminal social capital on repeat offenders, data on 118 terrorists involved in at least one of eight attacks were collected from open sources, including the John Jay and Artis Transnational Terrorism Database (JJATT) (Atran et al., 2008). JJATT is a public online database that provides network and attribute data for offenders involved in over 20 al Qaeda affiliated terrorist attacks. For the current study, data on five of the eight attacks perpetrated by JI in Indonesia was available on the JJATT database, while the remaining three attacks were collected from open sources. Data collected from JJATT relied not only on court transcripts, which has been cited as one of the most reliable methods of acquiring terrorist-related data (Sageman, 2004; Freilich et al., 2014) and national news reports, but was also supplemented by primary sources such as photos, letters, and interviews (Magouirk, Atran, & Sageman, 2008, p. 4) and has been used across numerous studies (e.g. Magouirk & Atran, 2008; Magouirk et al., 2008; Helfstein & Wright, 2011a; 2011b). Through these sources, JJATT mapped the network of every offender identified as being involved in the attack, with ties coded as present if offenders had been in contact, either through phone calls, letters, or in person-meetings. Hence, similar to the first two studies, the current definition of co-offending ties diverges from previous research, which defines a tie between two offenders according to their participation in the same crime event.

The JJATT database can be accessed at: http://doitapps.jjay.cuny.edu/jjatt/index.php
(e.g. McGloin & Piquero, 2009; 2010; Andresen & Felson, 2012a; 2012b; Lantz & Hutchison, 2015). Rather, the current study operationalizes a co-offending tie as a recorded interaction between two offenders who also participated in the same event (i.e. attack). Given the scale and scope of terrorist attacks, requiring a range of offenders directly involved in executing and attack, and others indirectly in its coordination, means that many of the individuals participating in the same event are not directly connected, or even aware of other co-participants. Thus, this definition allows us to capture variation in the structural position of individuals – and thus their criminal embeddedness – across participation in the eight attacks.

For the three additional attacks perpetrated by JI during this same period (2000 to 2005) in Indonesia, data was derived from open sources using two main strategies. First, reports familiar to the authors on JI, including two International Crisis Group reports, were consulted (International Crisis Group, 2002; 2006). Second, a systematic search of the literature using open sources was conducted. This search relied on the web-based search engines Google and Google Scholar using logical combinations of different key words such as Jemaah Islamiyah, terrorism, attack, bombing, and key words related to each attack (e.g. Bali; Australian Embassy) to collect a wide range of sources, including books, journal articles, and media sources. To maintain consistency, coding procedures followed those described for the JJATT database. Only core members and those offenders that directly contributed to the attack network were included in the data. Lacking access to primary sources precluded us from directly modelling the data collection procedures used by JJATT. However, when actors in the additional three attacks had also been involved in the five attacks listed by JJATT I relied on this latter source to code ties across the three additional attacks. For instance, if actors were connected in previous attacks (according to the JJATT database), I also coded them as being present in the three subsequent attacks.¹⁶

Across the attacks, 118 offenders were involved in at least one of the eight incidents. In order to examine participation in multiple attacks, 23 individuals were excluded from the sample either because their first attack did not occur until the eighth attack (n=17) or were involved in a

¹⁶ Only ten offenders’ first attacks occurred in one of the three attacks collected from open sources, with the other 25 offenders having previously participated in one of the JJATT attacks. For these 25 offenders, their information was collected from JJATT. Bivariate tests showed that few significant differences across measures used in the analysis emerged between offenders collected from JJATT and open sources. The only significant difference being that the ten individuals were more likely to have a minimum of a college education than individuals obtained from the JJATT source.
suicide mission \((n=6)\). This created a final sample of 95 offenders who had an opportunity to participate in a subsequent attack.

Our focus on Jemaah Islamiyah extends from the extensive network data available on the organization, but also the unique opportunity it provides to study re-offending across multiple attacks. As an enduring organization, JI was formally established in 1993 in Southeast Asia and survived for over two decades. The group’s primary ambition has been to create an Islamic State within Indonesia, eventually encompassing all of Southeast Asia. Seizing an opening, after the fall of the Suharto regime, JI increased their presence in Indonesia, perpetrating a series of attacks in the early 2000s that focused on domestic targets, to put pressure on the Indonesian government (e.g. a 2000 Christmas Eve bombing involved 39 coordinated explosions at different religious institutions; a 2000 bombing of a Philippine Ambassador’s residence in Indonesia, and two bombings in 2003 and 2004 at Christian places of worship). However, post-9/11 the group’s focus turned to Western targets, which included the targeting of three tourist facilities. This includes the 2002 Bali bombing of a night club, a 2003 bombing of the Marriott Hotel in Jakarta, a bombing of the Australian Embassy in 2004, and a second bombing of the Bali tourist district in 2005. Although domestic pressure in the early-2000s initially hindered the government from implementing repressive counter-measures, the high fatalities caused by the 2002 Bali bombings created a backlash among the public, with authorities creating an anti-terrorism task force that resulted in substantial arrests of suspected members and one of the core leaders (National Counterterrorism Center 2013). These eight attacks described above form the cornerstone of our analysis, allowing us to capture repeat involvement across stages in the group’s evolution and under intense government interdictions.

The co-offending ties across offenders involved in the eight attacks are used to construct a single network of the organization (Figure 5). Repeat offenders serve to bridge the eight attacks, with experienced offenders creating continuity in co-offending ties over time. These repeat offenders are represented by black nodes and one-time offenders by white nodes.\(^{17}\) The links that connect each offender represent the presence of a co-offending tie. Offenders’ placement within the network is done using the multi-dimensional scaling feature in the ORA software suite (Carley et al., 2013), which positions actors according to similar patterns of relations. That is, offenders

\(^{17}\) The network visualization represents 115 actors, excluding actors for which there was no network information \((n=3)\).
who share the same set of co-offenders are placed in proximity to one another, while offenders who are different in terms of their set of relations are positioned at greater distances from one another. This network visualization shows that repeat offenders appear to be more central to the network, not only having a higher number of co-offending ties to other offenders, but specifically to repeat offenders. However, this does not appear to be consistent across all repeat offenders, with a few black nodes positioned on the periphery of the network reflecting few co-offending ties.

In addition, the network visualization captures offenders’ aggregate set of co-offending ties across attacks; hence, it should be emphasized that repeat offenders are likely to have acquired additional co-offending ties across subsequent attacks. Recognizing this, our analysis only uses measures of network features at time of first attack for all 95 offenders included in the sample. In this way, the potential bias arising from offenders building their network of contacts across multiple attacks is removed, creating a criminal social capital baseline that is comparable across offenders.

**Figure 5.** The Jemaah Islamiyah Attack Network

Note 1. The network visualization represents 115 actors, excluding three actors for which there was no network information.
4.6. Measures

To assess factors associated with repeat offenders, a number of variables were constructed across the 95 offenders. A full list of these variables and their descriptive statistics are provided in Table 7 and outlined below.

*Number of attacks*. The number of attacks an individual participated in was used as the outcome variable in the analysis. While JJATT only supplied network information on five of the attacks included in this analysis, the dataset did provide information on whether individual offenders involved in one of these five attacks also participated in additional incidents beyond these attacks (e.g. attacks outside of Indonesia). Thus, if an offender within one of these five attacks also participated in another attack not included in the listed attacks it was included as one of their total attacks. This same procedure was used to collect data for offenders’ involved in the three additional attacks derived from open source searches. That is, the selected attacks were only the starting point for coding whether offenders were involved in multiple offences. While all repeat offenders in the sample participated in at least two of the eight attacks, some had participated in an additional attack outside of the incident sample.

<table>
<thead>
<tr>
<th>Offender Characteristics across Jemaah Islamiyah Attacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>(n=95)</td>
</tr>
<tr>
<td>Number of attacks</td>
</tr>
<tr>
<td>Part. first attack</td>
</tr>
<tr>
<td>Intervention</td>
</tr>
<tr>
<td>Human capital</td>
</tr>
<tr>
<td>Graduate-level</td>
</tr>
<tr>
<td>Bachelors</td>
</tr>
<tr>
<td>College/Certificate</td>
</tr>
<tr>
<td>High school</td>
</tr>
<tr>
<td>No high school</td>
</tr>
<tr>
<td>Criminal capital</td>
</tr>
<tr>
<td>Central staff</td>
</tr>
<tr>
<td>Militant experience</td>
</tr>
<tr>
<td>Criminal social capital</td>
</tr>
<tr>
<td>Degree</td>
</tr>
<tr>
<td>Betweenness</td>
</tr>
</tbody>
</table>

Note 1. These descriptive statistics represent the imputed values.
Criminal social capital. To examine the effect of criminal social capital on repeat offending, two network measures reflecting this concept were examined: degree and betweenness centrality. The first measure, *degree centrality*, is a simple measure of the sum of direct connections a member has with other members within the network (Wasserman & Faust, 1994). This measure has been suggested to capture an individual’s importance and influence in a network, reflecting their degree of activity and connectivity within the organization (Sparrow, 1991; Morselli, 2009), and more specifically, a greater ability to efficiently disseminate information across members of terrorist groups (Koschade, 2006; Pedahzur & Perliger, 2006). Thus, individuals with high degree centrality may not only have greater access to opportunities through their contacts, but may also have a vested interest in maintaining the continuity of the organization. All measures of degree centrality were calculated at the time of first attack. For instance, using the network data on offender’s co-offending ties, if an offender only knew three of the 15 offenders in the first attack, they would have a degree centrality of 20 percent. Taking an offender’s first offence allowed for a baseline measure across offenders, so as not to discriminate between measures of criminal social capital for those who only take part in one attack and those with criminal social capital acquired across multiple attacks. High degree centrality may increase an offender’s likelihood of being selected for a second event, with connectivity not only suggesting embeddedness within a group right from the start, but also greater access to opportunities.

Recognizing that mixed evidence has been found regarding the influence of the number of connections on an individual’s frequency of offences, with higher ties potentially leading to an increased likelihood of detection (Baker & Faulkner, 1993; Morselli, 2010), a second measure of criminal social capital, *betweenness centrality* was also included. Providing a more refined measure of centrality, betweenness centrality accounts for the fact that not all connections produce the same benefits – tapping into the quality of contacts rather than mere quantity of contacts. Providing a proxy for brokerage, betweenness centrality, measures the degree to which actors serve as bridges between unconnected others (Wasserman & Faust, 1994). Betweenness centrality is measured by calculating the degree to which an actor connects other actors through the shortest path (geodesic). Actors located along many geodesics in the network have higher betweenness centrality scores (Freeman, 1977). Individuals high in brokerage are important in that they connect otherwise unconnected members, controlling the flow of connectivity and information in the group, thus increasing their value and potential selection for a second offence. Consistent with degree centrality, all measures were taken at the time of first offence.


