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THE CO-EVOLUTION OF SOCIAL NETWORKS IN INSURGENT WARFARE

by

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September 2021

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THE CO-EVOLUTION OF SOCIAL NETWORKS IN INSURGENT WARFARE

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ABSTRACT

Extant literature has addressed empirical insurgent networks inadequately, insufficiently accounting for insurgent warfare's unique characteristics. Specifically, existing structural studies of insurgencies—those seeking to understand emergent social system patterns—have failed to capture the overlapping nature of competing, information-sharing networks in such contexts. This study focuses on the ways by which insurgent and authority social networks co-evolve in insurgent warfare. It extends previous research in four ways. First, it addresses empirical insurgent networks explicitly, which the “dark network” literature has largely ignored. Second, it takes a perspective that is consistent with insurgent warfare contexts. Using FARC as a case study, it analyzes two competing information-sharing networks at an operational level. Third, this study extends the application of Monge and Contractor's (2003) multitheoretical, multilevel (MTML) framework to co-evolving social networks in insurgent warfare, which is a perspective that synthesizes complex adaptive systems and social network research around key concepts inherently related to co-evolution and helps address gaps in extant literature. Finally, it identifies several multilevel, co-evolutionary effects between competing social networks in an insurgent warfare context, which challenges approaches that treat insurgents networks as completely external structures onto which counterinsurgents implement strategies.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	INSURGENT WARFARE AND SOCIAL SYSTEMS.....	1
B.	MULTITHEORETICAL, MULTILEVEL (MTML) FRAMEWORK: FUSING COMPLEX ADAPTIVE SYSTEMS AND SOCIAL NETWORK RESEARCH.....	5
C.	MULTILEVEL SOCIAL NETWORKS AND EMERGENCE.....	10
D.	SOCIAL PROCESSES AND SELF-ORGANIZATION IN THE MTML FRAMEWORK	12
E.	CO-EVOLUTION AND SOCIAL SYSTEMS	13
F.	CASE STUDY: THE REVOLUTIONARY ARMED FORCES OF COLOMBIA (FARC) INSURGENCY.....	15
G.	METHODOLOGY	16
II.	COMPETITION, INFORMATION, AND SOCIAL NETWORKS IN INSURGENT WARFARE	21
A.	COIN PARADIGMS	23
B.	COMPETITION FOR CONTROL OF A POPULACE	25
C.	THE CENTRAL ROLE OF THE POPULACE	28
D.	THE ROLE OF INFORMATION IN INSURGENT WARFARE	32
E.	SOCIAL NETWORKS AND SYSTEMS IN INSURGENT WARFARE.....	35
III.	MTML FRAMEWORK.....	43
A.	BRIEF OVERVIEW OF COMPLEX ADAPTIVE SYSTEMS RESEARCH	46
B.	BRIEF OVERVIEW OF SOCIAL NETWORK RESEARCH	52
C.	SUMMARY: MTML’S SYNTHESIS OF COMPLEX ADAPTIVE SYSTEMS OF SOCIAL NETWORK RESEARCH	56
D.	MULTILEVEL SOCIAL NETWORKS AND STRUCTURAL EMERGENCE	59
E.	SOCIAL PROCESSES AND SELF-ORGANIZATION IN THE MTML FRAMEWORK.....	63
F.	EVOLUTION, CO-EVOLUTION, AND SOCIAL SYSTEMS.....	69
G.	SOCIAL NETWORK RESEARCH: EVOLUTION AND CO- EVOLUTION	75
H.	MULTILEVEL HYPOTHESES: SELF-ORGANIZATION AND CO-EVOLUTION IN INSURGENT WARFARE	81
	1. Self-Organizing, Intra-Network Processes	81

2.	Co-Evolutionary Processes Between Insurgent and Authority Networks	85
IV.	DATA, MODELS, AND OPERATIONALIZATION	89
A.	INTRODUCTION.....	89
B.	BRIEF HISTORY OF THE FARC.....	90
C.	FARC’S ORGANIZATIONAL STRUCTURE DURING ITS INSURGENCY.....	94
D.	THE FARC’S INFORMATION AND INFORMAL SOCIAL NETWORKS.....	95
E.	DATA AND BOUNDARIES.....	97
F.	STOCHASTIC ACTOR ORIENTED MODELS (SAOMS)	102
G.	OPERATIONALIZING THE MODEL	108
1.	Network Evolution Effects—Self-Organization and Attribute-Based Processes.....	108
2.	Network Co-Evolution Effects.....	109
H.	RELIABILITY AND VALIDITY	110
V.	ANALYSIS	113
A.	INTRODUCTION.....	113
B.	DESCRIPTIVE ANALYSIS—GLOBAL PATTERNS.....	114
1.	Authority and Insurgent Information-Sharing Networks	114
1.	Global Social System Descriptive Statistics	117
C.	INTRODUCTION TO MODEL RESULTS - SAOMS	120
D.	SELF-ORGANIZATION AND ACTOR ATTRIBUTES—UNIVARIATE AND COVARIATE EFFECTS.....	123
1.	Authority Information-Sharing Networks.....	123
2.	Insurgent Information-Sharing Networks	126
E.	CO-EVOLUTIONARY SOCIAL PROCESSES—MULTIPLEX EFFECTS.....	128
F.	GOODNESS OF FIT (GOF)	131
G.	SUMMARY OF RESULTS	133
VI.	CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH	137
A.	CONCLUSIONS	137
B.	LIMITATIONS AND FUTURE RESEARCH.....	142
	APPENDIX A. CODEBOOK	145
A.	RELATIONS.....	145
B.	ATTRIBUTES.....	145

APPENDIX B. RSIENA CODE	147
C. LOAD PACKAGES.....	147
D. LOAD AND PREP DATA.....	147
E. SETUP DATA FOR MODELING	149
F. SPECIFY MODEL	149
G. ESTIMATE MODEL	150
H. WALD TEST	150
I. GOODNESS OF FIT	151
J. MODEL 2: CO-EVOLUTION MODEL	153
K. CO-EVOLUTION GOODNESS OF FIT	155
 LIST OF REFERENCES.....	 157
 INITIAL DISTRIBUTION LIST	 177

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LIST OF FIGURES

Figure 1.	Distinct Networks vs. Overlapping Networks	38
Figure 2.	Competing Information Networks	42
Figure 3.	Social System Levels and Example Hypotheses	60
Figure 4.	Examples of Self-Organizing, Social Processes	68
Figure 5.	Examples of Multilevel, Social Processes	79
Figure 6.	Progression from Distinct Networks to MTML Perspective	81
Figure 7.	Information Closure Hypothesis	82
Figure 8.	Information Cluster Hypothesis	84
Figure 9.	Information Hubs Hypothesis	85
Figure 10.	Information Multiplexity Hypothesis	86
Figure 11.	Mixed Information Cluster Hypothesis	87
Figure 12.	Competitive Hubs Hypothesis	88
Figure 13.	Southern Bloc's Area of Operation. Source: Colombian National Police (2012)	95
Figure 14.	Colombia: FARC and Authority Social System	119
Figure 15.	Venn Diagram—Insurgent, Authority, and Both	120
Figure 16.	Model 2 Goodness of Fit	133

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LIST OF TABLES

Table 1.	Summary of Model Effects and Hypotheses	110
Table 2.	Descriptive Statistics of Insurgent and Authority Networks	116
Table 3.	Descriptive Statistics of Social System—Combined Authority and Insurgent Networks	118
Table 4.	Self-Organization and Actor Attributes—SAOMs Univariate and Covariate Effects	126
Table 5.	SAOM Results.....	129

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LIST OF ACRONYMS AND ABBREVIATIONS

AUC	Autodefensas Unidas de Colombia (United Self-Defense Forces of Colombia)
BACRIM	Bandas Criminales (Criminal Gangs)
BRI	Belt Road Initiative
CAS	Complex Adaptive System
CMO	Civil-Military Operations
COIN	Counterinsurgency
COMINTER	Comité Internacional (International Committee)
COMISAF	Commander of International Security Assistance Forces
DIPOL	Dirección de Inteligencia Policial (Colombian National Police's Intelligence Directorate)
ELN	Ejército de Liberación Nacional (National Liberation Army)
EMC	Estado Mayor Central (Central General Staff)
EPL	Ejército Popular de Liberación (Popular Liberation Army)
ERGMs	Exponential Radom Graph Models
FARC	Fuerzas Armadas Revolucionarias de Colombia (Revolutionary Armed Forces of Colombia)
FM	Field Manual
FTO	Foreign Terrorist Organization
GOF	Goodness of Fit
GPC	Great Power Competition
GWESP	Geometrically Weighted Edgewise Shared Partners
IA	Information Assurance
IED	Improvised Explosive Device
IO	Information Operations
IW	Information Warfare
JP	Joint Publication
M-19	Movimiento 19 de Abril (April 19 th Movement)
MAS	Muerto a los Secuestreros (Death to Kidnappers)
MBNC	Movimiento Bolivariano por la Nueva Colombia (Bolivarian Movement for the New Colombia)

MILDEC	Military Deception
MISO	Military Information Support Operations
MTML	Multitheoretical, Multilevel
NGO	Non-Governmental Organization
OST	Open Systems Theory
PA	Public Affairs
PCCC	Partido Comunista Clandestino Colombiano (Clandestine Colombian Communist Party)
PIRA	Provisional Irish Republican Army
PRC	People's Republic of China
QAP	Quadratic Assignment Procedure
SAOMs	Stochastic Actor Oriented Models
SNA	Social Network Analysis
TFMC	Teófilo Forero Mobile Column
UP	Union Patriótica (Patriot Union)

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I. INTRODUCTION

A. INSURGENT WARFARE AND SOCIAL SYSTEMS

Insurgent warfare is violent competition, or struggle, between governments and insurgents that takes place among and for the control of a populace¹ (Galula, 2006; Kilcullen, 2010; Nagl, 2005). Each side's ability to acquire and disseminate information about a population and its adversaries plays a critical role in a conflict's outcome (Department of the Army, 2014; Galula, 2006; Guevara, 2007; Tse-Tung, 1989). While many means exist for both sides to obtain and spread information in operational settings, like social media-based interactions (e.g., Twitter), in-person social relations serve as critical conduits for the flow of information in social networks, including in insurgent warfare (Borgatti & Halgin, 2011; Cleveland et al., 2018; Galula, 2006; Guevara, 2007; Kilcullen, 2010; Pye, 1950; Tse-Tung, 1989; United States Government, 2013, 2014). As individuals exchange information pertaining to a populace and enemy in public spaces such as patrols, or private settings such as key leader engagements, whether they be combatants (e.g., insurgents or military) and/or noncombatants (e.g., civilians), they form information-sharing social networks that each side can leverage in the competition with their adversaries (Cleveland et al., 2018; Department of the Army, 2017).

In insurgent warfare, one can observe at least two of these competitive social networks that make up a larger social system throughout the duration of an insurgency: namely *authority information-sharing* and *insurgent information-sharing* networks. Each of these networks is built upon cooperative information sharing ties among combatants and noncombatants on one side of a conflict (i.e., intra-network ties). However, ties between the competing sides (i.e., inter-network ties) form too, such as when civilians provide information to both insurgents and soldiers, which means the two networks can intertwine through shared "nodes" and form a larger social system (Department of the Army, 2017;

¹ This term is used in a broad sense. Insurgencies can take many forms. For instance, O'Neill (2005) identifies nine types of insurgents: anarchists, egalitarians, traditionalists, pluralists, apocalyptic-utopians, secessionists, reformists, preservationists, and commercialists. Otto Heilbrunn (1962) identified three types of insurgencies, namely terrorist wars, small-unit guerrilla wars, and large unit insurgencies (see Arquilla, 2018).

Department of the Navy, 2017; Kilcullen, 2013; United States Government, 2016). Though these in-person, information-sharing ties may coincide with other types of social relations (e.g., family, and shared organizational affiliation ties), they are unique in that while conflict relevant information may flow through others, it does not mean it will. For instance, insurgents do not always share information about the populace or authorities with their family or friends, in part, because of security concerns. It is only when individuals pass or exchange information through these other forms of relations that the ties can be regarded as information-sharing ones, too.

Three bodies of relevant research, including counterinsurgency (COIN), social system, and social network research, often use terms such as “social networks,” “social structure,” “systems,” and “social systems” to describe patterns of interactions, including information-sharing ones, that largely define insurgent warfare² (Cleveland et al., 2018; Kilcullen, 2013). However, structural studies of insurgencies—those that seek to understand emergent social system patterns—have addressed empirical insurgent networks inadequately, insufficiently accounting for the unique characteristics of insurgent warfare, such as its competitive nature and overlapping information-sharing networks of insurgents, noncombatants, and government personnel. These gaps raise questions about the validity of counterinsurgency studies that treat insurgent structures as distinct from others (e.g., civilian vs. insurgent networks), and highlight challenges of understanding their dynamics. Specifically, while systems research has offered many strategic level insights into nonlinear dynamics of counterinsurgency and treats networks as open systems,³ it has overlooked empirical social networks in which combatants and noncombatants intertwine and compete in operational settings (Baker, 2006; Grynkewich & Reifel, 2006; Johnson, 1982; Mesjasz, 2015; Schoenenberger et al., 2014).

² While some researchers define “social structure” differently, the term is used here to refer to patterns of connections among individuals (Glanville & Bienenstock, 2009). A “social network” is a set of components (e.g., individuals or nodes in graph theory) and the relations among them (Borgatti et al., 2013; Robins, 2015; Wasserman & Faust, 1994). They are forms of social systems (Borgatti et al., 2013; Robins, 2015). Thus, this dissertation uses the terms “social networks” and “social systems” interchangeably and “social structure” as a term to describe patterns in them.

³ Open systems “exchange energy or information with their environment” (Cilliers, 2000, p. 24) and their boundaries are not clearly defined.

Similarly, social network research has failed to account for these same characteristics and has focused most of its attention on the broader category of “dark networks” (i.e., illegal and covert) rather than insurgent networks specifically (Bakker et al., 2012; Cunningham et al., 2016; Everton, 2012; Gerdes, 2015; Morselli, 2014). A major focus of these studies has been mapping empirical nefarious social networks and assessing how various “exogenous” effects, such as disruption strategies, impact their structure and performance (e.g., ability to conduct operations) (Bakker et al., 2012; Carley et al., 2003; Cunningham et al., 2016; Enders & Jindapon, 2009; Everton, 2012; Roberts & Everton, 2016, 2011). This research often treats insurgent networks as if there are clear boundaries around them that make them distinguishable from the populations in which they are embedded, as well as from the government networks with which they fight. While this assumption is useful for analyzing many types of dark networks (e.g., terrorist networks), analyzing insurgent networks in isolation fails to capture how conflict takes place among populations, as well as how combatants (i.e., authorities and insurgents) and noncombatants (e.g., civilians) often interact to acquire and disseminate information about one another in such settings. Moreover, this perspective assumes the “side” to which individuals belong is fixed over time, which is problematic because many people switch sides and/or often serve both in insurgent warfare (Department of the Army, 2017; Department of the Navy, 2017; Kilcullen, 2013; United States Government, 2016).

These limitations have consequences for understanding the dynamics of information-sharing social networks in insurgent warfare. A critical task of such efforts is identifying and untangling the ways by which individuals form connections—in this case sharing information—in response to others and their relationships; that is, the social processes that undergird social systems (Borgatti et al., 2013; Lusher et al., 2013; Padgett & Powell, 2012; Robins, 2015; Snijders et al., 2010). Analyzing the evolution of even a single social network, such as authority or insurgent information-sharing ones, is a difficult task. Individuals join and leave networks, as well as form and dissolve ties in response to their social environment, such as attempting to access new information through social ties pertaining to their (e.g., survive conflict) or their network’s goals (e.g., gain control over a populace). Yet, because authority and insurgent networks often interweave in insurgent warfare, it is likely they

evolve mutually too—or co-evolve—in part, because they are open systems and make up part of each other’s social environment. For instance, a prominent civilian leader with a history of providing information to the government about insurgent efforts may provide insurgents with information about local civilian-military projects after being threatened by a government soldier, or an insurgent sympathizer may “switch sides” and offer the government information about insurgent weaponry when the latter offers incentives to do so. In both cases, the result is a change in a network’s structure. When many of these interactions occur, often simultaneously, they combine into a complex set of social processes that help drive a network’s dynamics (Lusher et al., 2013; Robins, 2015; Snijders et al., 2010). These points suggest both intra- and inter-network social processes may drive an insurgent network’s evolution simultaneously. Therefore, this dissertation examines the following question: *How do information-sharing social networks evolve mutually (i.e., co-evolve) as they compete in insurgent warfare?*

In particular, it serves three purposes. The first is to test hypotheses about social processes that underly how competing social networks co-evolve in insurgent warfare. Because networks are comprised of many levels, this study offers hypotheses about micro social processes that likely occur at individual, dyad, triad, and subgroup levels⁴ within and between empirical social networks (Goldstein, 1999; Lichtenstein, 2000; Lusher et al., 2013; McKelvey, 1997; Monge & Contractor, 2003; Snijders et al., 2010; Wycisk et al., 2008). Its second purpose is to analyze insurgent networks from a perspective on social systems that is consistent with insurgency and counterinsurgency literature: namely, social systems comprised of competitive, overlapping insurgent, civilian, and counterinsurgent networks in operational settings.⁵ With these points in mind, this dissertation’s final aim is to build upon Monge and Contractor’s (2003) framework, which fuses complex adaptive systems and social network research through a shared emphasis on co-evolution and related social system

⁴ These the basic units of analysis in social network research. An actor, which is often referred to as a node or vertex in graph theory, can be a person, organization, nation-state, etc. Wasserman and Faust (1994), who provide much of the foundation for much of modern day social network research, define dyads as subgraphs consisting of two nodes and the possible ties between them, where as they define triads are subgroups consisting of three nodes and all ties among them.

⁵ This point is related to the idea of social network or social system boundaries, which is a definition that determines the entities and relations to be included in a social system.

concepts, and apply it as a means to address gaps in the empirical study of co-evolving networks in insurgent warfare.

**B. MULTITHEORETICAL, MULTILEVEL (MTML) FRAMEWORK:
FUSING COMPLEX ADAPTIVE SYSTEMS AND SOCIAL NETWORK
RESEARCH**

This dissertation utilizes Monge and Contractor's (2003) multitheoretical, multilevel (MTML) analytic framework to study the co-evolution of competing, information-sharing social networks in insurgent warfare. This framework blends complex adaptive systems and social network research through its emphasis on co-evolutionary social processes that take place within and between multilevel social systems. This perspective on co-evolution focuses on systems' micro changes within and between system levels in response to an environment and how such dynamics give rise to emergent macro patterns (Benbya & McKelvey, 2006; Dooley, 1997; Lichtenstein, 2000; Monge & Contractor, 2003; Porter, 2006; Robins, 2015; Snijders et al., 2007). It integrates the two bodies' shared concepts closely related to co-evolution as well: namely, network emergence and self-organization (Monge & Contractor, 2003, p. xii). The former is the "arising of novel and coherent structures" (Goldstein, 1999) in dynamic systems from "local" interactions (Holland, 1998; Lichtenstein, 2000; Monge & Contractor, 2003), while the latter generally comprises of a broad range of pattern-formation processes that attempt to explain the emergence of stable patterns and structure from the interactions of a system's constituent parts (Haken & Portugali, 2016; Kauffman, 1993; Monge & Contractor, 2003; Prigogine et al., 1988).

The framework is *multitheoretical* in the sense that it argues that researchers should draw from a variety of network theories to explain emergent and evolving social systems. Specifically, the authors contend that co-evolution and self-organization, which encompass a variety of micro social processes, such as reciprocity⁶ and homophily,⁷ serve as central

⁶ Reciprocity is a return in some good or relationship. What is reciprocated depends on the context. For instance, person A may provide person B with information who, in turn, reciprocates and provides person A with information (Glanville & Bienenstock, 2009; Robins, 2015).

⁷ Homophily is the tendency of individuals to form relations with similar others, or those with common characteristics or attributes (Lawrence & Shah, 2020; Lazarsfeld & Merton, 1954; McPherson et al., 2001).

forces driving social network dynamics, often simultaneously. In line with complex adaptive systems and social network research, this perspective accounts for both categories of processes and focuses on how each one determines a social system's macro structure (Anderson, 1999; Choi et al., 2001; Dooley, 1997; Levin, 1998; Lusher et al., 2013; McKelvey, 1997; Monge & Contractor, 2003). The framework is *multilevel* in the way that it enables researchers to account explicitly for social processes that take place at various network levels and help undergird larger social systems, including the actor or degree level (e.g., behaviors), various structural levels within a network (e.g., dyad, triads, cluster, and global), and across social networks (e.g., multiplex relations⁸).

In line with Monge and Contractor's (2003) framework, as well as others' research (Lane, 2006; Padgett & Powell, 2012; Sawyer, 2005), this study draws insights from both complex adaptive systems and social network research perspectives to examine co-evolving social networks in the context of insurgent warfare. Complex adaptive systems research, which accelerated during the 1990s and 2000s and is part of the broader "complex systems" domain, builds upon decades of social systems research. While no single definition exists, scholars often describe complex adaptive systems as those in which higher level patterns, aggregate behaviors, or order emerge from the actions and localized interactions of its adaptive components (e.g., individuals) rather than from centralized control; that is, they self-organize (Anderson, 1999; Gell-Mann, 1994; Goldstein, 1999; Holland, 1992; Holland & Miller, 1991; Levin, 1998; Mitchell, 2009; Sawyer, 2005). In addition to self-organizing behavior, these multilevel systems co-evolve with their environments, often as a result of competition for resources (Benbya & McKelvey, 2006; Dooley, 1997; Lichtenstein, 2000; McKelvey, 1997; Monge & Contractor, 2003; Porter, 2006). Complex adaptive systems, therefore, are different from other complex systems in the sense that individual components, often called agents, have cognitive abilities to collect information from their environment and adapt accordingly to try to reach their goals or the system's goals over time (Wycisk et al., 2008). They possess many other characteristics too, such as nonlinearity that produces unpredictable patterns and order, heterogenous and autonomous agents, radical openness and

⁸ Multiplex networks comprise of two or more types of relations among any number of same individuals.

porous boundaries, memory, dispersed interaction, flows between units (e.g., information), modular or clustered subsystems, cross-cutting hierarchical organization from self-organization and co-evolution, far-from-equilibrium dynamics, and novelty (Dooley, 1997; Holland, 1992; Holland & Miller, 1991; Levin, 1998; Miller & Page, 2007; Porter, 2006; Preiser et al., 2018).

Like complex adaptive systems research, social network research is a way of thinking about social systems (Borgatti et al., 2013; Robins, 2015). Social networks are social systems made up of social actors, such as insurgents, civilians, and government personnel, and the relations among them (Wasserman & Faust, 1994). A major underlying assumption of this research domain is that social systems are unique in that social beings, such as humans, have agency⁹ and are intentional. In other words, individuals can interpret information from their social environment and make decisions about how to act and behave (Choi et al., 2001; Emirbayer & Goodwin, 1994; Robins, 2015). Social context is important too. A social system in which individuals embed, including other actors and relationships, serve as their environment and can affect one's future ties, norms, beliefs, and behaviors, which is why the field generally considers both individual and system level factors in analyses (Borgatti et al., 2013; Borgatti & Halgin, 2011; Everton, 2012; Robins, 2015). Because of these characteristics, it is unlikely that a single theory or law explains all social networks. Instead, social network research emphasizes that a social system's structure is a consequence of dynamic social processes among social actors (Lusher et al., 2013; Monge & Contractor, 2003; Robins, 2015; Snijders et al., 2010), which suggests information-sharing ties in insurgent warfare, in part, come into existence between individuals in response to social environments comprised of other combatants and noncombatants (Lusher et al., 2013).

Consequently, social network researchers also emphasize the multilevel nature of social networks and have outlined many of the foundational ideas about social processes at multiple network levels (Kadushin, 2012; Lusher et al., 2013; Monge & Contractor, 2003; Robins, 2015; Snijders et al., 2010). The central idea is that many local, and often nested,

⁹ In a broad sense, agency is ability to “intervene meaningfully in the course of events” (Choi et al., 2001), such as choosing to form connections with others, and whereby the “system” does not necessarily determine outcomes (Emirbayer & Goodwin, 1994; Kadushin, 2012).

system effects, combine into a complex set of social processes that undergird social systems (Lusher et al., 2013). While many social networks, for example, exhibit underlying social processes such as preferential attachment (Barabási, 2016), many other plausible mechanisms can help researchers explain social network emergence and dynamics, such as structural processes other than preferential attachment (e.g., social exchange¹⁰), co-evolution, multiplexity, social selection (e.g., homophily), and social influence (e.g., diffusion). In other words, several social processes may be at play simultaneously and occur at different network levels in any given context (Borgatti et al., 2013; Lusher et al., 2013; Robins, 2015; Snijders et al., 2010).

Like complex adaptive systems research, social network researchers assumes that social systems are locally emergent in that repeated interactions of social entities give rise to emergent structures in which the whole is greater than the mere sum of its parts, including instances when multiple social networks overlap to make up a larger social system (Everton, 2012; Lusher et al., 2013; Padgett & Powell, 2012; Robins, 2015). Moreover, social ties function as conduits for the flow of information and resources, although typically social network studies do not conceptualize information as Shannon, pragmatic, or semantic¹¹ (Borgatti & Cross, 2003; Borgatti & Halgin, 2011; Crossley et al., 2015; Kadushin, 2012). Social network researchers recognize that social networks are dynamic as well, which is why researchers have increasingly examined how social networks self-organize, albeit in a much more implicit manner than complex adaptive systems research, as well as evolve over time, including how social networks co-evolve with others (Fujimoto et al., 2018; Lusher et al., 2013; Rambaran et al., 2015; Robins, 2015; Snijders et al., 2007; Steglich et al., 2006).

Monge and Contractor's (2003) MTML framework fuses complex adaptive systems and social network research around the two interdisciplinary research bodies' natural points of synthesis, such as shared assumptions (i.e., system components' interdependence through relations), the uniqueness of social systems (e.g., intentionality), and most pointedly, their

¹⁰ Social exchange is often indicated by the reciprocal exchange of some material or non-material good (Glanville & Bienenstock, 2009).

¹¹ Shannon information is a the "capacity of a channel through which a message passes," whereas pragmatic information is the "impact of a message on recipients," and semantic information is, "the meaning conveyed by a message" (Haken & Portugali, 2016, p. 1; Mitchell, 2009).

shared emphasis on the multilevel nature of social systems in which self-organizing and co-evolutionary social processes (i.e., multitheoretical) propel emergent structures at different levels. By doing so, this framework facilitates the study of co-evolving social networks in insurgent warfare and addresses important gaps in existing literature. Specifically, the complex adaptive systems perspective's unique contribution to the topic is that it aids analysis from a standpoint on system boundaries that is consistent with insurgency and counterinsurgency literature: namely, social systems that encompass open and competitive, information-sharing social networks that are comprised of dynamic social beings, specifically combatants and noncombatants, who influence and react to their social environment. This perspective offers a more realistic depiction of social systems in insurgent warfare than existing social network literature on "dark networks" and enables one to interpret them in a more complete and useful manner. Social network research's central contribution is its emphasis on identifying local social processes underlying empirical social systems. Though extant social network literature has failed to address insurgent networks adequately to date, this domain offers the most useful avenue to examine co-evolving, empirical social networks in operational settings, which addresses another major gap in the study of social systems in insurgent warfare.

Yet, the two research domains diverge in several notable ways for which one must account when leveraging the MTML framework. In addition to historical lineage and scope, a notable point of divergence is the extent to which the domains address relevant concepts explicitly, such as emergence and self-organization. Such concepts are central to complex adaptive systems research while they appear to receive relatively less overt attention in social network research. The MTML framework, as well as this dissertation, aligns more closely with the former view in that it argues that analyses should account explicitly for these concepts, especially when studying co-evolution (Monge & Contractor, 2003). Likewise, the two research bodies do not necessarily apply key concepts in the same manner. The concept of complex adaptive systems is at a high level of abstraction, and while it offers many insights into social systems, many of its concepts and principles in its orbit do not translate seamlessly nor are measured easily in the analysis of empirical social systems (Eidelson, 1997; Lansing, 2003; Sawyer, 2005). This challenge is apparent by the fact that empirical social network

studies rarely, if ever, explicitly incorporate and model relevant complex adaptive systems concepts and principles, such as bifurcations, self-organized criticality, homeostasis, and networks evolving at the edge of chaos (Borgatti et al., 2013; Cilliers, 1998; Eidelson, 1997; Kauffman, 1993; Robins, 2015; Root, 2020).

The two diverge in their main approach for understanding social systems as well. Complex adaptive systems researchers commonly leverage computational, agent-based models that generate structures and system behaviors based on *simulated* agent's decisions and interactions rather than map aggregate *empirical* social systems. While social network researchers recognize that individuals have cognition and it is an underlying assumption that information flows through social ties (Borgatti & Halgin, 2011), typically they do not model them explicitly. Monge and Contractor (2003) rely heavily on complex adaptive systems literature and agent-based modeling to illustrate and apply the MTML framework, yet they argue and demonstrate that social network models for empirical data are valid approaches too for analyzing complex systems (Lusher et al., 2013; Snijders et al., 2010; Snijders et al., 2007). Recent advances in social network statistical models since the authors published the framework have closed the gap between the two by permitting analysts to model dynamic, multilevel social processes on empirical social network data (Ripley et al., 2021).

With these points in mind, this dissertation's focus, like Monge and Contractor (2003), is on co-evolution and inherently related concepts, specifically emergence and self-organization, that both complex adaptive system and social network research address explicitly, albeit to varying extents, and can measure from a structural perspective. Nonetheless, little consensus exists about each concept's meaning and application; therefore, this dissertation's limited goal is to illustrate this framework's perspective for each concept and highlight their relevance to this topic, rather than offer an exhaustive review about philosophical debates surrounding each one (Koliba et al., 2016; Lane, 2006; Marcum, 2009; Walby, 2007).

C. MULTILEVEL SOCIAL NETWORKS AND EMERGENCE

The multilevel nature of social systems is a central aspect of the MTML framework and directly related to co-evolution. It is the idea that dynamic social processes take place at

multiple levels of analysis (Benbya & McKelvey, 2006; Goldstein, 1999; Levin, 2005; Lichtenstein, 2000; Lusher et al., 2013; McKelvey, 1997; Robins, 2015; Wycisk et al., 2008). A primary goal of co-evolution studies is to understand how “adaptive changes within and between” system levels and environment give rise to emergent patterns and behavior (Lichtenstein, 2000, p. 13). Drawing from complexity and social sciences, Monge and Contractor (2003) outline various theories that may help researchers hypothesize about social system dynamics at different network levels (i.e., individual, dyad, triad, subgroup, and global), most of which fall within the categories of self-organizing and co-evolutionary social processes.

The notion of multilevel social systems is inherently related to the concept of emergence (Goldstein, 1999; Holland, 1998; Lichtenstein, 2000; Monge & Contractor, 2003). It is a broad set of perspectives that assumes systems are made up of levels and that patterns, structure, and behavior at “higher levels” are greater than the mere sum of underlying parts (Wycisk et al., 2008). Focusing on structural emergence, Monge and Contractor (2003) claim that local or micro, self-organizing and co-evolutionary processes at their defined network levels generate emergent structural patterns at higher ones. At each system level, one cannot explain its structure, patterns, and behaviors wholly in terms of another level.

However, the notion of emergence is “less than an organized, rigorous theory than a collection of ideas” (Lissack, 1999, p. 112) which argue that dynamic patterns underlie global properties, such as behavior and structure (Corning, 2002). While the extent to which a level “determines” or “causes” others is a central question in emergence studies, the MTML framework accounts for both bottom-up processes, which are viewed as tie formation “tendencies” within a network, as well as top-down constraints from existing social structures (Kontopoulos, 1993; McKelvey, 1997; Monge & Contractor, 2003; Padgett & Powell, 2012; Robins, 2015). It also recognizes that feedback processes can drive dynamics at each level (e.g., reciprocity at a dyad level) and “external” influences, such as other social networks, may contribute to social system dynamics as well (Monge & Contractor, 2003, p. 13).