**Criminal capital.** Sharing a complementary relationship with criminal social capital, criminal capital refers to the crime-specific skills and expertise an individual has acquired (McCarthy & Hagan, 2001; Bouchard & Nguyen, 2010; Lussier, Bouchard, & Beauregard, 2011; Loughran et al., 2013). This measure accounts for the fact that offenders who have gained experience in committing attacks may be more proficient. Two variables reflecting this expertise were used: belonging to the group’s central staff and previous militant experience. Importantly, none of these measures require that offenders show their skills and competence in the context of one of the eight JI attacks studied here. These measures capture the perception of competence that this study was looking for as a predictor of selection for a first attack.

A leadership position within a terrorist network may reflect a certain degree of competency that allowed them to attain this position. Leaders of terrorist organizations have been cited to be highly skilled actors, requiring a degree of knowledge to coordinate and maintain the illicit group (Stern, 2003; Hoffman, 2004). Thus, these members may not only have acquired the necessary specialized knowledge or experience to occupy this position, but may also be among those who are most involved in coordinating attacks. The restricted nature of this position was highlighted within JI, with only a fraction of all offenders holding a position as central staff (12%). The central staff position was static, with members assessed as holding this status for the entire duration of their involvement in the eight attacks. While few offenders held central staff positions, many of the offenders selected for one or more of the eight attacks had previous experience in participating in militant operations, which may have impacted their recruitment. Given the political environment in Indonesia, specifically the degree of conflict during the 1990s and into the 2000s it is not surprising that the majority of offenders had previous militant experience (76%).

**Human capital.** Human capital, is criminal capital’s conventional counterpart, and refers to an individual’s personal attributes derived from experience and training that contributes to career achievement (Becker, 1962). Despite the lack of support for human capital in profit-driven crimes (McCarthy & Hagan, 2001), this form of conventional capital found support in Lussier et al.’s (2011) examination of sexual offending. It may also be pertinent for terrorist offences. For example, education has been positively associated with terrorist success, with Benmelech and Berrebi (2007) finding that bombers with higher education had more success in committing suicide attacks. While it is evident that these actors are precluded from selection into future attacks, these findings suggest that education provides a specialized skill set to conduct successful operations,
making these members more valuable to the overall group. This is consistent with studies who have found that suicide bombers are typically recruited as ‘cannon fodder’, consisting of less educated members (e.g. Ganor, 2000; Pedahzur, Perliger, & Weinberg, 2003; Weinberg, Pedahzur, & Canetti, 2003). Lacking education these individuals may be considered less valuable to the group and thus more disposable.

Offenders’ highest level of education acquired, a proxy measure of human capital (e.g. Lussier et al., 2011), was included in the analysis. Due to low frequencies for three categories, “Certificate” (n=1), “Some graduate” (n=3) and “Doctorate” (n=2), these categories were merged with others. “Certificate” was merged with “Some college”, and “Doctorate” with the “Master’s degree” and “Some graduate” categories. This created five categories, with the majority of offenders having little education beyond high school, while a select few had attained graduate-level studies.

Control variables. Two control variables were included in the analysis: participation in first attack and participation following an intervention. Participation in first attack was included in the analysis to account for some individuals who were simply not on the radar until much later on in the time period. Given that attacks are being analyzed for a specific time frame, individuals who participated earlier on have a higher chance of participating in multiple attacks. An intervention variable controlled for the fact that the organization operated with relatively limited law enforcement interference from 2000 to 2002. During this period, the Muslim majority of the country were resistant and skeptical of government anti-terrorism efforts. However, the 2002 Bali bombings served as a turning point for support of anti-terrorism policies. In October 2002, JI suicide bombers detonated explosives in the densely-populated tourist district of Bali causing 202 fatalities and approximately 300 injuries. The high number of casualties created a shift in anti-terrorism interventions and in July 2003 Detachment 88 – an anti-terrorism task force - was created with support from the U.S. and Australia. This Indonesian Police Unit conducted large scale arrests and killings of terrorist offenders in the months and years that followed (Everton & Cunningham, 2015). To capture the effect of this unit, an intervention variable was created indicating offenders whose first attack occurred either directly before the implementation of this agency (capturing the high number of individuals who were arrested after the 2002 Bali bombings), or any time after its implementation (2002 and onwards).
Multiple imputation methods were used to account for missing values in five of the independent variables: education (21%; $n=20$), militant experience (19%; $n=18$), degree centrality (3%; $n=3$), betweenness centrality (3%; $n=3$), and central staff (1%; $n=1$). Given the range of missing values across variables, imputing data allowed us to conserve all individuals and variables in the analysis, providing a more comprehensive assessment of repeat offenders and their predictors and reduce the loss of power that occurs from excluding variables. Attempting to represent a random sample of the missing values by creating a series of simulated values for each missing case, multiple imputation aims to restore error variance by reflecting the variability that would be found in the original data, minimizing bias in the estimation of parameters (Allison, 2000). The variables used to conduct the multiple imputation included independent variables in the analysis and the outcome variable. A total of ten imputations were conducted and the pooled results are reported.

To examine the impact of criminal social capital on repeat offending, this study runs two Poisson regression models. Poisson regression was used given that the outcome variable (number of attacks) comprised counts of a rare event. As a baseline, the first model examined the control variables (participation in first attack and the impact of the intervention), human capital (educational achievement), as well as measures of criminal capital (central staff and militant experience). Model 2 added in the measures of criminal social capital (measures of high and low degree and betweenness centrality) to examine its impact on repeat offenders. All analyses were run in SPSS Version 22 and robust estimators were used to account for violations of under-dispersion and independence of observations. First, the outcome variable suffered from under-dispersion, as indicated by a deviance/DF ratio that deviated significantly under one. Second, our measures of criminal social capital – an offender’s centrality within the network – violated the assumption of independence of observations. The robust estimator provided a means to account for covariance properties of the errors and observations, providing more consistent estimates of the standard errors when dependence is present.

4.7. Results

The repeat offenders in our sample, counted for nearly half of all offenders involved across the eight attacks (44%; $n=42$). These repeat offenders are not homogeneous, with some limiting their participation to two attacks and others involved in up to seven attacks. On average, the
repeat offenders, were involved in 2.9 attacks ($SD: 1.3$), with most involved in only two attacks (54%; $n=23$). Fewer repeat offenders are involved in three attacks (21%; $n=9$) and even fewer in four attacks (13%; $n=6$). Lastly, only four offenders are involved in at least five attacks, with two offenders in six attacks, and a final offender in seven attacks.

In addition, repeat offenders are distributed according to when they first participated with the organization. Table 8 distinguishes between repeat offenders who were involved from the very first attack and those who didn’t enter until later on in the organization’s trajectory. Almost all offenders who were involved in three or more attacks, were involved from the very beginning (68%). These offenders, serve to link the eight attacks, with experienced offenders creating continuity in membership across attacks. In contrast, offenders who didn’t enter until later on were typically only involved in two attacks (91%). These findings may suggest two scenarios. One, the possibility of a cohort effect, with the formation of a cohort of offenders who met at the beginning and follow each other across attacks. In contrast, the two-time offenders appear to have been brought in as needed - representing a pool of potential affiliates who were not consistently selected for attacks. This is supported by the fact that half of the offenders who were only involved in two attacks were brought in at different time points. Alternatively, offenders who are only involved in two attacks may reflect a lack of opportunity, having entered near the end of the group’s trajectory, when the group was more heavily targeted by government anti-terrorism forces.

<table>
<thead>
<tr>
<th>Number of attacks</th>
<th>2x</th>
<th>3+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involved in first attack</td>
<td>9%</td>
<td>68%</td>
</tr>
<tr>
<td>Joined after first attack</td>
<td>91%</td>
<td>32%</td>
</tr>
<tr>
<td>$N=42$</td>
<td>23</td>
<td>19</td>
</tr>
</tbody>
</table>

To examine whether there were any differences between the repeat and one-time offenders in our sample I first run a series of bivariate tests. Table 9 demonstrates the results of the bivariate analysis, finding that repeat offenders were significantly more likely to be involved in the first attack perpetrated by the organization ($p<.001$), and were less likely to consist of offenders whose first attack happened after the government increased their targeting of the group. In terms of education, repeat offenders were significantly more likely to have a graduate-level studies education as compared to one-time offenders ($p<.01$). In addition, offenders involved in multiple attacks primarily consisted of central staff members ($p<.001$). In contrast, individuals with
militant experience were no more, no less likely to be involved in multiple attacks. Repeat offenders were also more likely to have a high number of connections to other offenders within the attack network (p<.001). Thus, repeat offenders were more likely, on average, to join the organization at the time of first attack, have a higher number of contacts within the attack network, be part of the group’s central staff, and/or possess a higher level of education.

Table 9. Bivariate Analysis of One-time and Repeat Offenders

<table>
<thead>
<tr>
<th></th>
<th>One-time Offenders (%)</th>
<th>Repeat Offenders (%)</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part. first attack</td>
<td>2</td>
<td>36</td>
<td>.000</td>
</tr>
<tr>
<td>Intervention</td>
<td>58</td>
<td>29</td>
<td>.001</td>
</tr>
<tr>
<td>Human capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graduate-level</td>
<td>9</td>
<td>19</td>
<td>.001</td>
</tr>
<tr>
<td>Bachelors</td>
<td>17</td>
<td>19</td>
<td>.610</td>
</tr>
<tr>
<td>College/Certificate</td>
<td>13</td>
<td>14</td>
<td>.501</td>
</tr>
<tr>
<td>High school</td>
<td>21</td>
<td>26</td>
<td>.559</td>
</tr>
<tr>
<td>No high school</td>
<td>40</td>
<td>22</td>
<td></td>
</tr>
<tr>
<td>Criminal capital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central staff</td>
<td>2</td>
<td>24</td>
<td>.000</td>
</tr>
<tr>
<td>Militant experience</td>
<td>74</td>
<td>79</td>
<td>.378</td>
</tr>
<tr>
<td>Criminal social capital¹</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>.231</td>
<td>.346</td>
<td>.000</td>
</tr>
<tr>
<td>Betweenness</td>
<td>.002</td>
<td>.008</td>
<td>.163</td>
</tr>
<tr>
<td>N=</td>
<td>53</td>
<td>42</td>
<td></td>
</tr>
</tbody>
</table>

Note 1. The values for criminal social capital represent the median degree and betweenness score.