D. SOCIAL PROCESSES AND SELF-ORGANIZATION IN THE MTML FRAMEWORK

Self-organization is a central concept to the MTML framework and a pertinent concept in complexity science and social network research (Ashby, 1962; Bak, 1996; Haken, 1977; Kauffman, 1993; Lusher et al., 2013; Maturana & Varela, 1980; Robins, 2015). A foundational element of self-organizing behavior is that patterns emerge spontaneously from nonlinear dynamics and without the intervention and direction of a “central controller.” Monge and Contractor (2003) rely heavily on complex systems science literature and agent-based modeling to study self-organization, yet they argue and demonstrate that a social network research approach is valid for analyzing self-organizing and co-evolving social systems. Building on their work and other prominent network studies (Albert & Barabási, 2002; Barabási, 2002; Barabási & Bonabeau, 2003; Watts, 1999a; Watts & Strogatz, 1998), this analysis utilizes a social network research approach to self-organization because of its emphasis on empirical social networks. Specifically, it draws from Robins’s (2015, p. 34) definition of self-organization, which is structural processes “where the presence of some network ties sustains the ongoing presence of other network ties, or encourages them into existence.” From this perspective, self-organizing is a category of intra-network, social processes that contribute to social network emergence and dynamics (Lusher et al., 2013). Thus, the study of co-evolving social networks in insurgent warfare should account for self-organization to determine the extent to which it, rather than co-evolution, contributes to network dynamics (Anderson, 1999; Choi et al., 2001; Dooley, 1997; Levin, 1998; McKelvey, 1997; Monge & Contractor, 2003). Common self-organization processes in social networks are preferential attachment (actor level), reciprocity (dyad level), and triadic closure (triad level), all of which are dynamic and may occur in social networks simultaneously.

Using Robins’s (2015) definition of self-organization, one can imagine self-organizing behavior in insurgent warfare as combatants and noncombatants exchange information. The mixture of civilians and combatants in overlapping networks suggests many relations are informal, or naturally occurring ties created to access information, rather

than formal ones (Biancani et al., 2014; Kadushin, 2012).¹² Informal ties are far more likely to define spontaneous interactions and self-organizing than formal ties even though they often overlap, embed, are constrained by, and serve the same goals of formal ones (Goldstein, 1999; Kadushin, 2012, p. 39; Monge & Contractor, 2003, p. 10). While military and many insurgents, as well as civilians, tend to maintain formal organizational memberships with others, they are rarely, if ever, members of the same organizations during active conflict; instead, they appear to develop informal, information-sharing ties when they interact with others outside their formal structures. For instance, in 2007, U.S. forces successfully initiated informal agreements with tribal leaders in several Iraqi provinces, sometimes called “handshake agreements,” to establish information sharing ties, stop violence between the two, and fight al-Qaeda and other extremists (Cordesman, 2007; Kuehl, 2009). Competition between insurgents and government forces is only likely to fuel self-organizing behavior further (Astley, 1985; Cilliers, 1998; Monge & Contractor, 2003).

E. CO-EVOLUTION AND SOCIAL SYSTEMS

This study focuses on co-evolving, competing social networks in insurgent warfare, which is a key mechanism within the MTML framework. Like the concepts of emergence and self-organization, co-evolution has drawn interest from various research domains. Ehrlich and Raven (1964), the biologists who some have credited with coining the term co-evolution (McKelvey, 1997; Porter, 2006), describe it as the genetic change of one species in response to the evolution of another. Initially envisioned for biological applications, such as dynamic interactions between plants and herbivores and the study of genetic evolution (Kauffman, 1993), it has become a central concept to complex adaptive systems and social network research (Benbya & McKelvey, 2006; Dooley, 1997; Lichtenstein, 2000; McKelvey, 1997; Porter, 2006; Robins, 2015; Snijders et al., 2007). Scholars have applied it to examine how various types of social systems evolve mutually with their environments, whether it be firms and/or alliances and organizational networks (Baum & Singh, 1994; Koza

¹² In contrast to formal ties, or mandated structures (e.g., formal hierarchy) that guide how organizations coordinate activities, processes, and functions, informal social ties emerge naturally through voluntary interactions among individuals (Biancani et al., 2014; Kadushin, 2012). The U.S. military’s hierarchy is a straightforward example of formal connections.

& Lewin, 1998; Lewin et al., 1999), organizational strategy (Dooley, 1997), or social networks (Amati et al., 2021; Choi et al., 2001; Daniel et al., 2016; Fujimoto et al., 2018; Huitsing et al., 2014; Steglich et al., 2006).

While various research domains offer insight about co-evolving social systems and are not necessarily contradictory, many have operationalized the concept differently. For instance, it is common for researchers leveraging a complex adaptive systems perspective to study such systems using agent-based models built upon simulated agents driven by schema or decision-rules (Carmichael & Hadžikadić, 2019; Lansing, 2003; McKelvey, 1999; Miller & Page, 2007; Monge & Contractor, 2003). Yet, however insightful, many complex adaptive system principles and model assumptions are difficult to apply and measure in empirical social systems (Anderson, 1999; Eidelson, 1997). In fact, while Monge and Contractor (2003, pp. 294–295) explore co-evolving organizational networks from a complex adaptive systems perspective, they recognize these limitations and argue that several “emerging” social network research models, such as stochastic actor oriented models (SAOMs), enable researchers to leverage their framework. At the time of the MTML framework’s introduction, however, these models were in their infancy and not widely available.

Social networks researchers have increasingly examined the concept of co-evolution. Like complexity and organization sciences, social network co-evolution studies focus on how networked actors mutually evolve with their social environments consisting of other individuals and relations (Kadushin, 2012; Lazega & Snijders, 2016; Snijders et al., 2010; Walby, 2007). Such empirical studies commonly frame co-evolution as the interplay of actor behaviors (e.g., drug use) and a single type of relationship (e.g., friendships). The goal of such analyses is to untangle, and assess the extent to which, social influence, social selection, and self-organizing processes (i.e., purely structural) at multiple levels drive an empirical network’s dynamics. However, the multirelational or multiplex nature of social systems, such as those comprised of insurgent *and* authority information-sharing ties, also suggests micro social processes can involve multiple types of relations (Porter, 2006). In fact, existing research has demonstrated that social relations can interact at many network levels to produce structures by influencing the formation, maintenance, or dissolution of another (Amati et al.,

2021; Fujimoto et al., 2018; Gould, 1991; Granovetter, 1973; Huitsing et al., 2014, 2014; Lee & Monge, 2011; Monge & Contractor, 2003; Rambaran et al., 2015).

Interestingly, as statistical models for the study of empirical networks have become more sophisticated, as Monge and Contractor (2003) foretold, researchers have begun to consider multiplex dynamics as a form of co-evolution in which different networks are mutually constitutive at multiple network levels (Amati et al., 2021; Daniel et al., 2016; Ellwardt et al., 2012; Fujimoto et al., 2018; Htwe et al., 2020; Huitsing et al., 2014; Rambaran et al., 2015; Stadtfeld et al., 2020; Warren, 2016). Like the interplay of behaviors and ties, this approach seeks to untangle inter-network, self-organizing processes from co-evolutionary ones; however, this perspective characterizes co-evolution as multilevel social processes between overlapping social ties/networks in which the presence of one type can influence the presence, maintenance, or dissolution of another. This approach to co-evolution, therefore, focuses on inter-network dynamics rather than the interplay of behavior and a single network. Ultimately, this dissertation views co-evolution from this perspective in which overlapping authority and insurgent information-sharing structures evolve through *intra*-network, self-organizing processes as well as *inter*-network, co-evolutionary processes at multiple network levels, which is an approach that addresses important gaps within extant insurgent warfare literature. In line with the research question, the goal here is to untangle and assess the extent to which co-evolutionary processes contribute to empirical network dynamics in insurgent warfare.

F. CASE STUDY: THE REVOLUTIONARY ARMED FORCES OF COLOMBIA (FARC) INSURGENCY

To examine the co-evolution of social networks in insurgent warfare, this dissertation analyzes competing social networks in the conflict between the Colombian Government and the Revolutionary Armed Forces of Colombia (FARC). Founded in 1964, the FARC is a now defunct insurgent organization that until 2016, was one of the oldest insurgent organizations in the world (Cunningham et al., 2013; Jane's World Terrorism and Insurgency Centre, 2020). Beginning as a Marxist-Leninist group, it evolved into a violent, narcotics trafficking organization that coerced the peasant population it promised to protect (Cunningham et al., 2013; Metelits, 2010). In 2016, the FARC agreed to a peace plan with the Colombian

Government after decades of involvement in the illegal drug trade, kidnapping, and terrorism, as well as major successes and setbacks. Following the agreement, more than 11,000 fighters demobilized (Jane's World Terrorism and Insurgency Centre, 2020), and the group became a political party and renamed itself to the Fuerza Alternativa Revolucionaria del Común (Common Alternative Revolutionary Force—FARC).

As an active insurgency, the FARC's semi-distributed command system enabled it to establish social relations with noncombatants who served as critical conduits for information about the populace, other groups (e.g., narcotics trafficking groups), and the government (Jane's World Terrorism and Insurgency Centre, 2020; Metelits, 2010; Stanford University, 2019). It established information-sharing ties in both urban and rural areas through political, informant, recruitment, and other networks. Though the extent to which the FARC embedded in local, rural populations varied over the years, it largely drew most of its recruits, information, and other resources from this segment of the populace (Metelits, 2010). It established a presence in Colombia's cities with the creation of the Clandestine Colombian Communist Party (PCCC) and the Bolivarian Movement for the New Colombia (MBNC) in the 1990s (Cunningham et al., 2013; International Crisis Group, 2009), as well as worked with urban gangs and criminal organizations to cooperate in the drug trade and serve as informants in its conflict with the government (Jane's World Terrorism and Insurgency Centre, 2020; Metelits, 2010; Stanford University, 2019). As such, this insurgency serves as a useful case study to examine co-evolution in insurgent warfare given its historical significance as an insurgency, as well as the embedded nature of information-sharing networks comprised of insurgents, government, and noncombatants.

G. METHODOLOGY

This study takes a social network approach to investigate the dynamic interplay of authority and insurgent information-sharing networks in insurgent warfare. It applies a longitudinal complete network design to analyze a subset of the broader conflict in Colombia, namely competing networks in the Southern Bloc's area of operations during the January 2002-April 2003 timeframe. Based on official, unclassified Colombian Government "Demobilization Reports," this dissertation builds (and then analyzes) two longitudinal,

overlapping information-sharing social networks comprised of several types of actors, including government personnel, civilians, FARC militia members, and then-active and demobilized FARC members who shared information to serve the government's COIN efforts and/or the FARC's objectives (e.g., offering actional information about the FARC and providing "insider" government information). Many individuals were embedded in both networks simultaneously and at different times.

Drawing from Monge and Contractor's (2003, p. 3) description of communication networks, as well as Kadushin's (2012, pp. 39–42) notion of informal ties, this analysis defines information-sharing relations as *informal connections that are created by the flow of messages among individuals*. It is important to note four points about this definition. First, this definition is consistent with extant COIN literature's emphasis on the importance of in-person relations in insurgent warfare (Cleveland et al., 2018; Department of the Army, 2017; Department of the Navy, 2017; Kilcullen, 2010; McAdam, 1999; Pye, 1950; Sageman, 2004). Second, these in-person ties should not be confused with online, social media interactions. While social media is often used to disseminate narratives to larger audiences, mobilize populations, and can serve as a place where recruitment begins (Benigni et al., 2017; Hassanpour, 2014), additional research is needed to examine its specific role in operational level social networks, as well as online and offline relational dynamics in insurgent warfare (Kane et al., 2014; Robins, 2015). For instance, there is no evidence that social media played a role at the operational level in this particular case study, though this is likely due to its time frame (i.e., 2002–2003). Third, because this is archival research, this study is unable to assess the veracity of information passed through interactions as well as capture message quantity (i.e., Shannon information), impact (e.g., pragmatic information), and meaning (i.e., semantic information) (Haken & Portugali, 2016). It does, however, consider the frequency and duration of interactions (i.e., how many times two individuals shared information and for how long) to attempt to model "enduring" ties and address issues pertaining to informant accuracy, which reflects one's ability to recall interactions with others and is described in greater detail in Chapter IV. Fourth, like Monge and Contractor (2003, p. 3), the term "messages" is used in a broad sense here to refer to data, information, knowledge, and facts about the conflict that move from one person in a network to another.

This analysis utilizes a multivariate extension of SAOMs to test hypotheses about social processes undergirding the co-evolution of competing authority and insurgent networks. Generally, SAOMs are models designed to represent network dynamics and evaluate them based on the paradigm of statistical inference (Ripley et al., 2021; Snijders et al., 2010; Snijders, 1996, 2005; Steglich et al., 2006). The goal of SAOMs is to model empirical data on patterns of ties and behaviors and to identify a set of multilevel social processes that most likely *reflect* actor decisions. A common way to employ SAOMs is to treat observed networks as dependent variables and incorporate network dynamics, as driven by different tendencies, into models as independent variables (e.g., structural effects reflecting social processes, actor variables, and dyadic (or tie-based) variables). This approach captures how the network itself helps explain its own dynamics; that is, it accounts for self-organizing processes along with actor characteristics and behaviors (e.g., attitude, performance) that help drive evolutionary processes and undergird emergent structures (Ripley et al., 2021; Snijders, 1996).

While one can regard SAOMs as a form of agent-based model that align somewhat with agent-based modeling commonly used in complex adaptive systems research, these models are designed for empirical relational data and often used in social network research. They assume actors make decisions to create, maintain, or terminate ties to others, yet social actors are influenced by the networks in which they embed. However, the authors (Ripley et al., 2021, p. 9) are clear that, “actor oriented does not imply the assumption that they actors make decisions in any real sense,” nor do they, “reflect a commitment to or belief in any particular theory of action elaborated in the scientific disciplines.” Rather, this model class’s purpose is to help researchers explore and develop theories of networks at various levels from an actor perspective, recognizing that, like other regression models, SAOMs do not solve causal questions through modeling alone (Ripley et al., 2021).

This study uses a multiplex SAOM extension to examine dependencies between the competing networks. This extension, which is consistent with the MTML’s definition of network levels, uses similar modeling and statistical procedures as traditional SAOMs, but it produces three categories of parameters: uniplex ones for each network that reflect intra-network, self-organizing processes; actor level, or covariate parameters to show effects for

actor characteristics; and multiplex parameters that network represent co-evolutionary, social processes (Fujimoto et al., 2018; Huitsing et al., 2014; Rambaran et al., 2015; Ripley et al., 2021; Snijders et al., 2013). As with standard SAOMs, the models treat networks as dependent variables, while structural mechanisms at various levels (e.g., dyad, triad, and cluster) serve as independent variables for estimating self-organizing tendencies. The second set incorporate the effects of actor attributes on each network, whereas one can obtain the third set of parameters after combining the networks into a multiplex network, and subsequently testing for co-evolutionary dynamics at various levels.

This dissertation examines multilevel co-evolutionary processes between competing networks in insurgent warfare. To establish context, Chapter II describes counterinsurgency and insurgency theory and establishes the important roles that competition, populations, and information play in insurgent warfare. Chapter III presents the MTML framework as a means to examine dynamic social processes within and between social networks. Guided by Monge and Contractor (2003), it offers perspectives on network emergence, self-organization, and co-evolution, as well as hypothesizes about social processes that can help drive competing networks' dynamics in insurgent warfare. Chapter IV describes this study's use case, methodology, and modeling procedures, while Chapter V summarizes and discusses the results of the analysis. The final chapter, Chapter VI, presents this study's contributions and conclusions as well as describes its limitations and offers suggestions for future research.

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II. COMPETITION, INFORMATION, AND SOCIAL NETWORKS IN INSURGENT WARFARE

According to *Field Manual (FM) 3-24/MCWP 3-33.5* (Department of the Army, 2014), an insurgency is “the organized use of subversion and violence to seize, nullify, or challenge political control of a region.” Throughout history, insurgents have challenged governments to gain control over populations (Thompson, 1967). However, it becomes clear after a brief historical review that each insurgency is quite unique based on the context in which it occurs. According to David Galula (2006),¹³ a variety of factors shape the nature of insurgencies, such as their relationship with the authorities they seek to replace, whether they are rural or urban, and their ideology. Inspired by Galula’s work, FM 3-24 (Department of the Army, 2014) offers additional elements that influence an insurgency’s characteristics, including its leadership and objectives, the nature of external and internal support it receives, the phasing and timing of the conflict, and its organizational structure and modus operandi. These works highlight why insurgencies pose significant challenges for counterinsurgents to grasp their underlying causes, as well as respond effectively to their complexity.