A series of Poisson regression models were conducted to examine the impact of these predictors on the number of attacks in which offenders were involved (Table 10). As a baseline, the first model examined the effect of all independent variables with the exception of criminal social capital. Consistent with the bivariate analysis participating in the first attack increased an offender’s chance of being involved in subsequent attacks (b=.44; SE=.15; p<.01). In addition, the implementation of the anti-terrorism task force – intervention – was negatively associated with the number of attacks (b=−.29; SE=.14; p<.05). Educational achievement also influenced the likelihood of being a repeat offender. Using no-high school as the baseline category, results demonstrated that a graduate-level education (b=.54; SE=.23; p<.05), a bachelor's degree (b=.34; SE=.16; p<.05), and a high school diploma (b=.29; SE=.13; p<.05) were positively associated with the number of attacks in which offenders were involved. However possessing a college education or a certificate failed to attain statistical significance relative to the reference category. In terms of criminal capital, being a central staff member (b=.48; SE=.12; p<.001) was positively
associated with the number of attacks in which offenders were involved, in contrast to militant experience which was not a significant factor.

Table 10. Poisson Regression of Number of Attacks

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
<td>Estimate</td>
<td>SE</td>
</tr>
<tr>
<td>Intercept</td>
<td>.39**</td>
<td>.15</td>
<td>.34*</td>
<td>.13</td>
</tr>
<tr>
<td>Part. first attack</td>
<td>.44**</td>
<td>.15</td>
<td>.07</td>
<td>.19</td>
</tr>
<tr>
<td>Intervention</td>
<td>-.29*</td>
<td>.14</td>
<td>-.38**</td>
<td>.13</td>
</tr>
<tr>
<td>Human capital†</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Graduate-level</td>
<td>.54*</td>
<td>.23</td>
<td>.44*</td>
<td>.21</td>
</tr>
<tr>
<td>Bachelors</td>
<td>.34*</td>
<td>.16</td>
<td>.28†</td>
<td>.15</td>
</tr>
<tr>
<td>College/Certificate</td>
<td>.14</td>
<td>.15</td>
<td>.05</td>
<td>.15</td>
</tr>
<tr>
<td>High school</td>
<td>.29*</td>
<td>.13</td>
<td>.31*</td>
<td>.14</td>
</tr>
<tr>
<td>Criminal capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central staff</td>
<td>.48***</td>
<td>.12</td>
<td>.44***</td>
<td>.12</td>
</tr>
<tr>
<td>Militant experience</td>
<td>-.11</td>
<td>.15</td>
<td>-.26</td>
<td>.17</td>
</tr>
<tr>
<td>Criminal social capital</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>-</td>
<td>-</td>
<td>1.20**</td>
<td>.12</td>
</tr>
<tr>
<td>Betweenness</td>
<td>-</td>
<td>-</td>
<td>-3.09*</td>
<td>1.50</td>
</tr>
<tr>
<td>-2LL</td>
<td>39.92***</td>
<td></td>
<td>42.26***</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>270.70</td>
<td></td>
<td>272.35</td>
<td></td>
</tr>
</tbody>
</table>

†p<.10; *p<.05; **p<.01; ***p<.001

Note 1. 'No high-school' represents the reference category for education-level.

Model 2 added in measures of criminal social capital, to test whether the number or structure of co-offending ties were correlates of repeat offending. Results show that having a higher number of co-offending ties was associated with multiple attacks ($b=1.20; SE=.12; p<.01$). In contrast, offenders who occupied brokerage positions – bridging unconnected offenders – were less likely to be involved in multiple attacks ($b=-3.09; SE=1.5; p<.05$). Thus, controlling for other factors, offenders that had more connections to the network at the time of first participation were more likely to participate in subsequent attacks, while offenders who were brokers were less likely to be involved in future attacks. In addition, the variables from Model 1 maintained their significance, with intervention ($b=-.38; SE=.13; p<.01$), graduate-level studies ($b=.44; SE=.21; p<.05$), high school diploma ($b=.44; SE=.14; p<.05$), and central staff ($b=.44; SE=.12; p<.001$) all being associated with repeat offending. One exception was participated in first attack, which did not remain significant when measures of criminal social capital were included. In sum, Model 2 demonstrates that repeat offenders were more likely to have a higher number of connections to other members within the attack network, less likely to be brokers, more likely to occupy a central staff position, and to be better educated.
Ties that repeat. The above analysis suggested that a high number of contacts at first participation was associated with repeat offending later on. But is it simply about how many people you know? Given the variety of offenders involved in any given attack, it may be that certain types of ties may facilitate involvement in multiple attacks.

Taking an offender’s first attack, I classify the connections they made based on three possible types: 1) connections to experienced or “repeat” offenders at time of the attack, and 2) connections to first-time offenders like themselves but who would remain one-time offenders, and 3) connections to first-time offenders who would eventually be recruited in subsequent attacks and become repeat offenders.

Making a distinction between ties to repeat offenders, who have previously been involved in attacks, and repeat offenders who will be involved in future attacks allows for the potential identification of a “cohort effect” – i.e. whether these connections “followed” repeat offenders and were maintained in subsequent attacks. These additional analyses, presented in Table 11 examined the degree to which both one-time and repeat offenders were connected at the time of their first attacks.

Table 11. Types of Co-offending Ties across One-time and Repeat Offenders

<table>
<thead>
<tr>
<th></th>
<th>One-time Offenders (%)</th>
<th>Repeat Offenders (%)</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connections to one-time offenders who would remain one-time offenders</td>
<td>53</td>
<td>24</td>
<td>.001</td>
</tr>
<tr>
<td>Connections to first-time offenders who would become repeat offenders</td>
<td>16</td>
<td>61</td>
<td>.001</td>
</tr>
<tr>
<td>Connections to repeat offenders who had been involved in previous attack(s)</td>
<td>30</td>
<td>29</td>
<td>.960</td>
</tr>
</tbody>
</table>

Note 1. All measures of co-offending ties were calculated at the time of first attack. Analyses were run in UCINet to account for the dependency between actors.

The results suggest that participation in multiple attacks may be influenced by more than the sum of an offender’s ties. Connections to other first-time offenders who would become repeat
offenders was positively associated with involvement in multiple attacks. Table 11 demonstrates that repeat offenders were more likely to be connected to offenders who would be involved in subsequent attacks, than to one-time offenders \((p<.001)\). However, being connected to experienced repeat offenders – who were previously involved in attacks – did not distinguish between one-time and repeat offenders. In addition, one-time offenders were more likely to be connected to other one-time offenders \((53\%)\), while repeat offenders were less likely \((24\%; p<.001)\). These findings are consistent with the distribution of repeat offenders in our sample, which suggests that offenders involved at the beginning followed each other across subsequent attacks. The data do not allow us to discern whether our repeat offenders simply knew more of these future repeat offenders even prior to participation in their first attack. Yet, the findings do suggest the presence of clusters of offenders who participated across attacks as a cohort.

### 4.8. Discussion

This study examined the role of criminal social capital in explaining selection for future terrorist attacks. Results demonstrated that criminal social capital, measured by the number of terrorist members you know, predicted participation in multiple attacks. However, criminal social capital was not the only driver of repeat offenders, with central staff members and offenders with graduate-level education also more likely to participate in multiple attacks. This suggests that selection is based on more than an offender’s skill set, but also their embeddedness within the group.

The results regarding criminal social capital and repeat offending in a terrorism context are interesting in part because the size of the network was measured at time of an offender’s first attack, not based on a cumulative advantage that would emerge from repeat participation. Offenders appeared to come in with an advantage, or to have been able to develop this criminal social capital leverage in the process of planning and undertaking the attack. Though applied to a new context, these results are consistent with extensive research that underscores the central role of peers in influencing offending patterns more generally \(\text{Akers et al., 1979; Matsueda & Anderson, 1998; Piquero et al., 2007; McGloin & Piquero, 2010}\), but also within terrorist networks, where high connectivity has been shown to reflect high-degrees of activity \(\text{Sangal, Martin, & Carley, 2012}\) and commitment \(\text{Stevenson & Crossley, 2014}\). This is reinforced by the finding that clusters of offenders participated with one another across attacks, suggesting that repeat
involvement with the same co-offenders may have cemented relationships, and strengthened available opportunities for continued participation.

Yet, terrorist networks do not simply provide just another context. Diverging from profit-oriented crimes (also see Lussier et al., 2011), these offenders first and foremost share violent political ideologies, which provides an even more important role for the number of co-offending ties one has within the organization. A high number of ties to an organization may not only provide more opportunities, but also assist in solidifying radical beliefs. Being connected to like-minded extremists may reinforce current views and maintain these radical ideologies over longer periods. In addition, these ties may also amplify the costs of leaving, with highly connected desistors potentially facing higher social costs.

This may assist in explaining why offenders who were positioned as brokers within the network were less likely to continue participating in attacks. That particular finding contrasts with previous research on brokers. Using individuals high in betweenness centrality as a proxy for ‘instigators’ of criminal events, Lantz and Hutchison (2015) demonstrated that offenders positioned as brokers start offending at an earlier age and conduct more offences. The main argument being that brokers (or recruiters) are generally high-rate offenders who offend with low-rate offenders. In contrast to their sample of burglars, individuals who occupied these positions within the terrorist network were found to be more low-rate offenders. This may be related to the unique context of terrorist offending. While brokers are valuable in profit-motivated offences, bridging supply and demand chains or access to illicit opportunities, in a terrorist context embeddedness in a network may be more important to maintaining ideological orientations necessary to persist. This is consistent with major theories of terrorism that suggest transitions into terrorist groups require small densely, connected groups of offenders (e.g. Sageman, 2004; Nash & Bouchard, 2015), and empirical research that has found offenders who continue with a group over time are more likely to be central, and become more central over time (Stevenson & Crossley, 2014). Lastly, the current study’s finding of a cohort effect supports the importance of embeddedness, showing stable sets of repeat offenders followed each other across attacks.

The results also showed that repeat offenders were more likely to occupy a position as a central staff member, one of our measures of criminal capital. Individuals who have acquired a leadership role not only have the decisional power to get involved in subsequent attacks, but have clear incentives to do so to further advance their own cause. Leadership roles have been stated
to reflect a commitment to the group (Crenshaw, 1981) and acquisition of a certain degree of experience and knowledge (Carley, Lee, & Krackhardt, 2002). Further, it is worth noting that central staff members involved in multiple attacks also had a higher number of co-offending ties (degree centrality: .50) relative to repeat offenders that did not hold this position (degree centrality: .41), providing the necessary social resources to initiate and organize attacks. This finding also indirectly reveals that central staff members were available for participation in multiple attacks, which suggests that they are also less likely to be involved in roles that physically expose them during the attack, such as bombers or foot soldiers, limiting their risks of detection.

It is worth noting that only one measure of criminal capital, occupying a role as a central staff member, emerged as significant while the second measure, militant experience, was not found to be associated with repeat offenders. While it is possible that experience plays no role in repeat terrorist offending, I feel that the value of experience is dependent on context. In the case of JI, most offenders had acquired some form of militant experience (76%) and thus, given its ubiquity, may not have been as important a criterion when selecting future recruits. In contrast, few offenders occupied a position as central staff (12%). The fact that most offenders had experience does in fact tell us that this appears to very important for selection purposes, so much so that it does not emerge as a key characteristic to predict inclusion in multiple attacks.