The U.S. government defines counterinsurgency (COIN) as, “comprehensive civilian and military efforts designed to simultaneously defeat and contain insurgency and address its root causes” (Department of the Army, 2014, p. 2).¹⁴ Scholars and practitioners have addressed a variety of theoretical and practical topics pertaining to insurgencies, such as their characteristics (Galula, 2006; O’Neill, 2005), how to analyze them (United States Government, 2018a), how they begin and end (Paul et al., 2013), and what factors make them successful (or unsuccessful) (Paul et al., 2013). Foundational works by classical COIN scholars (Galula, 2006; Gann, 1971; Taber, 1965; Thompson, 1967; Trinquier, 2006), as well as more contemporary scholars (Berman et al., 2018; Kilcullen, 2010, 2013),

¹³ Galula’s book, *Counterinsurgency Warfare: Theory and Practice*, was originally published in 1964.

¹⁴ Though debates remain about the most useful definition of COIN, many scholars describe it as a comprehensive reaction to insurgent attempts to seize power (Galula, 2006; Kilcullen, 2015; Paul et al., 2016). It is, however, beyond this dissertation’s scope to enter this debate.

are commonly referenced resources in official U.S. government publications. For instance, *FM 3-24* (2014) and Joint Publication (JP) 35, *Countering Threat Networks* (2016), include lessons learned from recent insurgencies in Iraq and Afghanistan, and in large part, draw from the insights of these leading thinkers.

Building on this literature, the study of social networks in insurgent warfare will benefit by accounting for its competitive nature in which insurgents, authorities, and noncombatants (i.e., civilians) interact and exchange information. In its essence, insurgent warfare is competition between governments and insurgents that takes place among and for the support and control of a populace (Galula, 2006; Guevara, 2007; Kilcullen, 2010; Nagl, 2005; Tse-Tung, 1989). Because populations play a central role in conflict, information plays a decisive role in a conflict's outcome (Galula, 2006; Guevara, 2007; Tse-Tung, 1989). The centrality of information is why scholars address vital topics such as information operations (IO), as well as the capabilities that can enable them, such as military information support operations (MISO) and civil-military operations (CMO). While numerous means exist to acquire and disseminate information in operational environments, such as social media interactions (e.g., Twitter and Facebook), in-person social relations serve as critical conduits for the flow of information in social networks, including those in insurgent warfare (Cleveland et al., 2018; Galula, 2006; Guevara, 2007; Kilcullen, 2010; Pye, 1950; Tse-Tung, 1989). As individuals exchange information pertaining to a population or enemy in public spaces, such as patrols, or private settings, such as key leader engagements and intelligence reporting, whether they be combatants (e.g., insurgents or military) and/or noncombatants (e.g., civilians), they form information-sharing social networks that each side can leverage in the competition with their adversaries (Cleveland et al., 2018; Department of the Army, 2017; Department of the Navy, 2017).

This chapter begins with a brief discussion about two major approaches of COIN that lay the groundwork for the study of social systems in insurgent warfare. The two approaches, known as population-centric and enemy-centric viewpoints, diverge in notable ways; however, the nature of insurgent warfare highlights how noncombatants play central roles in such conflicts regardless of approach. Next, this chapter outlines the practical and theoretical roots of contemporary COIN, especially regarding competition and the

population-centric paradigm, which has emerged as the dominant, Western approach to COIN. Next, it describes the important role that information plays in insurgent warfare for combatants and noncombatants, as well as how offline, in-person social networks serve as important conduits for information exchanges within such competitive contexts. While systems and social network research domains have looked at insurgencies and related networks (e.g., terrorist networks and social movements) from “system” perspectives, they have not fully captured the competitive nature of insurgent warfare nor have they paid adequate attention to empirical social systems in such contexts. It closes by addressing these limitations and presenting a perspective on network boundaries that accounts for the competitive context in which combatants and noncombatants seek information and form overlapping structures.

A. COIN PARADIGMS

Two dominant COIN philosophies exist: namely population-centric and enemy-centric (Kilcullen, 2010; Paul et al., 2016). The population-centric view emphasizes the centrality of the populace for COIN success. It views the populace as an important source of survival for insurgencies, and therefore, focuses on luring it away from insurgents. This approach, often seen as a reaction to Mao Tse-tung’s (1989) influential writings on guerrilla warfare, is rooted in the views of classical COIN theorists, such as David Galula (2006), who believed that controlling populations deprives insurgents of the support and resources (e.g., recruits, information) they need to supplant authorities successfully. As contemporary COIN thinker David Kilcullen (2010) and others have pointed out (Gventer, 2014; Porch, 2013), this does not equate to being “nice” to populations; rather, it is about providing incentives to those who support authorities while imposing costs on those who do not.

The enemy-centric approach, on the other hand, views COIN more like conventional warfare in the sense that defeating the enemy militarily is the counterinsurgent’s main objective. As Paul (2016) explains, it is often described synonymously with the “draining-the-sea” approach in which brutality against insurgents, as well as civilians, can weaken an enemy rapidly by “draining” an area of all potential

insurgent inputs, such as information, recruits, and other resources. As with a population-centric approach, several variations of the enemy-centric approach exist, such as targeting key leaders (i.e., deception), attrition, and attacking insurgents' strongholds. Kilcullen (2007, para. 2) explains that while one can summarize the population-centric approach as, "first control the population, and all else will follow," the enemy-centric view suggests the opposite, "first defeat the enemy, and all else will follow."

These two philosophies lie at the epicenter of contentious debates in this domain. As COIN regained significant attention during the height of the insurgency in Iraq, scholars and practitioners contemplated which approach would enable the U.S. to prevent further conflict and instability in the country. Many population-centric thinkers argued that enemy-centric approaches alienate populations and lead to greater insurgent support, and in fact, are responsible for creating many of the challenges the U.S. faced in Iraq (Paul et al., 2016). As the population-centric view gained increasing attraction around the time of the "Surge" in Iraq (2007-2008), several experts expressed concern that apparent successes in Iraq led many to mythologize counterinsurgency practices, which they contend are risky and expensive, and that long-term nation building efforts rarely succeed in producing long-term stability (Gentile, 2013; Gventer, 2014; Porch, 2013). Adding fuel to this debate is that each view can claim historical successes and failures, which highlights that counterinsurgents can implement each approach effectively and counterproductively (Paul et al., 2016).

However, the dichotomy between population and enemy-centric approaches is likely a false one, especially from a Western perspective (Paul et al., 2016). As a collection of activities designed to address "irregular threats," namely insurgencies,¹⁵ COIN differs conceptually with "traditional" warfare by placing an emphasis on populations rather than on territory. While the population-centric view is straightforward in its emphasis on noncombatants, the enemy-centric view is less so, but it still appears to recognize the population's importance to successful COIN. The idea is that because insurgents hide

¹⁵ In addition to COIN, *Irregular Warfare: Countering Irregular Threats* (2010) outlines four other activities to address irregular threats: namely counterterrorism (CT), unconventional warfare (UW), foreign internal defense (FID), and stability operations (SO).

among the populace, counterinsurgents need information from noncombatants to identify and locate insurgents. According to McCormick's (Forthcoming; Wilson, 2006) "Diamond Model," for example, counterinsurgents have an information disadvantage compared to insurgents, which means they must strengthen their ability to access operationally useful information from the population before attacking the enemy's infrastructure and members. A counterinsurgent's use of excessive force within the context of enemy-centric COIN also may result in more insurgents, which is counterproductive to successful COIN.

Moreover, researchers and official U.S. military documentation recognize that COIN is likely to be more effective with an appropriate balance of the two approaches (Department of the Army, 2014; Paul et al., 2016; Trinquier, 2006). Counterinsurgents can apply the two simultaneously, or to the same insurgency at different points in time because of the dynamic nature of insurgencies (Kilcullen, 2007). As seen in Tel Afar, Iraq, in 2005, the U.S. and Iraqi forces phased in aspects of both approaches known as "clear, hold, and build," which in a general sense, involves clearing a contested area through security operations, and then holding that territory by providing security and protecting populations from insurgents (Gangs and Guerillas: Ideas from Counterinsurgency and Counterterrorism, 2011). During the build phase, counterinsurgents seek to provide economic incentives and "good-governance" to obtain (or maintain) legitimacy with the population.¹⁶

B. COMPETITION FOR CONTROL OF A POPULACE

In the foreword of an updated version of Galula's seminal book, *Counterinsurgency Warfare: Theory and Practice* (Galula, 2006, p. viii), COIN specialist John Nagl states, "An insurgency is a competition between insurgent and government for the support of the civilian population, which provides the sea in which the insurgent swims."¹⁷ This succinct statement encapsulates the central importance of competition, or struggle, as well as the

¹⁶ In other words, "Since irregular warfare is a context for legitimacy and influence over the relevant populations, the populations carry particular weight as both the battleground and object of the conflict" (Department of Defense, 2010, p. 13)

¹⁷ This quote refers to Mao's work on guerrilla warfare. See translated version (Tse-Tung, 1989).

significance of populations in insurgent warfare.¹⁸ Several scholars and practitioners have echoed this theme and described insurgent environments as competition for and among a populace (Berman et al., 2018; Herrington, 1982; McCormick et al., 2007; Metelits, 2010; Race, 1972). In *War Comes to Long An* (1972), Jeffrey Race discusses the notion of “balance of forces” in Vietnam, which he describes as, “the relative ability of contending forces to enforce their will on their opponents” (Race, 1972, p. 144). Using insights from interviews with former insurgents and government personnel, he outlines several factors that altered the power dynamic between the two sides of the conflict, such as sheer numbers on each side, technological factors (e.g., weaponry), organizational factors (structure and coordination), morale factors, as well as several others. Similarly, Berman et al. (2011) developed a model of insurgency as a three-way struggle over information among insurgents, government, and civilians. Within the competitive space, or areas in which state and non-state (i.e., civilians and insurgents) actors compete, the authors’ results suggest improved services for the Iraqi population reduced insurgent violence.

Start Herrington (1982), who like Race, served as a military officer in Vietnam, describes consequences of competition on the Vietnamese populace during the war. He writes (1982, p. 44), “Virtually every hamlet in Vietnam had at least one clandestine informant who would not hesitate to report to the Vietcong the name of a farmer who warned the Americans about a booby trap.” Certainly, this type of situation is not limited to Vietnam. Claire Metelits’ (2010) interesting research examines similar dynamics in Colombia, specifically relations between insurgents and civilians. Her fieldwork demonstrates that insurgents shape their strategy toward local communities according to the extent to which they face competition from other groups. Though one cannot assume the generalizability of her findings, competition and rivalry are so central to her research that she concludes that, “the existence of rivalry, not resources, is central to the insurgent-civilian dynamic” (Metelits, 2010, p. 191). Several other authors have described the effect that competition has on populations as well (Berman et al., 2011; Cleveland et al., 2018; Kilcullen, 2013). For instance, Kilcullen (2013) explains that when state and non-state

¹⁸ I am not arguing, however, that adversaries compete for *every* location within an active insurgency.

competition puts civilians in between two competing systems, populations adopt survival strategies, such as fleeing, passivity, autarky, hedging, swinging, commitment, and self-arming.

However, the end state of competition may be for control of a population rather than, as Nagl stated, its support (Department of the Army, 2014; Galula, 2006; Kalyvas, 2006; Trinquier, 2006). Kilcullen (2013) advocates for a “theory of competitive control” in which civilians, insurgents, and states compete for control. Just as importantly, non-governmental organizations (NGOs), government contractors (e.g., Blackwater), and other types of actors play substantial roles in conflict. Based on a theory of normative systems,¹⁹ he suggests that non-state groups, just like governments, can generate popular support as well as control and mobilize populations by creating predictable environments through a system of governance. They can compete with the state’s system of laws and control by using a combination of persuasive, administrative, and coercive actions. One can see how the Taliban’s “shadow governments,” or the “civil organizations” that Che Guevara (2007) outlined,²⁰ reflect this notion about control. Kilcullen suggests insurgents can “win an area” with unpopular laws and rules²¹ because they may resolve disputes and provide law and order effectively, which perhaps creates an unhappy, yet predictable, level of order for local populations. Gen (Ret.) Charles Cleveland and his colleagues (2018) make a similar claim by arguing that U.S. leadership must develop strategies that account for people, connectivity, and competition in light of the prevalence of irregular warfare, including in insurgent warfare.

¹⁹ Kilcullen (2013, p. 132) defines normative systems as a “set of rules correlated with a set of consequences.”

²⁰ Che Guevara (2007, p. 9) states something similar. He writes, “We must come to the inevitable conclusion that the guerrilla fighter is a social reformer, that he takes up arms responding to the angry protest of the people against their oppressors, and that he fights in order to change the social system that keeps all his unarmed brothers in ignominy and misery.”

²¹ As he points out, the Taliban had many archaic rules when they first seized Kabul in the 1990s, such as banning music in public, playing with birds, dancing, and music at weddings, etc. (Kilcullen, 2013, pp. 146–147).

C. THE CENTRAL ROLE OF THE POPULACE

The notion that the populace is central to insurgent warfare is rooted in “classical” insurgent and counterinsurgent literature. Prominent insurgent thinkers, such as Mao Tse-tung (1989), Che Guevara (2007), and Carlos Marighella (2002),²² emphasized the central role of populations in their writings on guerrilla warfare. Mao, who led the Chinese Revolution of 1949 and inspired the adoption of Maoism across the globe, famously compared guerrillas to fish and the populace to the water in which they swim. The idea is that insurgents require at least passive support from populations to survive (Taber, 2002; Tse-Tung, 1989). Che Guevara made similar claims. For instance, in an effort to distinguish between bandits and guerrillas, he writes, “They have all the characteristics of a guerrilla army, homogeneity, respect for the leader, valor, knowledge of the ground, and, often, even good understanding of the tactics to be employed. The only thing that is missing is support of the people; and, inevitably, these gangs are captured and exterminated by the public force” (Guevara, 2007, p. 9). Moreover, he emphasizes the importance of peasants and farmers in providing supplies to guerrilla forces, as well as outlines how guerrillas should establish hospitals to take care of the people in an area (2007, pp. 65–69). Similarly, Carlos Marighella (2002, p. 36), a prominent Brazilian guerrilla warfare thinker, states, “One of the permanent concerns of the urban guerrilla is his identification with popular causes to win public support.”

A handful of “classical” COIN thinkers have substantially impacted contemporary Western views of COIN as it pertains to maintaining legitimacy in the eyes of a populace. Galula (2006), a French officer who served in several theaters such as Algeria in the 1950s, is often credited as the foundational COIN thinker who placed the importance of the populace over killing insurgents (Paul et al., 2013). For example, his first “law” of COIN is that “the support of the population is as necessary for the counterinsurgent as the insurgent” (2006, p. 52). Throughout *Counterinsurgency Warfare: Theory and Practice* (2006, p. viii), he restates a population’s central role to successful COIN with statements

²² This list of insurgent thinkers is by no means an exhaustive list of prominent individuals. For example, Arquilla (2011) provides an excellent historical account of many irregular warfare actors that came well before those listed here.

such as, the “counterinsurgent cannot achieve much if the population is not, and does not feel, protected against the enemy.” His influence on contemporary thinkers is apparent in Gen. (Ret.) David Petraeus’s guidance as then Commander of the (U.S.-led) International Security Assistance Forces (COMISAF) in which he outlined his own twenty-four “rules” of COIN, such as “serve and secure the population,” “live among the people,” and “consult and build relationships, but not with those who just seek us out” (Gangs and Guerillas: Ideas from Counterinsurgency and Counterterrorism, 2011, p. 104). Unsurprisingly, the 2007 version of *FM 3-24* lists the book as one of “The Classics” in its “Annotated Bibliography” section (United States Government, 2007).