Finally, this study found that human capital may play a key role within JI, as individuals with graduate-level studies were more likely to be involved in multiple attacks. This extension of human capital into terrorist activities may be attributed to the degree of organization required to conduct elaborate attacks or gain access to legal venues. This is consistent with research on 148 Palestinian suicide bombers by Benmelech and Berrebi (2007) that found university educated bombers were better able to evade detection prior to detonation and target more prized locations. While suicide bombers are typically not repeat offenders (by virtue of their task), this does suggest that they possess a valued skill set, and is reinforced by the fact that suicide bombers are typically disposable members that lack education (Ganor, 2000; Pedahzur, Perliger & Weinberg, 2003; Weinberg, Pedahzur, & Canetti 2003).

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18 However, while an interaction between these two variables was created in the Poisson regression analysis no significant effect was found.
19 All central staff members in our sample also had previous militant experience.
There are a few limitations that should be taken into account when assessing these findings. The analysis of repeat offenders only examined a case study of members of Jemaah Islamiyah, which has been noted to have a distinct network structure that more closely resembles a hierarchy relative to other Islamic groups (Sageman, 2004). With many senior members having received military training in Afghanistan in the early 1980s and late 1990s, the organization has been stated to take on a more formal command structure. In addition, members have been recruited through Islamic school settings (International Crisis Group, 2003). This may not only impact findings on measures of network centrality measures, but means findings should also be interpreted within the unique context of JI, which operated in a distinct environment where recruits were often embedded in school environments and connected to others within a hierarchical organization. Thus further analysis should be conducted across different organizations to examine generalizability. Related to this, this study only examined eight attacks for a specific time period from 2000 to 2005, and thus lacks information on terrorists that participated outside of these eight attacks. While the analysis attempted to be as comprehensive as possible, given the covert nature of attacks, members and some attacks themselves, may have been missed. Thus, individuals that were coded as being involved in the first attack may have been involved in earlier attacks. In addition, members that were coded as being involved in a single attack may have participated in further attacks at a later time period. The data precluded verification of these possibilities.

Further, in terms of analysis, our models only allowed us to capture how an individual’s social embeddedness within an organization at the time of onset influence the number of attacks an individual participated in, but not their longevity with the group. Lacking data on an individual’s end date with an organization, this study was unable to properly model the duration for which members stayed. It is possible that individuals remained with the organization, but did not involve themselves in future attacks. Future studies may look at members’ continuity with a group and how variation in their structural position over time (e.g. become more or less embedded) influences their survival with the organization. Lastly, in terms of data, the sample size is worth noting. On one hand it is large – there are few occasions to study the networks of terrorists across eight attacks, with LaFree, Dugan and Miller (2015) finding that nearly half of all terrorist organizations perpetrate a single attack. On the other it is quite small, with only 95 offenders representing a smaller sample than ideal for multivariate analyses.
Despite these limitations, the study is among the first to establish a potential set of predictors to assess multiple offences among terrorists. The findings also have value when thinking about the targeting of terrorist groups, and the characteristics of individual members. Distinguishing between repeat offenders and their one-time attack counterparts permits effective allocation of limited resources, while allowing for the creation of tailored strategies to dismantle these groups. This study suggests strategies that focus on offenders who may be the most embedded, and thus committed to continuing and maintaining the group through multiple attacks may be the most effective. Focusing resources on individuals with high connectivity serves two purposes: it assists in dismantling the network by taking away those with the most social ties, and may serve to reduce the potential lethality of future attacks by removing offenders that are more likely to have acquired experience and perpetrate future attacks. Adopting an approach that examines networks to identify the most connected, aligns with research that demonstrates network approaches play an important role in desistance strategies for terrorists (Noriicks, 2009). For terrorist offences, mapping networks can assist in the identification of offenders whose removal would most effectively disrupt the organization. However, the most effective disruption strategies aim to take into account both an offender’s network centrality and their value to the network, often measured as their role or resources they bring (Carley et al., 2003; Roberts & Everton, 2011). This idea has been referred to as “network capital” accounting for an offender’s network importance in terms of both the intangible and tangible resources they bring to the network (Schwartz & Rouselle, 2009; Westlake, Bouchard, & Frank, 2011). Thus, an offender’s structural position along with their skill set should be accounted for to develop the most effective targeting strategies.

4.9. Conclusion

In a terrorism context, ties to other offenders play a salient role in providing opportunities. Covert environments reduce the pool of potential accomplices, placing a high importance on criminal social capital. In addition, the skills offenders’ bring to a group whether as central staff members or having acquired advanced education demonstrate that an individual’s value plays a role in selection to multiple attacks. Thus, not only an offender’s network position but also the context of their connections may assist in explaining terrorists’ trajectories and offending patterns.
While an individual’s degree of connectivity to a group should not be underestimated, repeat offending should not be reduced to the sum of an offender’s social ties. Being a repeat offender reflects two conditions: 1) selection for a future offence; and 2) willingness to be involved in a future offence. The finding that connections, central staff and level of education are all drivers of repeat offenders, may satisfy both these conditions. Offenders who have a high number of connections and occupy positions of status within a group may be more willing to continue participating, as they face greater costs should they choose to leave the group: losing both these social ties and the associated benefits of status. Consideration of these findings collectively suggests that selection to a terrorist organization may be a rational process, with individuals and groups weighing the benefits and costs of selection to further attacks. This approach is consistent with recent studies that have emphasized the rational processes of terrorist attacks (e.g. Hsu & Apel, 2015; Perry & Hasisi, 2015). Under this framework, a high number of ties to an attack network may serve to alter the perceptions of costs of behaviour. Individuals who would not otherwise engage in a behaviour may be more likely to do so in the presence of a high number of co-offenders; diffusing responsibility and increasing the costs of leaving. In addition from a group perspective, recruiting central staff and educated offenders with experience and specialized skills, aims to increase group capacity. This potentially suggests for future studies to look at selection in a terrorist organization as a rational process to understand terrorists’ trajectories and offending patterns. Informing us of the cost and benefit structuring of decision-making in terrorist offences, this framework could provide crime specific measures that decrease costs associated with desistance and target those most at risk of repeat offending.
Chapter 5.

Conclusion

This dissertation presented three studies that examined the relationship between a group’s network structure and its trajectory. Findings from the analysis led to the following main conclusions:

1. Only a minority of the members of a terrorist organization are directly involved in attacks. Yet, the majority have an impact on the evolution of the group.
2. Offenders' connectivity within terrorist organizations is guided by network processes of closure – with offenders more likely to collaborate when they have a co-offender in common – but, only during periods of decreased law enforcement activity.
3. Offenders socially embedded in the organization are more likely to be involved in multiple attacks.

The first conclusion is terrorist groups emerge from a wider set of interactions in which they are embedded. As terrorist groups form, new recruits who are being tested, and in turn testing out the group, influence members already embedded in it. Terrorist groups depend on this wider periphery to sustain the organization; however, transitions into collective violence requires consensus among members, a process that is challenged when these peripheral members become part of this process. Considering the peripheral members shows that terrorist networks evolve not as single cohesive units, but are rather structured into distinct subgroups. Assessments of these densely connected subgroups highlight how peripheral members are distributed across the network, and in the case of the Toronto 18, served as precursors into the groups eventual split and its transition into a major terrorist conspiracy. The distribution of peripheral members decreased cohesion among core members and internal discord. As a subset of the group transitioned into violence, peripheral members were closed out from the more radical elements, leading to the group’s split into two independent factions. This is consistent with previous studies that have shown transitions into violence are associated with the re-structuring of one’s social network into a small, densely connected group (e.g. Sageman, 2004; Nash & Bouchard, 2015), and that groups adopt more cohesive structures in the period leading up to the attack (Helfstein
& Wright, 2011a). Ignoring the non-criminal affiliates masks the full scope of covert groups and the variation that can assist in understanding how groups emerge and evolve.

The second conclusion is that network processes of closure are influenced by law enforcement activity. Examining the factors that lead offenders to collaborate across Al Qaeda attacks, showed that offenders are more likely to collaborate when they have a co-offender in common – self-organizing into densely connected subgroups – but only under periods of decreased risk. During periods of increased law activity triad closure does not play an important role in tie formation. This closely matches previous research which finds that observed network structures are influenced by the degree of risk (e.g. Morselli et al., 2007). Further, it helps resolve a discrepancy in the literature that states networks are more likely to adopt decentralized structures under increased risk, and empirical research that has demonstrated interdictions can increase a network’s connectivity (e.g. Dujin et al., 2014; Bright, 2015). Findings from Al Qaeda showed that while the connectivity of attack networks increased overall following increases in law enforcement activity, ties between offenders were not falling into patterns of localized, closed structures. Thus, showing that even though overall connectivity in a group might increase after heightened risk, individuals still organize according to principles of security, minimizing their opportunity for exposure. From this perspective, closure may be perceived as a good that can only be afforded in certain contexts to facilitate a group’s cohesion and efficiency, but may be sacrificed in favour of security in risker contexts.

The third conclusion is that offenders more socially embedded in the organization are more likely to end up being the repeat offenders that help sustain future attacks. Specifically, offenders with a higher number of connections are more likely to be involved in multiple attacks and these connections are more likely to “follow” repeat offenders in subsequent attacks. In contrast, offenders positioned as brokers – bridging otherwise unconnected others – are less likely to re-offend. The results suggest that participation in multiple attacks may be influenced by more than the sum of an offender’s ties. Overall a group’s longevity may be tied to a stable group of repeat offenders who link attacks, providing experienced membership that allows groups to persist over time. This is consistent with previous research by Stevenson & Crossley (2014) who observed that despite high leadership turnover over time, the Provisional Irish Republican Army maintained a stable core of leaders who became more central over time, and connected the group across the different time periods. And aligns with studies of delinquency more generally, that find
individuals are more likely to conform to a group when they are tightly connected (e.g. Haynie, 2001).

The general objective of the dissertation was to theorize and empirically examine the evolution of the networks of terrorist organizations. Each of the three studies presented focused on different segments of a group’s trajectory: emergence (the formation of the Toronto 18); evolution (changes to the Al Qaeda network before and after a major intervention) and persistence (repeat offenders across multiple attacks in the Jemaah Islamiyah organization). While individually each study tackled a different segment of the evolution of terrorist groups, looking across the three studies, they emphasize two main findings: 1) Terrorist organizations face challenges maintaining a stable group of extremists over time, consisting of both a periphery of ‘at-risk’ and central ‘action-oriented’ members who influence the group’s evolution; and 2) Leaders play a key role in terrorist groups’ trajectories, bridging together members and regenerating membership following voluntary and forced removal of members. Each of these points are elaborated and discussed in relation to the general literature on criminal groups, with a focus on street gangs, in the following section.

1. **Terrorist groups survival depends on organizing into a core group of members’ key for instigating the crime event and a wider periphery of supporters**

Collectively, the findings across the three studies emphasize the challenges of maintaining a stable group of extremists over time. Terrorist organizations are structured around a core group of offenders taking steps towards the crime event, and a wider periphery of at-risk members, who share the group’s ideas but are largely kept in the dark about the specific objectives. This larger periphery maintains the group over time – serving as a pool of potential recruits and source of support – yet also pose a potentially liability to the group’s survival. Creating a functioning group requires consensus among members, something that may be challenged when a wider periphery becomes part of the process. Cohesion facilitates the maintenance of unity and consensus among members. Bounded in tightly knit groups, and cut-off from outside influences, members’ views are more likely to be reinforced, and reflect those of more extreme members. This same high interconnectivity provides a monitoring mechanism, allowing others to detect divergent views, while decreasing the likelihood of individuals expressing them, and increasing the costs of not engaging in group behaviour through social exclusion (McCauley & Segal, 1987).
In legitimate enterprises a group’s size is correlated to its success. Often referred to as the ‘liability of smallness’ (Aldrich & Auster, 1986) firms with a smaller size have a lower chance of survival (Brüderl, Preisendörfer, & Ziegler, 1992). Yet, in illicit context there are limits to an organization’s growth and its ability to monitor group members. Sustaining the group’s growth requires divisions into sub-groups of more action-oriented members and a wider periphery of supporters. Taking steps towards the crime event requires a cohesive subset of individuals who can efficiently prepare and coordinate complex tasks. Yet the group depends on a larger cohort to sustain the group’s ideas, and serve as potential recruits to carry out the attack once the group approaches the criminal event. In efforts Groups must contend with attracting new recruits, while also maintaining satisfaction and support among current members. Thus, a group’s survival depends not only on its size, but how it structures and integrates this wider periphery. When peripheral members challenge the unity of the action – violent-oriented cluster - this can create internal conflict. This was observed in Study 1, where the larger periphery slowly became involved in the core group’s cluster, challenging more extreme perspectives, leading to disengagement, while simultaneously creating security concerns for the more criminal elements of the group.

The finding that groups organize themselves into clusters of members involved in instigating the crime event and a wider periphery is not unique to terrorism, but may be found across other criminal groups. Previous studies have outlined many of the features that extend across terrorist organizations to other groups, such as street gangs (Decker & Pyrooz, 2015a; 2015b). Links between the two have included the symbolic ends of group membership, with individuals across both groups citing belonging and peer affiliation, as a key reason for joining. This dissertation extends on this finding, that similar to offenders who join street gangs for the benefits of the ‘brotherhood’ and identity can be found among the clusters of ‘at-risk’ members of terrorist organizations. Both street gangs and violent terrorist organizations can divide themselves into two main categories: 1) The ‘at-risk’ offenders, or ‘wanna-bes’ and the 2) action oriented members. Both categories of membership are critical for a group to survive, with the ‘at-risk’ members serving as a pool of affiliates, who are often tasked with riskier tasks. And the action members orchestrating the larger crime events. Yet the two categories are distinct, with ‘at-risk’ members often kept in the dark and in it for the camaraderie, while action-oriented more involved in planning stages and organizing complex tasks.
Yet, parallels between terrorist organizations and street gangs are limited in two main ways. First, terrorist groups have fewer crime events over time. This 'time-to-task' influences how groups structure themselves and come together over time (Morselli et al., 2007). In street gangs, members organize themselves according to more sporadic, opportunistic events. In contrast, terrorist organizations can take months if not years to plan a single crime event. This creates additional challenges of maintaining cohesion, and creating a collective purpose to unite members, particularly those on the periphery. Crime events may serve a more utilitarian purpose to the group’s survival, in serving as a collective action that can unite members over time. In a terrorism context, lacking this, have training camps that can assist with training and creating this same unity over more extended periods. More challenging to sustain a group with fewer events. Second, this disenfranchisement is more likely to extent to peripheral members, which can influence larger group processes. A characteristic of terrorist organizations, is a tendency to split during their formation. In a terrorism context, the periphery is more likely to influence splits. This was also observed in the Toronto 18, with the wider periphery eventually integrated into the core, creating issues of security. Given the limits to their involvement don’t have same benefits of belonging, and are found in clusters of more peripheral members.

2. Leaders play a key role in the regeneration of terrorist groups

Across the three studies, leaders played a key role in the group’s emergence and in sustaining the organization. From the time terrorist organizations form until the crime event, leaders provide a consistent bridge to tie individuals together. Groups do not organize in a linear fashion, rather are characterized by a transient membership, with new recruits testing out the waters, screened by group members. At different points members may be removed through interventions, disenfranchisement, or social exclusion from the group. Leaders serve as stable members across the groups trajectory. This was observed across the three studies. In Study 1, the leaders were present from the time the group formed until its interdiction, bringing in new recruits and managing the coordination of the event. Both leaders provided complementary leadership styles, with one managing the new ‘at-risk’ recruits and the other, the action-oriented cluster. In Study 2, leaders were key for bridging the network, playing a key role in creating ties across members, even under periods of increased risk. This was also observed in Study, with leaders more likely to become repeat offenders, involved in multiple attacks. Leaders served as the core action component, both bringing the organization together into a coherent group and in maintaining this solidarity over time.
Considering the degree of coordination required to conduct complex operations, it is not surprising that leaders are key to this process. On the one hand, this is similar to what we find among criminal groups in general, with a subset of offenders serving as the instigators to the crime event, bringing together a set of co-offenders to complete the act. On the other hand, leaders operating in a terrorism context diverge from what we traditionally see in criminal groups. Leaders of terrorist organizations are required to coordinate an event over an extended period of time, maintaining membership. This is in contrast to more opportunistic crimes, that don’t require planning, but rather availability of potential co-offenders and a suitable criminal target. This reduced level of cooperation required to meet collective goals influences the structure of gangs, and reliance on a leader to orchestrate and plan out the crime events. In more sporadic, opportunistic crimes, leadership takes a back seat, with the members able to plan out and carry out crime events. In contrast, terrorism requires a centralized leadership to preparer and create a coherent plan for the management of the attack. Taken together the results of these three empirical studies carry important conceptual and practical applications for the study of terrorist groups. From a theoretical perspective, the findings highlight the utility of the collective criminal career paradigm for understanding the trajectory of organizations, including their emergence, continuity, and decline. Groups have their own trajectory independent of the individuals embedded within them, and an understanding of the processes that sustain groups can shed light on the factors that sustain and promote criminal behaviour. Conceptually, the findings provide a baseline to create a framework on the relationship between network structure and group trajectories. This is where the conclusion now turns, drawing from the collective criminal career framework to examine how findings across the three studies and extant literature may help explain variation in the life-cycles of terrorist groups – creating a structural typology of group trajectories.

5.1. A Structural Typology of Terrorist Group Trajectories

Despite the lack of a common terrorist profile, previous research has found that terrorist groups may be classified into two distinct ‘types’: groups who endure over extended periods, conducting multiple attacks; and groups who desist shortly after their emergence, conducting few if any attacks. An analysis of all terrorist groups listed in the Global Terrorism Database demonstrated that most organizations (74%) are active for less than a year (Dugan, 2012). This same founding has been shown across databases, including the International Terrorism: Attributes of Terrorist Events (ITERATE) database, which showed that most organizations only
perpetrate a single attack. However, while only a fraction of groups last an extended period, they have been found to account for the majority of attacks. Dugan (2012) demonstrated that of the 26 percent of all organizations who lasted more than a year, they were responsible for 93 percent of all attacks. Despite representing two very distinct trajectories, the factors that distinguish these two types of groups are poorly understood. This section outlines how a group’s organizational characterize may help explain why some groups survive and others end shortly after they begin.

Typologies that aim to explain terrorist groups’ longevity have argued that a group’s organizational characteristics can shed light on the processes that amplify or attenuate the likelihood a group will end over time (e.g. Crenshaw, 1991; USIP; 1999; Jones & Libicki, 2008). Structural characteristics, such as “coherent organizational structure[s]” (Crenshaw, 1991, p. 78), and “hierarchical organizations” (Jones & Libicki, 2008, p. 14) have all been claimed to be associated with a group’s resilience and duration, mediating the impact of law enforcement interdictions and the likelihood of internal discord that could lead to organizational breakdown. Popular case studies have been used to support these claims. The Front de Libération du Québec’s decentralized cellular structure has been stated to have enhanced the group’s longevity, allowing independent cells to emerge despite large-scale arrests (Charters, 2008). While, centralized groups, such as the Front de la Libération Nationale, have been cited as prone to failure, with the group’s demise linked to the network’s dependence on key actors (Kilberg, 2012). This work has suggested that the key mechanism distinguishing the longevity of groups is the degree of connectivity to other members.

However, whereas many studies have argued that organizational characteristics are a key mediating mechanism of a group’s trajectory, empirical examinations of groups’ network structures has not supported these claims. Perliger (2014) who examined network characteristics associated with 18 terrorist organizations who operated anywhere from six to 46 months (average 18 months), found that there was no consistent structural profile across the ‘one-hit wonders’ and the more resilient organizations. While Perliger (2014) found that groups who had longer trajectories tended to have lower density (fewer connections between all members), there was extensive variation even across resilient groups, and little differentiated them from the ‘one-hit wonders’ who lasted short durations and only conducted a single attack.

This section argues that this discrepancy between theoretical arguments of a group’s trajectory and empirical support may be primarily attributed to the measures used to assess these
networks. While Perliger (2014) found that little network variation existed across the longevity of organizations, this assessment was primarily based on measures of the overall connectivity (e.g. the overall proportion of ties across all members). While density provides an overall measure of cohesion, assessments of overall connectivity can mask pockets of clustering present in these networks (Friedkin, 1981). In fact, when Perliger (2014) turned to a group’s local degree of connectivity, found that groups who survived longer periods tended to have a higher degree of clustering. This is consistent, with previous examinations of terrorist networks that have found groups tend to organize into compartmentalized structures, often having a core ‘action’ component, and a larger periphery that helps coordinate and support incidents (e.g. Krebs, 2002; Rodríguez, 2005). Network measures that only look at overall connectivity may mask these small clusters, and thus assessments of a group’s ‘centralization’ or ‘decentralization’ that moderates their overall trajectories.

Drawing from extant literature on the relationship between a group’s network structure and life cycle, as well as the findings from this study, I develop a preliminary typology of group trajectories that helps differentiate between organizations who endure over long periods and those with short life spans. The main argument is that a more nuanced view of a group’s network structure – beyond their overall connectivity – can refine these mechanisms and help us understand why some groups persist over time while others end. Our review shows that two processes that are typically not accounted for in examinations of groups’ trajectories: 1) the distribution of cohesion between core and peripheral group members; and 2) the rate of actor turnover – may help explain the mechanisms that separate these two ‘types’ of groups.