Galula is not alone, however, in influencing today’s COIN thinking. Roger Trinquier, another French officer who served in Indochina (1946-1954) and Algeria (1954-1962), argued a population’s support is the most important objective in what he called “modern warfare.” At the time of its release, his book *Modern Warfare: A French View of Counterinsurgency* (2006),²³ provided a cautionary tale for U.S. efforts in Vietnam in that military tactics and battlefield successes would not lead to victory if it did not address the insurgency’s political dimension and obtain the population’s unconditional support. Counterinsurgents, according to Trinquier, must assure the people their protection, as well as create and train organizations among the populace capable of identifying enemies. Robert Taber’s *War of the Flea* (2002)²⁴ makes similar claims about the centrality of the populace in guerrilla warfare. He argues that the population is key to the entire struggle between guerrillas and governments. Specifically, he contends that the guerrilla is “of the people” in the sense that the civilian populace serves as “his camouflage, his quartermasters, his recruiting office, his communications network, and his efficient, all-seeing intelligence service” (2002, pp. 11–12). Without support and aid from the people, Taber argues, guerrilla operators cannot survive.

²³ Trinquier’s book, *Modern Warfare: A French View of Counterinsurgency*, was originally published in 1964.

²⁴ Taber (2002, p. 20) famously uses the analogy of a flea and dog in that, “the guerrilla fights the war of the flea, and his military enemy suffers the dog’s disadvantages: too much to defend; too small, ubiquitous, and agile an enemy to come to grips with. If the war goes on long enough, the dog succumbs to exhaustion and anemia without ever having found anything on which to close its jaws or rake with its claws.”

Sir Robert Thompson and Sir Gerald Templar, both of whom worked closely during the Malaya Emergency (1948-1960), are two British COIN thinkers who have inspired modern, population-centric views of COIN (Fitzsimmons, 2008). Thompson argued that counterinsurgents should have a clear political aim and security forces must employ offensive operations against insurgents, yet operate within the law, as well as impose control measures over a populace, including its physical separation from insurgents through resettlement. Specifically, he contended that “strategic hamlets,” which the British employed in Malaya, as did the U.S. in Vietnam, could minimize the effectiveness of underground organizations, and unite noncombatants against insurgents. Thompson also believed in the use of “minimum force” and that counterinsurgents could gain the population’s support and undermine an insurgency with good governance and providing services, such as improving health care and education (Fitzsimmons, 2008; Thompson, 1967).

Templar, whose perspective aligns with Thompson’s, introduced the concept “hearts and minds” in the early-1950s based on British experiences in Malaya.²⁵ He apparently remarked that, “The answer (to the uprising) lies not in pouring more troops into the jungle, but in the hearts and minds of the people” (Dixon, 2009). This concept lies at the heart of population-centric warfare. Often seen as a response to Mao’s approach to guerrilla warfare, it prioritizes civilian welfare and less coercive tactics over violent approaches. By doing so, Templar suggests that counterinsurgents will improve their chances of securing a population’s support. As commissioner and director of operations in Malaya, he shifted British approaches of “collective punishment” to the protection of the community through physical separation of the populace and insurgents, among other things.²⁶ According to scholar Kalev Sepp (2005), Templer strove for political and social equality of all Malays through his actions, such as granting Malay citizenship to over a million Indians and Chinese, requiring Britons to register as Malay citizens, elevating the

²⁵ According to Sepp (2005, p. 12), President John Adams coined this phrase in 1818 regarding the American Revolution.

²⁶ Moreover, he addressed coordination issues between intelligence, civilian, and military serves, and shifted from large-scale operations to small-unit operations.

public role of women, and constructing schools, clinics, and police stations, to name just a few. Many scholars have credited this approach to Britain's "success" in Malaya (Nagl, 2005), which led many to believe that public services would win over populations during the Iraq and Afghanistan Wars (United States. et al., 2014).

However, scholars and practitioners have spent considerable time describing the true meaning of the "hearts and minds" model, as well as its utility in insurgent warfare. The former has implications for how much consent and coercion counterinsurgents should apply in practice (Dixon, 2009). Support and control are not necessarily the same thing. In their important study, RAND's Leites and Wolf (1970) viewed "hearts and minds" as a cost-benefit trade off rather than a focus on a population's inherent preferences. They argue that combinations of coercion and reward can be effective in countering guerrillas and that constraining insurgent behavior is more likely to be effective than attempts to persuade populations with economic aid. *FM 3-24* (United States Government, 2007) echoes this sentiment by describing "hearts and minds" as convincing a populace that their best interests rest in successful COIN, and that counterinsurgents can protect them and resistance is pointless. In his critique of the model from a British perspective, Dixon (2009, p. 363) defines "hearts" as "winning the emotional support of the people" and "minds" as "the people as pursuing their rational self-interests." Drawing from Britain's experience in Malaya and the U.S.' involvement in Vietnam as examples, he claims the phrase may be useful in public relations to justify operations, but it is not a useful guide for how to conduct them.

Several scholars have argued that historical accounts of the "hearts and minds" model have been misguided. For instance, critics contend that the British, in fact, used highly coercive measures during its "successful" Malaya campaign (Dixon, 2009; Gentile, 2013; Porch, 2013). They point to the Briggs Plan (1950) that forcibly resettled hundreds of thousands of Malaya's Chinese population, as well as enacted harsh laws during the campaign, including strict curfews, identity cards and movement restrictions, arson of homes of communist sympathizers, mandatory death penalty for carrying arms, and imprisonment for providing insurgents with supplies. This suggests that the phrase disguises what really happened in Malaya and, in fact, that this so-called "successful"

campaign may provide empirical support for coercive COIN approaches rather than population-centric methods (Dixon, 2009; Porch, 2013).

Nevertheless, the population remains at the center of insurgent warfare regardless of one's position in these debates. In the Malaya Campaign, for example, it was the populace to which the British applied both coercive and consensual tactics in efforts to separate it from insurgents and "win" the competitive space. Therefore, while these debates serve as a useful background for this study, taking a side is beyond its scope. What is more pertinent is that civilians are caught between competing systems, and because of that, they need information to survive. They are not alone, however. Insurgents and authorities must acquire and disseminate information in support of their operations as well; in fact, insurgent warfare is very much a battle of ideas.

D. THE ROLE OF INFORMATION IN INSURGENT WARFARE

While acquiring material resources, such as money and weapons, is critical to insurgencies, several prominent insurgent thinkers have recognized that information about populations and one's adversaries is also a crucial resource (Guevara, 2007; Tse-Tung, 1989). Mao, for example, outlined the significance of collecting information from noncombatants in his book, *On Guerrilla Warfare* (1989). In his first phase of guerrilla warfare known as "organization, consolidation and preservation of base areas," he explains that trained and committed "volunteers" must set out in small groups to "persuade" and "convince" local noncombatants to provide them with supplies, recruits, and information (Tse-Tung, 1989, p. 21). As guerrillas establish footholds in areas, he pressed that they must establish invasive intelligence-based networks through which they can extract information from all noncombatants, regardless of their age, sex, and profession. These networks can provide guerrillas with intelligence critical to their operations, including knowledge about physical terrain, local noncombatants, government strength and morale, as well as grant them the initiative to attack at will. At the same time, Mao argued that guerillas must do everything they can to deny information to their enemies (Tse-Tung, 1989).

Inspired by Mao, insurgents have sought actionable information through various means. Che Guevara (2007), for instance, contends that gaining timely and accurate information from noncombatants about enemies is critical to insurgent operations. He writes (2007, p. 81), “Nothing gives more help to combatant forces than correct information. This arrives spontaneously from the local inhabitants, who will come to tell its friendly army, its allies, what is happening in various places; but in addition it should be completely systematized.” As seen recently in places like Iraq and Afghanistan, insurgents also often use violence and torture to extract information from noncombatants, as well as acquire useful information (e.g., government troop movements, morale) through infiltration, which is especially the case when a population’s allegiance is divided (Pirnie & O’Connell, 2008; Trinquier, 2006, p. 80). For instance, Sunni insurgents in Iraq have obtained useful information by infiltrating the Iraqi government and army, and the Taliban has successfully infiltrated the Afghan army and police as seen with “green on blue” violence.²⁷

Disseminating information is just as important to insurgents as collecting information. More specifically, propaganda is a key political tool that insurgents must employ to succeed. Throughout history, insurgents have used words and imagery to influence target audiences. Propaganda serves as a useful means for insurgents to communicate messages to noncombatants and create narratives about “illegitimate” authorities, contentious issues (e.g., political, cultural), as well as offer their own solutions to address root causes of conflict. Though delivery mechanisms have changed over time, from the printing press during Mao’s time, to contemporary uses of social media by groups such as the Islamic State of Iraq and Syria (ISIS), insurgents have been explicit about propaganda’s foundational importance to insurgent warfare. Mao (1989) and Guevara (2007) paid considerable attention to propaganda at both local and national levels in their respective works, as have contemporary “insurgents,” such as ISIS and al Qaeda, who have leveraged global media and social media successfully to reach regional and international audiences (Benigni et al., 2017; Ibrahim, 2007).

²⁷ See the *Long War Journal*’s site for more information, https://www.longwarjournal.org/archives/2012/08/green-on-blue_attack.php.

COIN literature emphasizes the significance of information to operations as well. As *FM 3-24/MCWP 3-33.5* (2014, p. 20) states, “counterinsurgents must gather, analyze, and disseminate civil information pertaining to the population.” Information from noncombatants, which counterinsurgents can process into intelligence, is thought to help improve both offensive and defensive operational effectiveness because it helps them understand the identity, networks, and locations of insurgents (Galula, 1964; Kalyvas, 2006; McCormick, Forthcoming). Berman et al. (2018) elaborate on the significance of operational level information with the notion of information-centric warfare. They contend that the U.S. should focus its future efforts on acquiring information about insurgents from the people rather than attempting to win their “hearts and minds.” The authors offer practical advice, such as recommending that practitioners enable information sharing by creating safe mechanisms for noncombatants to do so (e.g., cell towers), and they argue that counterinsurgents can improve their operational effectiveness and exploit insurgents’ relative weakness in firepower and mobility with better information from civilians. Others have offered additional benefits of obtaining reliable information from the population as well, such as that well-informed soldiers can take more thoughtful and confident actions as they interact with the populace (Libicki et al., 2007).

An authority’s ability to communicate effectively to a local population can have a major impact on whether the population will be willing to cooperate against an insurgency. Nagl goes as far as saying that, “the control of information is strategically decisive in counterinsurgency,” and it is therefore crucial for counterinsurgents to fight an information war because the key terrain is “the political loyalty of the people who inhabit that space” (Galula, 2006, p. ix). Like insurgents, governments utilize information, and process it into intelligence, to achieve their goals.²⁸ The importance of information strategy and tactics is why scholars address vital topics such as information operations (IO) and information warfare (IW) along with capabilities that can enable them, such as public affairs (PA), information assurance (IA), military information support operations (MISO), military

²⁸ The rules for using information, however, are not the same for both sides. According to Galula (2006), insurgents can lie, cheat, and exaggerate to delegitimize the authorities and seek control over the population, whereas the authorities must remain accountable if they want the populace to see them as a legitimate governing entity, which is a critical characteristic in COIN.

deception (MILDEC), and civil-military operations (CMO) (United States Government, 2014). The U.S. military conducts extensive training in this domain, and releases doctrine through official publications, many of which address both transmitting and receiving various forms of information to and from populations. For example, *JP 3-13 Information Operations* (2014) and *JP 3-57 Civil-Military Operations* (2013) outline guidance on such operations, both of which can be in support of counterinsurgency operations.

Existing COIN literature recognizes that in-person, social relations are critical conduits of information about a populace and enemies in operational environments. Pye's (1950) noteworthy research on the Malaya Communist Party (MCP) in the 1940s highlights how the party disseminated pro-Communist information through personal relationships. Through his analysis of interviews with surrendered insurgents, he describes how the MCP used front organizations to provide noncombatants with information from a Communist perspective (1950, p. 177). Haim's (Forthcoming) recent research on family networks in the Philippines aligns with Pye's findings in the way that information obtained from friends and family in surrounding villages can shape noncombatant views of local military control. Such research parallels studies in other domains in which personal relationships are critical for recruitment and conversion (McAdam, 1999; Sageman, 2004; Stark & Bainbridge, 1980), as well as publications that focus on related topics such as the "human domain," "countering threat networks," and "network engagement," which recommend developing in-person, trust-based networks for the purpose of acquiring information and enabling operations (Cleveland et al., 2018; Department of the Army, 2017; Department of the Navy, 2017; Kilcullen, 2010; United States. et al., 2014).²⁹

E. SOCIAL NETWORKS AND SYSTEMS IN INSURGENT WARFARE

In the competition for the control over the populace, one can observe information-sharing social networks as individuals, whether combatant or noncombatant, exchange information through in-person social relations. In other words, such relations serve as

²⁹ For instance, Cleveland et al. (2018, p. 180) state in reference to irregular warfare of which COIN is a main activity, "Military power can no longer be measured singularly by counting tanks and airplanes. Connections and how information and resources flow between actors across networks matters as much, if not more, than the number of individuals fighting units."

important mediums through which individuals present and share knowledge or facts about conflict. When a soldier questions a civilian about potential insurgents, or when a civilian voluntarily provides information to an insurgent, they form a social connection. As more and more of these and similar types of interactions take place, and in many cases become repeated interactions, they collectively form the basis of larger social structures. Therefore, the literature often uses terms such as “social networks,” “social structures,” and “social systems” interchangeably to describe such patterns of interactions. Two recent examples include Cleveland et al. (2018, p. 19), who claim civilian and other networks make up social systems that define the “human domain,” and Kilcullen (2013), who paints a picture of “future warfare” in which local leaders, militants, and civilians comprise urban networks nested and connected to broader regional and global structures. This type of language appears rooted in social systems and social network research, as well as empirical evidence in practice. However, each research domain has failed to capture unique characteristics of insurgent warfare that may contribute to social network dynamics.

Several renowned scholars and practitioners have described insurgent environments as comprised of systems (Department of the Navy, 2017; Johnson, 1982; Kilcullen, 2010, 2013). Most notably, Kilcullen’s (2010, 2013) work echoes several themes within the social systems research in which counterinsurgents’ actions can cause unintended consequences as a result of interconnectivity and feedback with adversaries and populations. The well-known notion of the “strategic corporal” reflects this perspective in insurgent warfare. Other researchers have offered insightful system models to examine the interconnected challenges posed by violent networks, including insurgent networks (Baker, 2006; Grynkewich & Reifel, 2006; Kenney, 2007; Mesjasz, 2015; Schoenenberger et al., 2014). Like Kilcullen, these scholars emphasize the negative consequences that arise from certain counter-network policies and actions, most of which counterinsurgents can avoid by analyzing feedback processes within insurgent systems. However, seldom have system scholars examined the effects of counter-network actions at an operational level of insurgent warfare, which is where substantial interaction takes place among authorities, local populations, and insurgents. Furthermore, systems scholars have largely overlooked

empirical social systems, including in-person information-sharing networks that are critical to insurgent warfare outcomes.

Like system research, the social network domain has paid relatively little attention to empirical, insurgent networks. This is unfortunate given COIN's emphasis on social networks along with practitioners' explicit description of social network analysis (SNA) as a useful intelligence tool in COIN (Cleveland et al., 2018; United States Government, 2007). To date, much of the "dark network" literature has focused on criminal and terrorist networks (Cunningham et al., 2016; Everton, 2012; Gerdes, 2015; Morselli, 2014). For instance, Gerdes' (2015) edited volume, *Illuminating Dark Networks: The Study of Clandestine Groups and Organizations*, offers many insights into the challenges and opportunities of studying such networks, but it contains only a single chapter addressing insurgent networks directly. At least two factors appear to have contributed to this trend. First, access to rich, unclassified data on insurgent networks is difficult to obtain. Second, a growing interest in nefarious online, social media-based networks and their use of platforms like Twitter and YouTube to recruit, disseminate propaganda, and globalize their activities, seems to have overshadowed offline network studies that could capture insights about operational level insurgent networks (Benigni et al., 2017; Carley, 2015).