Core and periphery: Distribution of cohesion across terrorist groups. Previous research on terrorist organizations has tended to distinguish between two types of network structures: centralized and decentralized. While the latter has been associated with security, minimizing connectivity and exposure to law enforcement, the former has been associated with efficiency, with higher connectivity providing the necessary communication chains to coordinate complex crimes. However, measures of these network structures are often taken at the aggregate-level, looking at connectivity across all members. While measures of overall connectivity are important, only examining a group’s aggregate properties ignores a body of research that shows criminal groups tend to organize into small, tightly knit clusters that are embedded within a larger, more peripheral network (Short & Strodtebeck, 1965; Klein & Crawford, 1967; Warr, 1996; 2002; Reiss,
1998; Sarnecki, 2001; Krebs, 2002; Daly, 2005; Rodríguez, 2005). These structures often referred to as core/periphery structures in network terms provide insight into the operation and continuity of groups.

In a core/periphery structure, core nodes are reasonably well-connected to peripheral nodes, but the latter are not well-connected to a core or to each other. Hence, a node belongs to a core if and only if it is well-connected both to other core nodes and to peripheral nodes. A core structure in a network is thus not merely densely connected but also tends to be ‘central’ to the network. Thus, groups who have a small core relative to their periphery may appear decentralized using overall network measures to assess their connectivity. Network measures that capture these core and periphery structures can shed light into a group’s structure, and the distribution of cohesion across members that guide key group processes.

Previous research has shown that a group’s core is important to their continuity. Identification of these core members are important as individuals embedded within these structures are likely to be influenced by group processes specific to the structure of their immediate network. McCarthy and Hagan (1995) argued that being embedded in a criminal network enhances the formation of relationships with other members, in turn, increasing skills and attitudes associated with the group, while reducing access to legitimate opportunities. This is supported by Study 1 and research by Stevenson and Crossley (2014) who found that individuals socially embedded in the group are more likely to stay with the group for longer. Core, central members have also been found to be key for maintaining a group, serving as experienced members who may also set the direction of groups’ objectives (Pedahzur & Perliger, 2006).

However, a network’s longevity depends on more than the core offenders. A multitude of players are needed to ensure the continuity of criminal groups. While the periphery of a group is more ephemeral – with few connections to core members or other peripheral members – the group depends on these members as the pool of affiliates from which they may select from for future incidents (Bouchard & Morselli, 2014) and to take on more risk-adverse roles (e.g. Krebs, 2002). Previous research has argued that the survival of the core depends on being embedded in a wider periphery of participants. For instance, the 9/11 hijacking network’s success in evading detection leading up to the incident, has been attributes to the hijackers occupying peripheral, decentralized positions in the network. These individuals, connected through few ties, were sustained by a larger core network, who increased overall network connectivity (Krebs, 2002).
These core members were not directly involved in the attacks, but rather relied on the periphery to carry out the attacks on their behalf. Thus, the action component maintained few connections to the core members of the organization, minimizing their exposure and protecting core members from direct involvement in the attacks. Successful networks may therefore be those who are able to balance the need for efficiency to ensure effective coordination (achieved through local clusters of cohesive subgroups who coordinate criminal activities) and provides flexibility and security (periphery who are directly involved in crimes).

Turnover. Furthermore, groups who survive for any extended period also must contend with a second mechanism that moderates longevity – actor turnover. As noted by Reiss (1986) thirty years ago, “almost all groups that endure for any period of time experience turnover in members, with some leaving and others joining” (p. 140). This key feature of illicit groups has been found across terrorist organizations (e.g. Stevenson & Crossley, 2014) and other criminal groups (e.g. Short & Strodtbeck, 1965; Klein & Crawford, 1967; Tremblay et al., 1989). What distinguishes a group that can survive over time from one that ends, is its ability to replace members who leave due to external interdictions or internal discontent. First I outline previous research that has examined the factors that mediate a group’s actor turnover and consequent longevity. I then build on this, turning to the mediating role of cohesion in actor turnover.

A group’s survival has been found to be linked to its turnover rate. Tremblay et al. (1989) showed that early on in a criminal group’s trajectory recruitment exceeded dissolution, with the inverse process occurring near the group’s end. The authors argued that the ratio of incoming recruits to outgoing members was moderated by changes in the benefits (e.g. attractiveness and opportunities embedded in belonging to a group), and the costs (e.g. degree of risk) of belonging to the group. Creating an ‘opportunity hypothesis’, they argued that the benefits of belonging to a group captures the degree of opportunities that members would not have if they did not operate in a collective. Factors including a groups’ ability to maintain monopoly of a specific market can influence the appeal of joining a group, while loss of control of a market may reduce the incentives of group belonging. These same opportunities are also weighed in relation to the potential costs of belonging, such as the probability of apprehension. Given that successful groups are also more likely to attract law enforcement resources and attention; an assessment of costs may change over their life cycle. In these instances, a group may increase one’s chances of apprehension, as well as any additional penalties associated with affiliation. Thus changes in law enforcement
activity may influence the number of actors that are attracted to and remain with a group over time. This study showed that processes both internal to the group (e.g. access to otherwise unavailable opportunities); as well as external (e.g. degree of risk) influences whether a group can attract membership to regenerate and sustain itself over time.

Turnover and cohesion. The importance of cohesion is that it directly moderates other group processes, in particular actor turnover – that are key for maintaining a group’s longevity. I argue that actor turnover is not spread uniformly across a group, but rather varies in tandem with internal structure. That is, structure directly moderates opportunities and risks that influence whether members stay or leave a group. Not all group members benefit equally to belonging to a group and the opportunities embedded in belonging are directly related to an individual’s position within the group. Individuals with a high number of connections to a group may have greater access to opportunities embedded in these relationships. Klein and Crawford (1995) found that individuals embedded in the group were more likely to be committed to the group objectives. In addition, a higher number of ties may increase an individual’s dependence on the network (Horowitz, 1983) and increase the costs of leaving the group. At the same time, individuals’ central to the group may be at a greater likelihood of detection and face higher sentences if detected (Baker & Faulkner, 1993).

Cohesion may also moderate the rate of actor turnover. From a group perspective, high rates of membership turnover, requires acquiring new members. From an individual member perspective, “it means transitory affiliations with some group members and adapting to the exodus or former members and an influx of new members” (Reiss, 1986, p. 130). Previous research has demonstrated that an individual’s dropout propensity increases when their immediate connections drop out of the group (Sandell, 1999) and Study #3 showed that offenders’ were more likely to stay with a group when they were connected to other repeat offenders. At the group-level, whether actor turnover occurs in the core or the periphery may create two different effects on its longevity. Turnover in the core of the group may have a tendency to create an exponential effect – reducing the cohesion of the remaining members, and creating higher attrition rates of committed members who are more likely to leave when their immediate connections leave. In contrast, turnover in the periphery may exert little effect on the group’s longevity. Lacking connections to the overall group, the loss of peripheral members may be less likely to influence the remaining group members.
The intersection of these two mechanisms – cohesion and turnover – may help explain why measures of overall connectivity does not tend to discriminate between groups’ longevity. Measures of a group’s density does not capture subgroups that are embedded in a wider periphery of criminal affiliates. The following section brings together these two dimensions to explain groups’ trajectories.

**Stability and cohesion: A structural typology of group Trajectories.** Building on previous explanations of terrorist groups’ longevity, I go beyond a group’s overall connectivity, and argue that it is the intersection between a group’s network structure and actor turnover that explains a group’s duration. Specifically, two dimensions of a group’s structure (core; periphery), and the degree of turnover across these dimensions (high; low) can be merged to create three group trajectories (Figure 6). These trajectories are distinguished according to whether high/low turnover occurs in the cohesive, core components of the network, or the peripheral segments. The first two trajectories aim to explain short-lived groups: 1) *stagnant* trajectories capture groups who have a stable core and periphery (centralized and low turnover); and 2) *volatile* trajectories represent groups that have an unstable core and periphery (decentralized and high turnover). The third trajectory characterizes groups who persist over time: 3) *resilient* trajectories are groups that have a stable core (low turnover) and unstable periphery (high turnover), adopting both centralized and decentralized structures. Below I describe each trajectory in further detail and provide case examples of each.

**Stagnant trajectories (Short-lived).** The first trajectory consists of groups who have low membership turnover in both the core and the periphery. This trajectory is characterized by stable membership, with few members joining or leaving the group. These groups are more likely to
have higher connectivity across members, with stability fostering closure across actor ties over time (e.g. Bichler & Bush, 2016; Volker et al., 2016). Thus, rather than representing a true core/periphery structure, stagnant trajectories capture highly connected, centralized groups.

The short duration of stagnant trajectories stem from their dependence on a stable set of connected members, which decreases their resilience to external and internal shocks. Stagnant groups are more at risk of external shocks, in the form of law enforcement interdictions, with interconnectivity across members increasing the likelihood and impact of detection. In highly connected groups the likelihood of detection is increased, as groups must rely on central actors to conduct operations. This also influences the impact of interdictions as the detection of any one member can lead to the exposure of the entire network. Furthermore, internal shocks in the form of disagreements or disillusionment across any one member can have a greater impact on the overall group – with discordant views more likely to be spread across all members in the network. The impact of a loss of any one member is also exacerbated, as lacking a periphery, the group does not have access to potential recruits to sustain or replace core members should any members leave voluntarily or through forcible removal.

This trajectory characterizes groups such as Aum Shinrikyo, whose transition into a highly connected, dense group has been linked to its downfall. Aum Shinrikyo who are best-known for the 1995 Sarin nerve attacks in Japan’s public transportation system, killing 13 and injuring thousands, consisted of 20 members who were all connected, with any one member knowing all other members involved (Koschade, 2005). The group ensured stability through low actor turnover, even killing one member who became disillusioned early in the group’s formation, while increasing compliance through connectivity, requiring more than one member be involved in each criminal activity (Danzig et al., 2011, p. 12). While this served to insulate the group from detection, decreasing the likelihood of informants entering the group and others from defecting, once they conducted attacks and were on law enforcement radar, the group was quickly detected and arrested. Lacking the popular support and replacement mechanisms that may be maintained through more peripheral members – led to their dissolution.

Volatile trajectories (Short-lived). The second trajectory consists of groups who have high membership turnover in both the core and the periphery. This trajectory is defined by unstable membership, with central and peripheral members leaving and entering the group over time.
These groups are more likely to exhibit decentralized structures, with high turnover leading to the dissolution of relationships across members.