A major focus in the study of "dark networks" (i.e., illegal and covert networks) has been on the examination of various "exogenous" effects (e.g., counter-network operations) on such networks (Bakker et al., 2012; Carley et al., 2003; Cunningham et al., 2016; Enders & Jindapon, 2009; Everton, 2012; Roberts & Everton, 2016, 2011). These studies imply that a violent network's structure is tied to tradeoffs between performance and resilience. For example, some research suggests that centralized networks can operate more efficiently in some contexts (e.g., mobilizing people and resources) (Arquilla, 2009), but they may be vulnerable to targeting strategies that focus on key members (Bakker et al., 2012; Sageman, 2004; Statement to the National Commission on Terrorist Attacks upon the United States, 2003). Other scholars, specifically Roberts and Everton (2016, 2011), have been more explicit about possible exogenous effects, such as disruption strategies, on terrorist networks, and have provided insights about a variety of kinetic and non-kinetic strategies that can be used. Yet, current social network literature generally has not

incorporated empirical, authority networks into analyses (Stys et al., 2020), and while a few exceptions exist (Diviák et al., 2019; Kenney, 2007; Papachristos & Smith, 2014; Stys et al., 2020), researchers have largely treated illicit networks as separate from populations, thereby missing potentially important interactions among all “sides” that may underly network emergence and dynamics (Everton & Cunningham, 2015; Gerdes, 2015; Koschade, 2006; Krebs, 2002; Morselli, 2014). This gap is particularly pertinent to insurgent warfare in which conflict takes place among and for a populace. In Figure 1, the networks on the left depict the analysis of social networks in isolation and highlight a choice of boundaries that misses important ties among various types of actors. The image to the right provides a more realistic, yet imperfect, illustration of overlapping social networks in insurgent warfare in which combatants and noncombatants have ties.

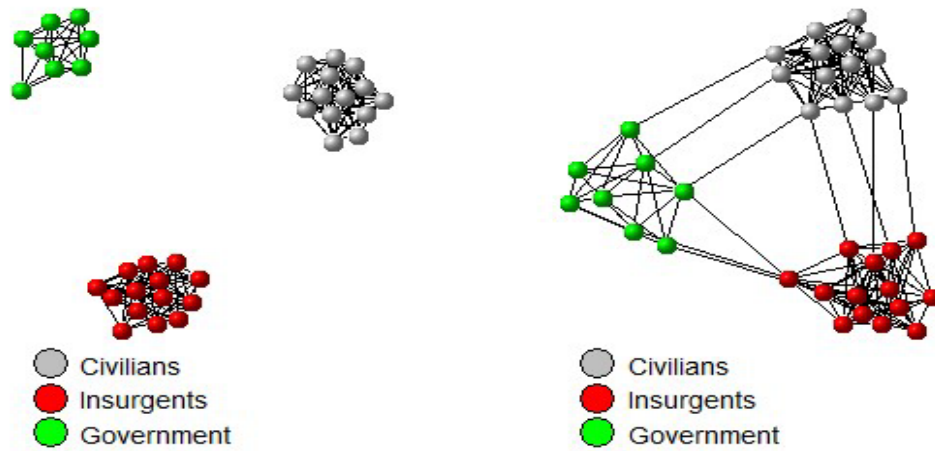


Figure 1. Distinct Networks vs. Overlapping Networks

As with many criminal settings, the lines between nefarious and other types of networks in insurgent warfare are often murky, in part, because they overlap with legitimate social circles (Diviák et al., 2019; Papachristos & Smith, 2014; Stys et al., 2020).³⁰ Ultimately, their embedded nature presents unique challenges for classifying

³⁰ The extent to which an insurgency embeds in a local population will vary (Sarbah, 2014).

actors into neat categories such as “insurgent,” “government,” and “civilian” groupings. Frameworks of insurgencies comprising of active insurgents, auxiliaries, guerillas, underground, and civilian supporters (passive and active) reflect this idea. Gventer (2014), who spent considerable time in Iraq during the active insurgency, describes the Iraq War as a “honeycomb of conflict” in which rogue members of Iraqi security forces, multifarious sectarian, terrorist, and criminal groups, as well as several outside powers, contributed to violence that plagued the country during the height of turmoil. Kilcullen (2013) describes a similar phenomenon in Afghanistan in which noncombatants perpetrated violence based on tribal grievances rather than on behalf of the Taliban. Herrington’s (1982) work on Vietnam demonstrates that this phenomena is not limited to recent conflicts. He highlights dense connectivity among insurgents, politicians, and noncombatants that made the lines between the groups often difficult to ascertain.

A few recent official U.S. military publications have begun to capture this idea by drawing attention to the important role that all types of actors, such as civilians, play in insurgent warfare. Specifically, the U.S. Army (2017) and Marine Corps (2017) have both published texts on “network engagement”³¹ in response to the limitations of kinetic, “attack the network” focused approaches that dominated Iraq and Afghanistan for substantial periods throughout the conflicts. Both broadened the scope of network-based activities beyond attacking “threat” networks by emphasizing the importance of engaging “friendly,” “neutral,” and “unknown” networks. And both offer definitions for each network based on individual and group support (or lack therefore) for U.S. objectives and provide examples of potential entities that may fall within each category. For instance, the Army’s version lists host nation military forces and government officials as potentially “friendly” entities and business leaders in “neutral” human networks (Department of the Army, 2017).

³¹ The Marine Corps (2017) uses JP 3-25’s (2016, p. x) definition of network engagement, which is “interactions with friendly, neutral, and threat networks, conducted continuously and simultaneously at the tactical, operational, and strategic levels to help achieve the commander’s objectives within an operational area.”

Both documents also highlight the challenges of binary thinking when categorizing individuals into networks. For example, based off recent lessons from Iraq and elsewhere, the authors of the Army's version describe how individuals may embed in multiple social circles with statements such as, "Some network functions, entities, groups, organizations, and member's activities span the friendly, neutral, and threat realms, making networks complex and difficult to understand" (Department of the Army, 2017, p. 22). FM 3-24 (2014) and JP 3-25 *Countering Networks* (2016) allude to the same idea that entities may connect various types of networks. While these publications offer some of the most useful descriptions of social networks in operational environments to date, they fail to pay explicit attention to heart of the problem: boundary specification, which makes untangling competing social networks based on existing guidance quite difficult.

As such, structural analysis of insurgent networks will benefit by setting system boundaries accounting for their competitive, information-sharing networks of all types of actors. Operational level networks consist of many types of individuals with various motivations who exchange information with one another that may benefit one or more sides of a conflict. It is appropriate, therefore, to define individuals' network membership(s) based on the side(s) for which they seek and provide information in the competition between state and insurgents. While in many cases individuals may serve only one side of the conflict, such as a U.S. soldier deployed overseas, others can benefit both. For example, a civilian may provide insurgents with information simply out of fear, while subsequently passing useful information to counterinsurgents about their interaction with insurgents, or vice-versa.

Accounting for the overlapping nature of competing networks in insurgent warfare, therefore, is important too and suggests analysts should take a broader, macro system view that insurgencies embed in larger social systems. Individuals who exchange information through social ties on behalf of insurgents and authorities, regardless of their true allegiances or how one categorizes them, serve as critical nodes intertwining open, competitive social networks. One cannot partition individuals into separate networks in operational environments without violating a fundamental assumption of "social networks" and "systems" research: interdependence. Furthermore, a perspective that does not account

for how insurgencies embed in larger social systems prohibits one from identifying and untangling all the ways by which all the relevant types of individuals (i.e., insurgents, government, and civilians) form connections in response to their social environments. In other words, it limits one's ability to understand social processes that undergird and drive social system dynamics (Borgatti et al., 2013; Lusher et al., 2013; Robins, 2015).

In such settings, therefore, one can observe at least two overlapping, in-person social networks that make up a larger system and seek to acquire and disseminate information about a populace and adversaries as a part of efforts to compete for control over a populace: namely *authority information-sharing* and *insurgent information-sharing* networks.³² While some scholars have presented similar arguments by demonstrating the role of “brokerage networks” in which covert and overt networks are mutually constitutive (Stys et al., 2020), and by highlighting how legitimate and illegitimate networks intersect (Diviák et al., 2019; Papachristos & Smith, 2014), they have not explored this characteristic in the context of insurgent warfare.

In Figure 2, the network on the left depicts boundaries based on the side(s) for which individuals exchange information in the competition between state and insurgents and ignores if an actor is civilian, insurgent, or government. The network on the right shows the proposed model of overlapping social networks in which civilians, insurgents, and authorities seek information and boundaries are not chosen based on actor categories. This depiction represents the larger social system of competing social networks. The presence of relations between clusters pushes and pulls actors into new network positions, whereby some civilians, for example, appear in different clusters than before.

³²Indeed, as Gventer (2014) highlighted with the notion of “mosaic war,” the number of competing structures may vary depending on the context but at least two must exist for a competition to exist.

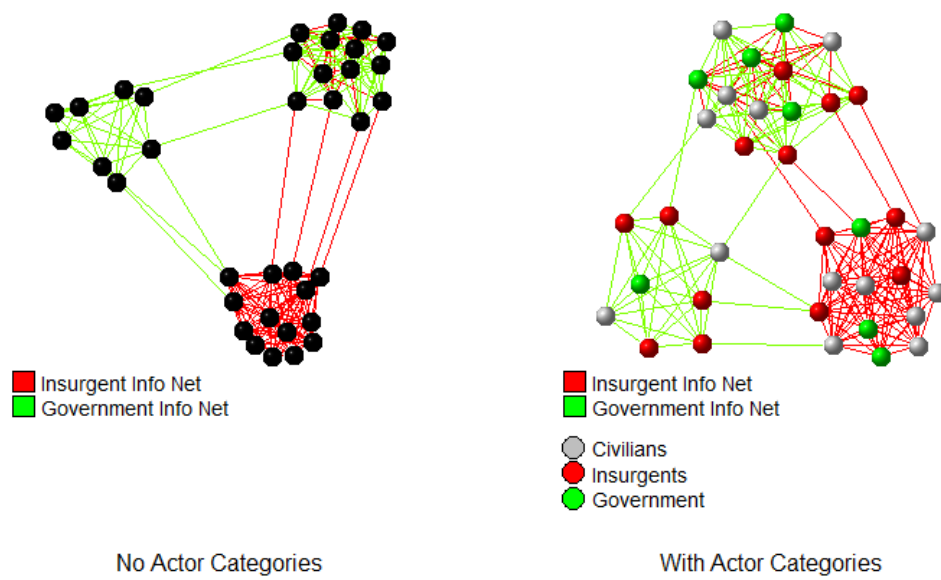


Figure 2. Competing Information Networks

III. MTML FRAMEWORK

This dissertation utilizes Monge and Contractor's (2003) multitheoretical, multilevel (MTML) analytic framework to study the co-evolution of competing, information-sharing networks in insurgent warfare. This framework encourages a broader system view of competing networks and blends complex adaptive systems and social network research through its emphasis on co-evolutionary social processes that take place within and between multilevel social systems. It integrates the two bodies' shared concepts closely related to co-evolution as well: namely, network emergence and self-organization (Monge & Contractor, 2003, p. xii). The framework is *multitheoretical* in the sense that it argues that researchers should draw from a variety of network theories to explain emergent and evolving social structures within macro social systems. Specifically, the authors argue that co-evolution and self-organization, which encompass a variety of multilevel social processes, such as reciprocity and triadic closure, serve as forces driving system emergence and dynamics, often simultaneously. In line with complex adaptive systems and social network research, this perspective accounts for both categories of processes and focuses on the extent to which each one determines a social system's macro structure (Anderson, 1999; Choi et al., 2001; Dooley, 1997; Levin, 1998; McKelvey, 1997; Monge & Contractor, 2003). This framework is *multilevel*³³ in the sense that it enables researchers to account explicitly for social processes at various social network levels, including those pertaining to the actor level (e.g., behaviors), various structural levels within a network (e.g., dyad, triads, subgroup, and global), and across social networks that make up larger social systems (e.g., multiplex relations).

To understand the MTML framework and its application to co-evolving social networks, it is necessary to provide a brief overview of the two interdisciplinary fields that serve as its foundation and highlight the extent to which they overlap and offer useful perspectives to examine this dissertation's topic. Over the last few decades, progress in

³³This is not necessarily the same as "multilevel" network analysis in which researchers analyze associations between individuals and collectives, such as organizations, thereby linking together micro and macro levels through a meso level. See Lazega and Snijders (2016).

complex adaptive systems and social network research has improved the understanding of social structures and the mechanisms driving their evolution. These broad, overlapping domains have offered useful perspectives on multilevel network dynamics, although separately in most cases (Anderson, 1999; Dooley, 1997; Lusher et al., 2013; McKelvey, 1997; Monge & Contractor, 2003; Snijders et al., 2010; Wycisk et al., 2008), and have described scale-free properties (Albert & Barabási, 2002; Barabási, 2002; Barabási et al., 1999; Barabási & Bonabeau, 2003), small-world effects (Watts, 1999a, 1999b, 2003; Watts & Strogatz, 1998), and actor level mechanisms for tie formation in social networks (e.g., homophily) (McPherson et al., 2001), to name a few. The two research bodies also account for the unique nature of social networks, such as agency, as well as share and address a constellation of interrelated concepts inherently tied to co-evolution for which one should account when studying the concept, such as network emergence and self-organization (Monge & Contractor, 2003; Robins, 2015; Sawyer, 2005).

This chapter begins with a description of social systems theories upon which complex adaptive systems is built for its application to social settings. This section's purpose is to outline common complex adaptive system characteristics and illustrate how the MTML framework applies them to social systems. Next, it describes social network research and highlights its emphasis on empirical social networks, which are forms of social systems. After these background sections, it outlines how the MTML framework synthesizes the two research bodies around mutual assumptions, concepts such as co-evolution and self-organization, and a shared focus on multilevel structures. It also incorporates more recent scholarly work and developments that bolster key MTML themes. In doing so, the MTML framework offers a useful perspective that fills important gaps in the study of social network dynamics in insurgent warfare.

As Lane (2006) and others contend (Koliba et al., 2016; Marcum, 2009; Walby, 2007), while co-evolution and related concepts (e.g., emergence and self-organization) form a cluster of associated ideas and fuse various research domains, little consensus exists about their meaning and application. With these concepts and constraints in mind, this chapter's limited goal is to illustrate this study's perspective for each concept and highlight their relevance to this topic, rather than offer an exhaustive review about their history and

resolve philosophical debates surrounding each one. It continues by addressing multilevel social networks and structural emergence in which social systems comprised of competing social networks emerge from self-organizing and co-evolutionary micro social processes, which is consistent with central ideas within complex adaptive systems and social network research. In line with Monge and Contractor's (2003) framework, the limited goal here is to illustrate how macro social structures emerge from micro, social processes/interactions at different levels, as well as present this study's perspective on the concept's relationship to the notion of multilevel networks, such as "micro-" and "macro-determination."

Next, it describes this study's perspective on self-organization. A common theme in social system-based, co-evolution studies is that one should account for self-organization to determine the extent to which it, rather than co-evolution, contributes to network dynamics (Anderson, 1999; Choi et al., 2001; Dooley, 1997; Levin, 1998; McKelvey, 1997; Monge & Contractor, 2003). Monge and Contractor (2003) rely heavily on complex systems science literature and agent-based modeling to address this topic yet they argue and demonstrate, like others (Kilduff et al., 2006; Robins, 2015; Snijders et al., 2007), that social network research is a valid and useful approach to examine the topic. Building on their work and other prominent network studies, as well as more recent works (Albert & Barabási, 2002; Barabási, 2002; Barabási & Bonabeau, 2003; Lusher et al., 2013; Robins, 2015; Snijders et al., 2010; Watts, 1999a; Watts & Strogatz, 1998), this analysis incorporates the latter perspective on self-organization because of its emphasis on empirical social networks rather than on simulated ones. From this perspective, self-organizing is a category of intra-network, micro social processes that contribute to social network emergence and dynamics.

This chapter then outlines this dissertation's perspective on co-evolutionary social systems. Initially envisioned for biological applications (Ehrlich & Raven, 1964), such as genetic evolution (Kauffman, 1993), organization scientists and social network researchers have applied the concept broadly to examine how various types of social systems evolve mutually with their environments. This perspective places its attention on systems' micro "adaptive changes within and between" (Lichtenstein, 2000, p. 13) system levels in response to an environment and how such dynamics give rise to emergent macro patterns

(Benbya & McKelvey, 2006; Dooley, 1997; McKelvey, 1997; Porter, 2006; Robins, 2015; T. A. B. Snijders et al., 2006). However, while various domains offer insight about co-evolving social systems and are not necessarily contradictory, many have operationalized the concept differently. Ultimately, this dissertation views co-evolution from an empirical social network perspective in which overlapping authority and insurgent information-sharing structures evolve through intra-network, self-organizing processes as well as inter-network, co-evolutionary processes at multiple network levels. Finally, this review will outline hypotheses about social processes that likely drive the co-evolution of competing networks in insurgent warfare.