The key to volatile groups’ failure is an unstable core, which hinders their ability to sustain membership over time, while opening up the risk of infiltration. The absence of a committed core group to sustain the group, creates conditions for dissolution, with actors deriving fewer opportunities to remain with the group. These groups lack the sustaining mechanisms and benefits, such as belonging, that are created through a cohesive set of interactions to other members. In addition, being embedded in a network with high turnover can facilitate disillusionment, with other members losing faith in the cause, not allowing ties to form or build trust, and hindering steps towards conducting and sustaining effective operations. While the decentralized structure of volatile trajectories have been suggested to be more effective at reducing exposure to law enforcement, their high turnover influences opportunities for infiltration. In efforts to sustain themselves, volatile groups may seek to invite new members in efforts to replace old recruits. This turnover increases the chances of entry of both new members, but also the potential for exposure.

Volatile trajectories characterize groups such as the ‘Toronto 18’. While the two ringleaders stayed with the group the length of its trajectory, they did not consist of a cohesive core. High turnover across members of the core and periphery increased disillusionment and security concerns, eventually causing a fracture between the two leaders. Despite the ability to attract new membership, the group’s evolving membership was challenging to maintain and led to the steady dissolution of the group. Furthermore, inviting new actors in also increased their attention to law enforcement, with the group’s quick acceptance of new members in both the core and the periphery of the group, leading to two informants infiltrating the group. These informants were quickly brought into the core and connecting to key leaders and members, allowing law enforcement agencies to acquire the necessary intelligence to secure charges across the main actors.

Chronic trajectories. Chronic trajectories consist of groups who have high turnover in the periphery, but low turnover among core members. This trajectory is characterized by a stable core group of offenders, and a peripheral pool of affiliates who have few connections to the core. The balance between a stable core group of offenders, and a periphery of pool of affiliates are key to a group’s resilience – affording groups both the security and efficiency to maintain themselves
over time. This balance between maintaining a stable set of offenders to sustain effective operations over time, while still having a flexible peripheral membership - increases internal commitment to the group and decreases the impact of external shocks. In the core a connected group of individuals sustain and reinforce violent ideologies, while also increasing the social costs of leaving and risks of non-conformity.

However, key to these groups resilience – and what differentiates it from stagnant trajectories – is the unstable periphery. A transitory periphery serves two primary purposes: it provides 1) internal security to core members, serving as a ‘buffer’; and 2) a pool of potential recruits for future attacks. Actors in the periphery may be used to directly participate in attacks, allowing core members to take on more indirect roles that insulate them from detection and direct involvement. Previous research has supported the finding that offenders who execute the attacks are more likely to be found among the group’s periphery (Pedahzur & Perliger, 2006). In addition, a high turnover in the periphery shows the ability of the group to attract and bring in new members on an as-needed basis. Despite law enforcement efforts to dismantle membership, the periphery can provide the network with a pool of criminal associates who are willing to continue participating in future incidents. Without this turnover committed members may be less likely to stay – deriving their social position/status from this larger context, as well as their insulation, allowing them to adopt more hands-off roles.

Two of the case studies – Al Qaeda and Jemaah Islamiyah – may be characterized as chronic trajectories. In both cases, the organizations depended on a densely connected, core group of members who bridged the attack networks, coordinating operations, and a periphery who had few connections to the core and only stayed for isolated incidents, but were key for carrying out attacks. For Jemaah Islamiyah, the group was maintained over time by a stable set of experienced offenders who continued to conduct operations over time. These individuals were more likely to be highly educated and leaders, reflecting their positions as coordinators. In the case of Al Qaeda, key actors were also responsible for coordinating a series of attacks, relying on sets of peripheral actors to carry out the operations. This enhanced the group’s longevity, and also limited the detection of key actors, who often managed the attacks outside of the target country. This network structure has also been observed across groups such as the Provisional Irish Republican Army (PIRA) where Stevenson and Crossley (2014) found that despite high
turnover, the group maintained a stable core of members who became more central over time, and connected the group as it evolved.

Summary. These trajectories intend to resolve why a range of structural features (as measured by their overall connectivity) do not always account for a group’s longevity. While decentralized structures have been argued to be the most resilient, and shown to survive the longest in licit settings (e.g. Albert, Jeong, & Barabasi, 2000), criminal groups lack formal, licit mechanisms to advertise for membership and attract newcomers to a group, while also having to contend with external forces attempting to end the groups. Thus, terrorist organizations depend on a subgroup of cohesive offenders embedded in a wider periphery to sustain the organization over time. Groups who exhibit both properties of centralization (a stable core), and decentralization (unstable periphery) facilitate both commitment to the group and resilience to external interdictions. In contrast, groups who adopt centralized (stable-core/stable-periphery) and decentralized (unstable-core/unstable-periphery) are at greater risk of failure.

This typology is not intended to replace other causal mechanisms of the longevity of groups, or to extract trajectories from the context in which they are embedded, but rather serve as an examination of the mediating processes that may explain why efforts to defeat terrorist organizations do not always have the same effect. This merely represents a first step in specifying the structural characteristics associated with a group’s duration. Future research would benefit from going beyond the current strategy of creating a typology based on a selection of case studies, and from large-scale empirical studies across multiple groups to refine and test the propositions put forward. The aim was to go beyond describing the structural features associated with terrorist groups, and examine how specific characteristics influence groups’ trajectories.

5.2. Limitations and Future Directions

This dissertation represents a first step toward examining the relationship between terrorist group trajectories and the collective criminal career. As such, it is not without limitations that can help guide future research. Each study outlined limitations specific to the analysis; here I examine three limitations that extend across the studies.
The first limitation is the dynamic nature of the data. One of the main arguments of the dissertation was that dynamic networks are required to capture group processes; however, two of the case studies (Study #2 and Study #3) relied on cross-sectional networks at the time of the attack. Aggregating offenders' ties at the time of the attack misses the order in which relationships were formed, and may misconstrue network processes. For instance, in a cross-sectional network, three actors (A1, A2, and A3) may all be connected to one another. However, a longitudinal network may show that A1 only began interacting with A2 after A1 severed ties to A3. Thus, at no point in time were all three actors connected. While this scenario may be unlikely to occur in terrorist networks, with previous research showing that terrorist groups generally become more cohesive over time (and thus have a greater tendency for ties to build on one another, rather than dissolve) (e.g. Helfstein & Wright, 2011a; Bichler & Bush, 2016). In the absence of longitudinal data, cross-sectional data collected at different time points in the group’s trajectory (across each attack) provided a means to assess how a group’s network structure changed over time; however, this does not serve as a perfect example of a dynamic network. Future research should examine how the set of ties come together (e.g. similar to Study 1) to see how processes leading up to and following attacks influences group processes.

The second limitation extends from the biases in the data sources used to construct the networks. Our main variable of interest is the social organization of the group; however, the two sources used to assess to map the networks – self-reports and official records – both carry their own unique limitations. Self-reports are limited to the perspective of the individual reporting the relationships between members. This has implications for the network that is created, as 1) members that the individual is unaware of will not be reported as part of the group; and 2) only members for which the individual is aware of having a relationship will be reported as such. These limits can misconstrue the network as smaller, and more decentralized network than it actually was. Thus, in cases where it is not possible to interview all members of the group – which is typically the scenario in covert settings – an ideal mapping of a network requires access to additional sources. Official data can serve as a complementary source, providing a birds-eye perspective from law enforcement who have been investigating the organization over an extended period; however, is also limited in that it primarily surveys the charged members, and those who were detected. Official data tends to focus on detected criminal elements, and only reports the interactions that are known to law enforcement. Thus, official sources may extract groups from the social setting in which they are operating from. Merging these two sources can help mitigate
the limitations of each respective source, providing a more accurate representation of the network. This was observed in the Toronto 18 where self-reports and court documents serving as complementary sources, with many of the individuals reported through interviews not disclosed in court documents (n=6), and some of the individuals mentioned in court documents not disclosed in interviews (n=10). If we built the network data from self-reports would have missed a segment of the organization that followed the split; and had we only relied on court documents, the study would have missed the wider periphery of members from which the group emerged. From this perspective, the networks mapped for Al Qaeda (Study 2) and JI (Study 3) are biased in that we did not have access to self-report data. This may have created the perception of a smaller group structure than was actually present, missing the wider periphery of members who supported the groups objectives but were not criminally involved.

The third limitation of the dissertation is the reliance on three independent case studies. Ideally, the dissertation would have tested the research questions across a large sample of terrorist organizations. To do this, would have required access to longitudinal network data that extended 1) across terrorist groups; and 2) across members directly and indirectly involved in terrorist groups (i.e. charged and non-charged members). However, access to group-level data requires substantial resources and time. Below I outline how previous studies have approached the study of groups, and possible future directions for the study of groups.

The primary challenge in developing and testing parameters of the collective criminal career extends from the availability of data. Advances in criminal career research – at the individual-level – has benefited from longitudinal birth cohort and panel studies (e.g. Philadelphia Birth Cohort Study (Tracy et al., 1990; Wolfgang et al., 1972); Cambridge Study in Delinquent Development (Farrington, 1995)), which aim to sample both delinquent and non-delinquent individuals prior to the age of onset of delinquent careers. These research designs attempt to approximate experimental designs, in efforts to isolate the causal mechanisms that explain the criminal career. For similar advances to be made in the study of collective criminal careers requires access to longitudinal group-level data.

Yet, access to comprehensive databases on criminal groups is rare. Previous research that has conducted quantitative analysis across a large number of terrorist groups have relied on incident-level data from open sources, such as the Global Terrorism Database (e.g. Miller, 2012), and RAND-MIPT Terrorism Incident Database (Jones & Libicki, 2008). These data sources
provide a means to capture variation in the activity-level of groups but at a trade-off to detailed data on the groups themselves, in particular on their structural characteristics. If the individuals who make up these groups and the pattern of their interactions is key to understanding group trajectories – as this dissertation argues – access to detailed network data is necessary to understand these processes.

To further our understanding of criminal groups, a few different avenues may be pursued. The first avenue, would be to systematically collect detailed network data across groups from open sources, such as court documents and government reports. Given the ‘group’ element in many criminal definitions of terrorist organizations (LaFree & Dugan, 2004), court documents may serve as a resource to map out a group’s internal structure. While this approach is limited to the individuals mentioned in court transcripts, and may be biased toward the criminal elements, Study 1 showed that many of the actors identified in interviews (with an individual embedded in the organization), were also mentioned in court documents. However, this approach, which requires mapping the internal structure of terrorist organizations across a high number of groups would require access to extensive resources. Some examples of this type of data collection include the John Jay and Artis Transnational Terrorism Database, one of the only publicly available datasets of terrorist networks. This dataset was compiled over a three-year period with funding from the Air Force Office of Scientific Research, relying on a team of data collectors and coders (Atran et al., 2008). However, while representing one of the most comprehensive terrorist network datasets (capturing the networks of over 20 attacks and over 2,000 terrorist offenders) the data set is limited to Al Qaeda attacks – only representing a single group. Other examples of network data, looking across groups, include efforts by the Mitchell Centre for Social Network Analysis. The Mitchell Centre has been compiling existing network datasets across studies to examine structural characteristics across criminal groups (Oliver, 2014). However, while useful for comparing network designs, differences in data collection across studies limits systematic comparisons across groups.