A. BRIEF OVERVIEW OF COMPLEX ADAPTIVE SYSTEMS RESEARCH

Complex adaptive social systems research builds upon decades of investigation into social systems. Offering one perspective on social system theories history, Sawyer (2005) describes three waves during which specific theories dominated:³⁴ structural functionalism (1950s-1960s), social systems derived from general systems theory (1960s-1980s), and complex adaptive systems (1990s-2010s). According to the author, the first wave, or structural functionalism, is most associated with Talcott Parsons (1951) who provided insights into social system concepts, such as feedback and emergence. Influenced by cybernetic concepts of self-regulation through negative feedback, the idea of functional analysis is to identify how social systems maintain themselves in the face of changing environments (Monge & Contractor, 2003). This line of inquiry, however, has encountered significant criticism for its emphasis on control and “structure-preserving” behavior even when societies could make important changes to benefit their people and address systemic problems, such as racial or economic inequality. Other criticisms include Parson’s emphasis on society’s hierarchical nature, which critics contend is not a good reflection of modern society (e.g., the economy) (Sawyer, 2005; Walby, 2007).

³⁴ Sawyer’s approach is not the only one (for example, see Wycisk et al. (2008)), and I am not suggesting it is without its limitations. For instance, the waves do not match up precisely with the timeline of seminal publications for each theory and the waves do not replace one another linearly but build upon one another; however, Sawyer’s waves serve as a useful way to categorize the evolution of systems theories.

The second wave, which includes major influences such as general systems theory (GST) (von Bertalanffy, 1972), cybernetics (Wiener, 1948), as well as living systems (Miller, 1995) and chaos theories,³⁵ is an assortment of related work that contributed to substantial progress on nonlinear dynamics, as well as offered insights into open systems (e.g., insurgent networks); that is, those systems that interact and exchange “matter” (e.g., money, information, and recruits) with their external environment (e.g., a populace). In this body of work, researchers sought to develop universal laws of all systems, ranging from microsystems to the world system (Sawyer, 2005, p. 14). Most notably, the biologist Ludwig von Bertalanffy’s work on GST and open systems theory (OST) emphasized the scientific examination of “wholes” and contended that systems laws manifest themselves as “logical homologues” to all phenomena. He defined systems as, “a set of elements standing in interrelation among themselves and with the environment” that can be “expressed mathematically in different ways” (von Bertalanffy, 1972, p. 417). His framework of open systems has informed decades of research, including co-evolution studies, and is why “systems thinking”³⁶ permeates many research domains today.

Norbert Wiener (1948), based on developments in self-regulating and goal seeking machines (i.e., teleological systems), information theory,³⁷ and computer technology, introduced the term “cybernetics” to describe a field of science that sought to find generalities related to the “control and communication in machines and animals” (Drack & Pouvreau, 2015, p. 526). This interdisciplinary field³⁸ emphasizes the regulation and control of systems through feedback between system and environment (Ashby, 1962). An

³⁵ In general, when applied to “chaotic systems,” it is the notion that “even minuscule uncertainties in measurements of initial position and momentum can result in huge errors in long-term predictions of these quantities” (Mitchell, 2009, p. 20). A common example is the so called, “butterfly effect,” in which a small change in initial conditions can lead to radical change in a later state of the system. Prigogine and Stengers’ (1988) work highlight the discovery of order from “chaos.” When compared to complex systems, which are built up from large numbers of interacting components, chaotic systems may have very few interacting subunits but interact in such a way that produces very intricate dynamics.

³⁶ Systems thinking is way of thinking about the world and understanding problems using a systemic approach; that is, by focusing on relationships and interdependencies among entities.

³⁷ This term refers to Shannon’s Information Theory (see Mitchell (2009)).

³⁸ Cybernetics is not as “monolithic” as it appears here. According to Drack and Pouvreau (2015), one can distinguish between first order and second order cybernetics. For instance, first order emphasized negative feedback where the second included positive feedback.

important assumption is that all machines and living systems have goals and purpose, and they will strive to achieve them as they interact with and adapt to their surrounding environments. In an oversimplified sense, when a system's environment alters its course away from reaching its goal, the system's "controller" must adjust to get the system back on track toward its goal. A system's controller, therefore, requires information and feedback from the environment (i.e., a "signal") to do so.³⁹ Naturally, this domain has played a role in the social sciences and the development of complex adaptive systems research, including co-evolutionary studies (Sawyer, 2005).

However, second wave theories have several limitations when applied to social systems. In addition to facing similar criticisms that Parsons received, several scholars have pointed out that while the second wave provided useful concepts to look at social systems, such as nonlinearity, it failed to recognize their qualitative differences from the biological and other systems around which many theories developed (Cilliers, 2000, 2001; Eidelson, 1997; Padgett & Powell, 2012; Sawyer, 2005). Specifically, critics suggest that social systems are more open and "complex" than "simpler" complex systems, such as the brain and insect colonies, and human agency is an important aspect of social systems for which studies must account (Levin, 2002; Robins, 2015). As such, translating many concepts from biological systems to social systems poses many challenges. For instance, Miller's (1995) notion of "living systems" and Maturana and Varela's (1980) "autopoiesis"⁴⁰ are essentially biological models that others adopted to view society (Sawyer, 2005, p. 20). As Padgett and Powell (2012, pp. 56–57) contend, the use of such models offers only moderate applicability to social systems that are "more open" than other types of complex systems. For example, they note that autopoietic systems emphasize autonomy and self-enclosure, which is contrary to real-world social networks, which intersect and exchange information, as well as transform one another.

Complex adaptive systems research, which accelerated during the 1990s and 2000s and is foundational to the MTML framework, represents the third wave of social system

³⁹ Common analogies to describe cybernetics are thermostats and a Captain steering a ship.

⁴⁰ Autopoiesis means "self-making" (Capra, 1996, p. 97)

theories (Sawyer, 2005). Like the broader category of “complex” systems, basic complex adaptive system features include individual components (e.g., individuals) and relations whereby in the whole’s behavior is more than the mere sum of its parts. While no single definition exists, scholars often describe these dynamical systems as those in which higher level patterns, aggregate behaviors, or order emerge from the actions and localized interactions of its adaptive components (e.g., individuals and organizations) rather than from centralized control; that is, they *self-organize* (Anderson, 1999; Gell-Mann, 1994; Goldstein, 1999; Holland, 1992; Holland & Miller, 1991; Levin, 1998; Mitchell, 2009; Sawyer, 2005).⁴¹ In addition to self-organizing behavior, these multilevel systems, and thus their subcomponents (i.e., subsystems and individual components) too, *co-evolve* with their environments as a result of competition for resources (Benbya & McKelvey, 2006; Dooley, 1997; Lichtenstein, 2000; McKelvey, 1997; Monge & Contractor, 2003; Porter, 2006). Complex adaptive systems, therefore, are different from other complex systems in that individual components, often called agents, have cognitive abilities to collect information from their environment and act accordingly to try to reach their goals or the system’s goals over time; hence, they and the systems in which they embed adapt (Wycisk et al., 2008).

A foundational and well-known aspect of complex adaptive systems is nonlinearity and feedback that produces unpredictable patterns and order, but they often possess other characteristics too, such as heterogenous and autonomous agents, radical openness and porous boundaries, memory, dispersed interaction, flows between units (e.g., information), modular or clustered subsystems, cross-cutting hierarchical organization from self-organization and co-evolution, far-from-equilibrium dynamics, and novelty (Dooley, 1997; Holland, 1992; Holland & Miller, 1991; Levin, 1998; Miller & Page, 2007; Porter, 2006; Preiser et al., 2018). Naturally, many commonly referenced complex adaptive systems include the human brain, immune system, ant colonies, ecosystems, economies, societies, and social networks, such as supply networks, competitive firms, and teams (Choi et al., 2001; Dooley, 1997; Koza & Lewin, 1998; Levin, 1998; Lewin et al., 1999; Mitchell, 2009;

⁴¹ For instance, a leading CAS thinker, John Holland (2006, p. 1), defines such systems as, “systems that have a large number of components, often called agents, that interact and adapt or learn.”

Porter, 2006; Preiser et al., 2018; Root, 2020; Stacey, 1995; Wycisk et al., 2008). Some have described how insurgencies and other nefarious networks possess many of these characteristics, yet fall short of explicitly adopting a complex adaptive systems framework (Department of the Navy, 2017; Kenney, 2007; Kilcullen, 2013).

Though no single set of criteria exists for a social system to qualify as a complex adaptive system, authority and insurgent information-sharing networks meet many, if not all, commonly used criteria to describe them. They are nonlinear, feedback systems because when two individuals interact with one another, it often leads to mutual reactions that have consequences for them. Similarly, both networks consist of individuals with different motivations and characteristics (i.e., heterogenous) who work together through cooperative information sharing relations, and as such, informal information-sharing networks emerge without a central controller or deliberate organizing. While the presence of military hierarchies suggests some structure is imposed or formal in insurgent warfare, interactions among combatants and noncombatants within each network are often informal and bottom-up in insurgent warfare rather than top-down and forced (Pirnie & O'Connell, 2008). They are dynamic too. Individuals die and defect, as well as form and dissolve ties during an insurgency. Both networks, regardless of context, are likely to maintain some degree of modularity due to repeated interactions among component parts; for example, shared organizational affiliations (e.g., military or insurgent unit) and similar geographic proximity (e.g., same area of operation) create opportunities for individuals to share information and establish relationships (Kadushin, 2012; McPherson et al., 2001). Moreover, each side's social network's open nature and porous borders are apparent in that they intertwine as they compete for and among a populace (Department of the Army, 2017; Gventer, 2014; Herrington, 1982; Kilcullen, 2013).

As insurgent and authority information-sharing networks interconnect, they make up a larger social system that maintains common complex adaptive system characteristics. Heterogeneity remains apparent in such systems comprised of cooperating and competing civilians, insurgents, authorities, and everyone in-between. As subsystems of a larger system, each network is likely to maintain a modular structure through their respective components' repeated interactions. Because the networks intertwine, yet are not fully

connected, one can assume individuals on each side of the conflict interact more frequently within their subsystem than with others in an adversarial one (hence, modular patterns). Individuals simultaneously learn and adapt to friend and foe based on local information passed through in-person, information-sharing relationships. On the one hand, no single “controller” organizes the broader system consisting of insurgents, authorities, and civilians, which suggests macro system patterns emerge, in part, from self-organizing processes. On the other, because the competing social networks intertwine in a competitive context for information, it is likely that “feedback loops emerge, that, in turn, force co-evolving adaptive responses” within and between each one (Wycisk et al., 2008, p. 113); in other words, they co-evolve too.

An important topic in the study of complex adaptive systems is the extent to which self-organization and environmental conditions determine a system’s features, such as its macro structure (Anderson, 1999; Carmichael & Hadžikadić, 2019; Choi et al., 2001; Dooley, 1997; Levin, 1998; McKelvey, 1997; Monge & Contractor, 2003). For instance, Choi et al. (2001) claim that three foci become evident when studying such systems: internal mechanisms (e.g., agents and self-organization), environment, and co-evolution. While the line between internal and external forces is not always clear due to the open nature of social systems (Root, 2020), this perspective’s main point is that system components’ parallel actions within the system itself—that is self-organizing behavior—as well as feedback between agents and their social environments—or co-evolutionary behavior—drive the emergence of macro behavior and structure. While some argue that co-evolution is at the heart of self-organizing behavior, in part, because self-organization requires systems to import energy from outside the system (Kauffman, 1993; McKelvey, 2002), the MTML framework maintains that one should account for both internal, structural behavior as well as the impact of system-environment interactions.

While the set of tools varies across domains that have adopted a complex adaptive systems perspective, many researchers have embraced computational methods, specifically “agent-based models,” to model such systems (Carmichael & Hadžikadić, 2019; Miller & Page, 2007; Monge & Contractor, 2003; Ripley et al., 2021). This “bottom-up” approach permits researchers to create and explore how agent interactions, such as local social

processes, generate emergent patterns, order, and behavior (e.g., social norms and language) within an environment. It characterizes agents as following sets of rules, or schema,⁴² that represent social rules that one believes exist in the real-world (e.g., in insurgent warfare) and that govern agent interactions and can affect other agents, their own rules, and their environment. Thus, agent-based modeling, as well as similar approaches like multi-agent systems (MASs), enable researchers to conduct “thought” experiments about several relational mechanisms simultaneously, and account for important social system characteristics, such as their multilevel nature and human intentionality. Researchers can compare their results to empirical systems and data as well (Anderson, 1999; Koliba et al., 2016; Lansing, 2003; Monge & Contractor, 2003; Sawyer, 2005).⁴³ In other words, unlike approaches that focus on mapping aggregate, empirical social system structures, such as social network analysis, or interacting system variables, like in system dynamics, agent-based models focus on simulated agents’ decisions and do not assume to know a real-world’s system structure but rather seek to generate it (Miller & Page, 2007).

B. BRIEF OVERVIEW OF SOCIAL NETWORK RESEARCH

Like complex adaptive systems research, social network research is a way of thinking about social systems that are made up components (i.e., social actors or nodes in graph theory) and the relations among them (Borgatti et al., 2013; Robins, 2015; Wasserman & Faust, 1994). One can trace modern social network studies back to Jacob L. Moreno’s and Helen Jennings’ sociometric studies in the 1930s (Freeman, 2004; Moreno, 1932, 1934; Moreno & Jennings, 1938). From the 1930s onward, several universities began research programs that continue to develop the foundation of social network research by focusing on different aspects of data collection and analysis techniques, visualizations, and mathematical and computational models (Freeman, 2004). These early efforts underly its interdisciplinary nature. In fact, similar to the complex adaptive systems domain, social

⁴² For instance, one simple rule might be that an agent may change his attitude about a topic based on the sum of attitudes about the topic among his alters with whom he communicates weighted by the amount the agent communicates with each of his neighbors (Monge & Contractor, 2003, p. 127).

⁴³ In terms of studying information-sharing social networks, such an approach permits researchers to model information inputs and outputs, such as the timing of inputs and the type of information that flows in a network (Miller & Page, 2007).

network research has become an engrained scientific institution with its own journals (Connections, Social Networks, and Journal of Social Structure) and conferences (e.g., Sunbelt), as well as methods and software (e.g., UCINET, Pajek, and ORA).

Overlapping with this research body is “network science,” which is a commonly used term to describe researchers who systematically examine interdependent entities that form complex structures (e.g., social networks). It is common to find references to several prominent network scientists mentioned in complexity science books, and vice-versa. Based on the seminal work of notable researchers, such as Milgram’s (1969) notion of a “small world” and Granovetter’s (1973) concept of “weak ties,” several renowned scientists have fused complex systems and network research domains under the network science umbrella through attempts to identify unifying principles of all networks. Watts and Strogatz’s (1998) research is a good example. Their influential work on “small-worlds” highlights that the random rewiring of ties among networked entities can have a substantial impact on average path distances among nodes in a structure. Though the authors looked at simple, “regular” networks, one can observe many real-world structures, social and otherwise, that possess small-world properties. In fact, Barabási and his colleagues have contributed substantially to the study of networks through their work on scale-free structures (Albert & Barabási, 2002; Barabási, 2002; Barabási et al., 1999; Barabási & Bonabeau, 2003). Specifically, they identified that networks of all sorts, such as the World Wide Web and transportation networks (e.g., airline industry), possess “scale-free” properties whereby the presence of “hubs” lead to small-world structures as well as clustering/modular patterns.

Like “second wave” systems critics, social network scholars emphasize the unique nature of human social systems from others, such as transportation networks (Everton, 2012; Monge & Contractor, 2003; Padgett & Powell, 2012; Robins, 2015; Sawyer, 2005). Many argue, like rational choice theorists in other fields, that social systems are unique in the sense that social beings, such as humans, have agency and intentionality. While diverse perspectives on agency and “intentionality” exist, a major assumption is that individuals can interpret information from their social environment and make decisions about how to act and behave (Emirbayer & Goodwin, 1994; Robins, 2015). Social context is important

too. A social system in which individuals embed, including other actors and relationships, serve as their environment and can affect one's future ties, norms, beliefs, and behaviors, which is why the field generally considers both individual and system level factors in analyses (Borgatti et al., 2013; Borgatti & Halgin, 2011; Everton, 2012; Robins, 2015).