A second, more efficient, approach to study the collective criminal career would be to rely on existing longitudinal network datasets. Previous studies have shown that co-offending data (e.g. Lantz & Hutchison, 2015; Hashimi et al., 2016) and survey data (e.g. Kreager et al., 2011) may be used to identify and study delinquent groups. This method stems from the work of Kreager et al. (2011) who used friendship nominations, derived from school survey data, to identify the
presence of friendship groups in schools. The identification of groups relied on identifying clusters of students who all nominated each other as friends, and nominated few individuals outside their cluster as part of their friendship network. The novelty in this approach lies in the fact that group boundaries are not established by the researchers, or by the participants, but rather through network methods which sets the boundaries of the groups using quantifiable measures. This same method has been used to study criminal groups, with previous studies using co-offending data from official sources to identify clusters of offenders who frequently co-offend with one another, but with few others outside the cluster (e.g. Lantz & Hutchison, 2015).

A major benefit of this approach is the access to already collected data (e.g. co-arrest data), as well as the fact that these sources often have a collection of other theoretically relevant variables that could help explain group trajectories as well as group’s structural features. However, aggregating individual units of analysis can greatly reduce sample sizes. For instance, Lantz and Hutchison’s (2015) population of 270 offenders was reduced to 50 groups, thus requiring access to large datasets. In addition, given that official sources capture the detected offenders, it masks dynamic social context in which offenders are embedded. This may have implications for understanding how groups emerge and evolve over time. And lastly, official data are unlikely to detect terrorist groups, who are typically not involved in the wider pattern of criminal activity, but rather would reflect a few isolated, large-scale arrests. Despite these limitations, in the absence of detailed network data across groups, official sources would provide a starting-point to further our understanding of criminal groups.

5.3. **Policy Implications**

The findings of these analyses lend further support for the oft cited recommendation that effective interventions require accurate assessments of the problem. However, it advocates that network methods, which capture a group’s organizational structure, should form one of the cornerstones of the problem analysis. How groups organize and structure themselves are key to designing effective interdiction strategies. Mapping a group’s network structure can have important implications and may serve as a means to 1) how groups evolve in response to criminal interdictions; and 2) a more precise understanding of the mechanisms of recruitment.
Terrorist groups are not stable across their life span. As demonstrated by Study 2, as law enforcement shift their interdiction strategies, so do the illicit networks they target. While some interdictions may be effective early on in a group’s trajectory, they may have little effect later on. For example, increases in law enforcement activity may reduce the likelihood that members form ties with other co-offenders. Thus, interdictions early on in a group’s trajectory could detect a higher rate of offenders, while later on groups may become more covert, thus reducing the effectiveness of disruption strategies. If members become more decentralized or dispersed, it may require law enforcement to adopt alternate strategies to have the same effect. Overall, findings from the current dissertation recommend that interventions be designed to eliminate criminal groups, rather than any single member. Because groups are often able to sustain themselves long after any single member, policy interventions that aim to target the group itself may be most effective, disrupting the very mechanism that sustains and promotes criminal activity.

In regard to the last point, network methods provide a means to identify a stable cohort of offenders who link and instigate attacks. Interventions may be most effective when aimed to eliminate these repeat offenders, versus any individual member. While a body of research exists on how the removal of specific individuals may best disrupt the overall organization (e.g. Carley, Lee, & Krackhardt, 2002; Tsvetovat & Carley, 2003; Price, 2012), these studies have highlighted that key actors are often easily replaced (Tsvetovat & Carley, 2003). Given the flexibility and resilience of criminal group, interventions designed to target sets of cohesive actors may be more amenable to reducing a group’s likelihood of survival. Findings from the current dissertation showed that cohorts of offenders bridged attack networks and sustained groups over time, providing them with a consistent set of experienced offenders. This aligns with previous research, which has suggested that degrading a terrorist network may require eliminating “5 to 15 percent of all hubs at once. Otherwise, with time, new hubs will take the role of the eliminated ones and restore the network’s ability to function” (Sageman, 2004, p. 141). By mapping the network, interventions can see the full set of interactions that bring members together, and the subset of offenders who are key to driving the group’ overall actions. Targeting sets of actors who are most central to the organization - key for instigating and coordinating events - have a higher likelihood of disrupting internal processes. This approach may have a greater deterrence among the remaining members, who lose both their immediate connections and the cohesive structure that
sustained their involvement. The more we understand the networks of recruitment, the more precise the interventions.

5.4. Summary

If groups are the key to driving criminal behaviour, terrorist organizations epitomize this, providing a collective avenue to carry out large-scale attacks, and the necessary cohesive structures to facilitate transitions into violent radicalization. This dissertation aimed to show how a group’s network structure is key for amplifying or attenuating a group’s life cycle. Findings across each study showed how a different aspect of a group’s social organizations influenced offending pathways, with subgroups of densely connected offenders driving terrorist groups’ trajectories, impacting their emergence and persistence over time. Yet, these analyses only serve as a first step in exploring the trajectory of criminal groups. Future research should test and refine the role of organizational structure and actor turnover in predicting group trajectories that was outlined above. Studies may also consider examining the properties of groups that promote and sustain transitions into violence. While densely connected groups of offenders have been shown to be associated with violent behaviour, studies should look across criminal groups and individual attributes to help develop thresholds whereby certain group-level and situational-level factors may influence a group’s tipping point into violence. The objective of the current dissertation was to further our understanding of criminal groups, shifting the focus from the individual to the group setting in which offenders are embedded, providing a means to isolate the mechanisms that lead individuals to engage in criminal activity that they would not do if not for the group.
References


Appendix A.

Inclusion/Exclusion Criteria

1. Studies that simulated terrorist networks (e.g. agent based modeling) were excluded.
2. Studies that looked at online networks of terrorists (e.g. discussion forums) were excluded. One exception were studies that looked at both the online and offline components of terrorist networks (e.g. Nash & Bouchard, 2015 who examined an ego’s network using both online and offline actors).
3. Studies that focused purely on the financial networks of terrorist organizations were excluded (e.g. FARC drug trafficking network (Hernandez, et al., 2012)).
4. Studies that did not provide any systematic mapping of the network; rather provided a narrative of individuals’ connections over time were excluded (i.e. did not provide a network, network measures, or clear methodology).
5. Studies that used previously existing data on a terrorist network to demonstrate a new methodology were excluded (e.g. present a new centrality measure).
6. Only studies that used individuals or groups as the unit of analysis were retained (e.g. sources that looked at the networks of terrorist offenders and police events, or organizations and number of terrorist incidents were excluded (Jordan, 2012; 2014)).
7. Only French and English sources were consulted.
## Appendix B.

### Coding and Analysis of Sources

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset</td>
<td>Original  Secondary</td>
</tr>
<tr>
<td>Sources consulted to create the network</td>
<td>Court documents  Existing terrorism databases (e.g. Global Terrorism Database; Terrorism Knowledge Database)  Government reports  Interviews  Media sources  Peer-reviewed articles</td>
</tr>
<tr>
<td>(more than one could be selected)</td>
<td></td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Individual  Group</td>
</tr>
<tr>
<td>Network Boundary</td>
<td>Event (e.g. Attack network)  Organisation</td>
</tr>
<tr>
<td>Directed Ties</td>
<td>Yes  No</td>
</tr>
<tr>
<td>Dynamic network (Network was analyzed across different points in time)</td>
<td>Yes  No</td>
</tr>
<tr>
<td>Time Period</td>
<td>Time period for which network data was collected (in years)</td>
</tr>
<tr>
<td>Ego Network</td>
<td>Yes  No</td>
</tr>
<tr>
<td>One-mode</td>
<td>Yes  No</td>
</tr>
<tr>
<td>Ideology</td>
<td>Left-wing  Religious  Right-wing  Separatist  Supremacist</td>
</tr>
<tr>
<td>Country</td>
<td>Country the organization primarily operated in; or country where the attack was executed (for event-level data)</td>
</tr>
<tr>
<td>Size</td>
<td>The total number of actors included in the network (for dynamic network data – the aggregated size of the network across time points)</td>
</tr>
<tr>
<td>Density</td>
<td>Measures the total network’s connectivity.  The sum of all ties that directly connect actors divided by the total possible number of connections (for dynamic)</td>
</tr>
</tbody>
</table>

126
network data – the aggregated size of the network across time points).

<table>
<thead>
<tr>
<th>Network measures</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clustering Coefficient</td>
<td>Measures clusters of local connectivity within the network. It is calculated by taking the density of each individual’s ego network averaged across the entire network (for dynamic network data – the aggregated size of the network across time points).</td>
</tr>
<tr>
<td>Average Degree</td>
<td>The number of direct contacts of each individual averaged across the entire network (for dynamic network data – this represents the aggregated size of the network across time points).</td>
</tr>
</tbody>
</table>

**If study applied statistical analyses**

<table>
<thead>
<tr>
<th>Method</th>
<th>The primary statistical method used by the study (e.g. ANOVA; Exponential Random Graph Models; Regression models; SIENA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent Variable(s)</td>
<td>All independent variables used in the study.</td>
</tr>
<tr>
<td>Network IV (did the study use a network variable as an IV?)</td>
<td>Yes  No</td>
</tr>
<tr>
<td>If yes, the network variable used</td>
<td>(e.g. Betweenness centrality; Degree centrality, …)</td>
</tr>
<tr>
<td>Dependent Variable(s)</td>
<td>All dependent variables used in the study.</td>
</tr>
<tr>
<td>Network DV (did the study use a network variable as a DV?)</td>
<td>Yes  No</td>
</tr>
<tr>
<td>If yes, the network variable used</td>
<td>(e.g. the presence of a tie; betweenness centrality; degree centrality)</td>
</tr>
</tbody>
</table>

**Network results**

A synthesis of the main findings from the analyses, focusing on results pertaining to the network variables.
Appendix C.

Goodness of Fit

ERGM depends on simulated networks to estimate the likelihood of tie formation. Thus, requiring goodness-of-fit are key to interpreting models. One method to assess goodness-of-fit is to compare network properties across the observed network and the simulated networks (Hunter et al., 2008). Specifically, we plotted the distribution of network measures from the MCMC sample with the same network measure in the observed network. A well-fitting model is indicated by similar measures across the observed and simulated networks. In Figures A and B we have plotted network statistics for the observed and simulated networks. The black line represents the network statistic for the observed network, while the box-and-whisker plots indicate the mean value of the sampled networks and the 95 percent confidence intervals. Across the pre- and post-War on Terror networks, the simulated networks reproduce structural properties, including the degree and triad census, of the observed networks.

Figure A. Goodness-of-Fit pre-War on Terror Attack Networks
Figure B. Goodness-of-Fit War on Terror Attack Networks