Because humans have agency and are embedded in unique social environments, it is unlikely that a single theory or law explains all social networks.⁴⁴ Instead, social network research emphasizes that a social system's structure is a consequence of dynamic social processes among social actors (Lusher et al., 2013; Monge & Contractor, 2003; Robins, 2015; Snijders et al., 2010). Social ties, such as information-sharing ties in insurgent warfare, come into existence between individuals in response to social environments. For instance, a civilian living in an area with an active insurgency may offer useful information to another noncombatant who has provided him with information in the past about insurgents operating in his neighborhood, thereby forming a reciprocal information-sharing relationship. Yet, dependencies involving several actors and ties may create relatively complex local structures beyond the simple pairs of individuals (i.e., dyad level), or at "higher levels." In the case of the information-sharing civilians, the probability that either one knows the highest-ranking government commander operating in their neighborhood is low. However, if one of the civilians establishes an information-sharing relationship with one of the commander's soldiers, then his chances of establishing a tie with the commander increase substantially (i.e., triad level) (Lusher et al., 2013).

Consequently, social network researchers also emphasize the multilevel nature of social networks and have outlined many of the foundational ideas about social processes at multiple network levels (Kadushin, 2012; Lusher et al., 2013; Monge & Contractor, 2003; Robins, 2015; Snijders et al., 2010). The central idea is that many local, and often nested,⁴⁵ system effects combine into a complex set of social processes that undergird

⁴⁴ This view is a predominant view but not the only one about the role of agency and culture (Emirbayer & Goodwin, 1994; Everton, 2012, pp. 29–30). *Structural Determinism*, for example, gives no credence to human agency and culture, while *Structural instrumentalism* assumes human agency is important. The views here align more with *Structural Constructionism* in which culture and agency as well as structure are important.

⁴⁵ For instance, reciprocity between two individuals can be nested inside a triad.

social systems (Lusher et al., 2013). While many social networks, for example, exhibit underlying social processes such as preferential attachment (Barabási, 2016), many other plausible mechanisms can help researchers explain social network emergence and dynamics, such as self-organizing processes other than preferential attachment (e.g., social exchange), co-evolution, multiplexity, social selection (e.g., homophily), and social influence (e.g., diffusion). In other words, several social processes may be at play simultaneously and occur at different network levels in any given context, which is a point at the heart of the MTML framework and one that has become more apparent in social network research over the last two decades (Borgatti et al., 2013; Lusher et al., 2013; Robins, 2015; Snijders et al., 2010).

In addition to placing an emphasis on multilevel social systems, social network and complex adaptive systems research share key assumptions and address many of the same concepts. Like the latter perspective, social network research assumes that social networks are locally emergent in that repeated interactions of social entities give rise to emergent structures in which the whole is greater than the mere sum of its parts, including in instances when multiple social networks overlap to make up a larger social system (Everton, 2012; Lusher et al., 2013; Padgett & Powell, 2012; Robins, 2015). As seen in the vast amount of diffusion and “social capital”⁴⁶ studies, social network researchers assume social ties function as conduits for the flow of information and resources, although typically social network studies do not conceptualize information as Shannon, pragmatic, or semantic (Borgatti & Cross, 2003; Borgatti & Halgin, 2011; Crossley et al., 2015; Everton, 2012; Kadushin, 2012). They recognize that social networks are dynamic as well. Like complex adaptive systems research, this domain’s researchers have increasingly examined how social networks self-organize, albeit in a much more implicit manner, as well as evolve over time, including how social networks co-evolve with others (Fujimoto et al., 2018; Lusher et al., 2013; Rambaran et al., 2015; Robins, 2015; Snijders et al., 2007; Steglich et al., 2006). Thus, it too recognizes nonlinearity within social systems and attempts to capture it through models for empirical social networks, such as SAOMs, that permit

⁴⁶ Many definitions exist, but in a broad sense, social capital is the idea that social networks have value for individuals, such as access to information and resources (Kadushin, 2012, p. 162).

researchers to untangle self-organizing social processes from co-evolutionary ones (Lusher et al., 2013; Snijders et al., 2010; Snijders et al., 2007).

C. SUMMARY: MTML'S SYNTHESIS OF COMPLEX ADAPTIVE SYSTEMS OF SOCIAL NETWORK RESEARCH

Monge and Contractor's (2003) MTML framework fuses complex adaptive systems and social network research around the two interdisciplinary research bodies' natural points of synthesis, such as shared assumptions (i.e., system components' interdependence through relations), the uniqueness of social systems (e.g., human intentionality), and their shared emphasis on the multilevel nature of social systems in which self-organizing and co-evolutionary social processes (i.e., multitheoretical) propel emergent and dynamic structures at different levels. By doing so, this framework facilitates the study of co-evolving social networks in insurgent warfare, as well as addresses important gaps in existing literature. Specifically, the complex adaptive systems perspective's unique contribution to the topic is that it aids analysis from a standpoint on system boundaries that is consistent with insurgency and counterinsurgency literature: namely, social systems that encompass open and competitive, information-sharing social networks that are comprised of dynamic social beings, specifically combatants and noncombatants, who influence and react to their social environment. This perspective offers a more realistic depiction of social systems in insurgent warfare than existing social network literature on "dark networks," including insurgent ones, and enables one to interpret them in a more complete and useful manner. Social network research's central contribution is its emphasis on identifying local social processes that undergird empirical social systems. Though extant social network literature has failed to address insurgent networks adequately to date, this domain offers the most useful avenue to examine co-evolving, empirical social networks in operational settings, which addresses another major gap in the study of social networks in insurgent warfare.

With these contributions in mind, social network and complex adaptive systems domains diverge in several notable ways for which one must account when leveraging the MTML framework. For example, as mentioned in Chapter 1, the two research bodies differ in their historical lineage and scope. For instance, von Bertalanffy (a biologist), as well as

contemporary network scientists such as Barabási (a physicist), sought to establish unified system theories (Sawyer, 2005). Social network researchers, on the other hand, have been less eager to do so, in part, due to their emphasis on the importance of context in the study of social systems. Another notable point of divergence is the extent to which the domains address relevant concepts explicitly, such as emergence and self-organization. Such concepts are central to complex adaptive systems research while they appear to receive relatively less overt attention in social network research.⁴⁷ The MTML framework, as well as this dissertation, aligns more closely with the former in the sense that it argues that analyses should account explicitly for these concepts, especially when studying co-evolution (Monge & Contractor, 2003).

Most importantly, the two research bodies do not necessarily apply key concepts in the same manner. Like with other social system models, the concept of complex adaptive systems is at a high level of abstraction, and while it offers many insights into social systems, many of its concepts and principles do not translate seamlessly nor are measured easily in the analysis of empirical social systems (Eidelson, 1997; Lansing, 2003; Sawyer, 2005). This challenge is apparent in the fact that empirical social network studies rarely, if ever, explicitly incorporate and model relevant complex adaptive systems concepts and principles, such as bifurcations, self-organized criticality, homeostasis, and networks evolving at the edge of chaos (Borgatti et al., 2013; Cilliers, 1998; Eidelson, 1997; Kauffman, 1993; Robins, 2015). One reason for this might be that several scholars have cautioned against relying too heavily on metaphors from other types of systems, such as biological systems, that may “muddy” concepts and confuse aspects of social systems rather than enlighten (Eidelson, 1997; Padgett & Powell, 2012; Sawyer, 2005).

Similarly, they diverge in their main approach for understanding social systems. Complex adaptive systems researchers commonly leverage computational, agent-based

⁴⁷ The complexity domain spends considerable time diving into these concepts’ philosophical implications, but social network research appears to accept them simply as key assumptions of most social systems. For instance, see *Emergence* (<https://www.tandfonline.com/toc/hzze20/current>) and *The Journal of Complexity* (<https://www.journals.elsevier.com/journal-of-complexity>). A few exceptions in social network research exist, however. For instance, Lusher et al. (2013) and Robins (2015) address self-organization explicitly.

models that generate structures and system behaviors based on simulated agents' decisions and interactions rather than map aggregate empirical social systems. While social network researchers recognize that individuals have cognition and it is an underlying assumption that information flows through social ties (Borgatti & Halgin, 2011), typically they do not model them explicitly. One practical explanation for this is that collecting such data is often impossible for context specific, empirical studies, especially archival studies (Tasselli et al., 2015).⁴⁸ Monge and Contractor (2003) rely heavily on complex adaptive systems literature and agent-based modeling to illustrate and apply the MTML framework, yet they argue and demonstrate that social network models for empirical data, such as ERGMs and SAOMs, are valid approaches too (Lusher et al., 2013; Ripley et al., 2021; Snijders et al., 2010; Snijders et al., 2007).⁴⁹ As described in Chapter 4, recent advances in SAOMs since the authors published the framework place this model class at the intersection of the two domains by permitting analysts to model dynamic, multilevel social processes on empirical social network data.

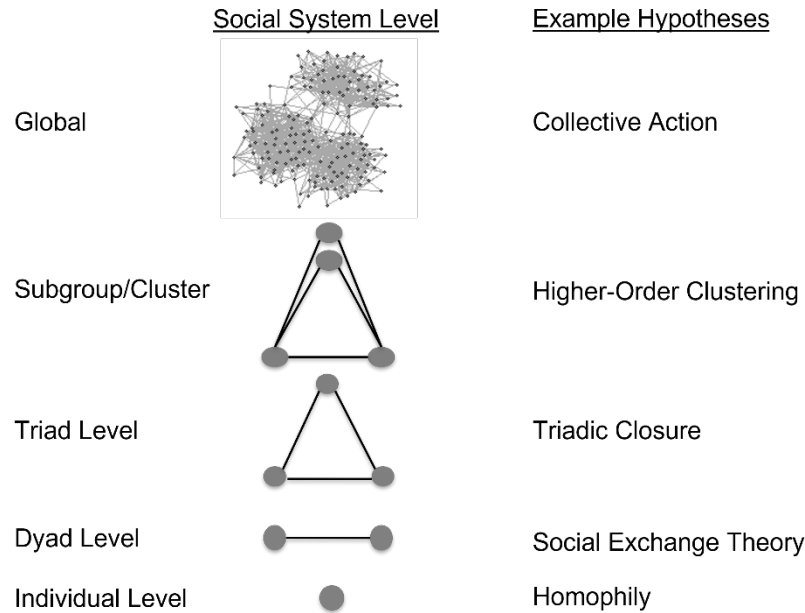
With these points in mind, this dissertation's focus, like Monge and Contractor (2003), is on co-evolution and inherently related concepts, specifically emergence and self-organization, that both complex adaptive system and social network research address explicitly, albeit to varying extents. Nonetheless, little consensus exists about each concept's meaning. Therefore, it is important to describe the MTML's perspective on each one, as well as highlight how this dissertation diverges from it (Hodgson, 2000; Koliba et al., 2016; Lane, 2006; Marcum, 2009; Walby, 2007).

⁴⁸ Other reasons certainly exist. For example, social network researchers, in part, focus on empirical networks because they emphasize the importance of context in which social networks embed. In fact, researchers from both domains appear to recognize the context-dependent nature of social systems, which suggests it is difficult to fully specify human "behavior" behind bottom-up processes (Miller & Page, 2007; Robins, 2015). This dissertation does not argue that one approach is superior to the other.

⁴⁹ In fact, the two approaches complement one another. For instance, researchers often apply computational models and then compare them to empirical network data.

D. MULTILEVEL SOCIAL NETWORKS AND STRUCTURAL EMERGENCE

The multilevel nature of social systems is a central aspect of the MTML framework and directly related to co-evolution. It is the idea that dynamic social processes, such as co-evolutionary and self-organizing ones, take place at multiple levels of analysis (Benbya & McKelvey, 2006; Goldstein, 1999; Levin, 2005; Lichtenstein, 2000; Lusher et al., 2013; McKelvey, 1997; Robins, 2015; Wycisk et al., 2008). For instance, Lichtenstein (2000, p. 13) describes a primary goal of co-evolution studies is to understand “adaptive changes within and between” system levels and environment that give rise to emergent patterns and behavior. Though scholars give the term “multilevel” various meanings (Lazega & Snijders, 2016), Monge and Contractor (2003, p. 21) take a structural approach and define “levels” as individual, dyad, triad, subgroup, and global levels. They contend that “explaining” social system dynamics requires one to recognize their multilevel nature, as well as incorporate theoretical perspectives that occur at these various levels. Drawing from complexity and social sciences, they outline various theories that may help researchers hypothesize about social system dynamics at different network levels, most of which fall within the categories of self-organizing and co-evolutionary processes. Figure 3 depicts various network levels, as well as example hypotheses pertaining to each one.



Adapted from Monge and Contractor's (2003) social system levels and hypotheses. The latter are a subset of potential hypotheses that one can incorporate into the MTML framework and do not necessarily align with the "configurations" depicted in the "Social System Level" column. It is also important to note the visual examples for each level are not the sole way to depict each one. For instance, one can depict the triad level as an open triad in which only two ties are present and there are many ways to depict and measure subgroups.

Figure 3. Social System Levels and Example Hypotheses

The notion of multilevel social systems is inherently related to the concept of emergence, which is the "arising of novel and coherent structures" (Goldstein, 1999) in dynamic systems from "local" interactions (Holland, 1998; Lichtenstein, 2000; Monge & Contractor, 2003).⁵⁰ It is a perspective that assumes systems are made up of levels and that patterns, structure, and behavior at "higher levels" are greater than the mere sum of underlying parts (Root, 2020; Wycisk et al., 2008). Taking a structural perspective of emergence, Monge and Contractor (2003) contend that local or micro, self-organizing and co-evolutionary processes at their defined network levels help generate emergent structural patterns at higher ones. At each system level, one cannot explain its structure, patterns, and behaviors wholly in terms of another level. For instance, one cannot explain scale-free

⁵⁰ Though no consensus exists among scholars, common characteristics of emergent properties are novelty, that is, features not previously observed in the system, dynamical processes at lower levels, unpredictability, and irreducibility (Cilliers, 1998; Corning, 2002; Sawyer, 2005).

networks, a common global property in networks, with a single social process such as preferential attachment, or by simply adding up all social processes occurring at actor, dyad, triad, and subgroup levels.

However, as Lissack (1999, p. 112) points out, the notion of emergence is “less than an organized, rigorous theory than a collection of ideas” that a system and its properties, such as its structure, emerge from interactions of its component parts (Corning, 2002). A major debate has been the extent to which levels “determine” or cause others (Miller & Page, 2007; Monge & Contractor, 2003). Kontopolous (1993) offers a useful view for network emergence and identifies five epistemic perspectives relating to micro-macro determination: namely, reductionism, construction or compositional emergence, holism, hierarchy, and heterarchy. As Monge and Contractor (2003, p. 15) point out, the “reductionist” and “holist” viewpoints are the most extreme versions on the continuum of perspectives. The former implies that lower levels completely determine higher levels, and therefore, researchers can investigate and explain macro phenomena solely in terms of lower level phenomena. Yet, this point of view has many critics who claim it ignores potential “top-down” effects on individuals and their relations, such as existing social norms and social structures (Monge & Contractor, 2003; Sawyer, 2005). Similarly, the construction or compositional emergence perspective emphasizes bottom-up “causality,” as well as contextual factors (Holland, 1998). From a network perspective, this point of view contends that interactions among lower level components give rise to the next level up in a network.

Contrary to bottom-up perspectives, “holism” is the view that investigation and explanation of systems and their properties is insufficient; that is, it best encapsulates the notion that the “whole is greater than the sum of its parts.” A commonly used example demonstrating this perspective are water’s emergent properties. The argument is that one cannot explain water’s effect on say, fire, by looking at its individual components: namely, hydrogen and oxygen (i.e., H₂O). Individually, the two components fuel fire; however, when combined in a certain manner they form properties with the opposite effect (Everton, 2012). From a network perspective, this view focuses on how structure constrains individual behavior.

The validity of these views is widely discussed, and while some scholars take a side on this matter, many consider aspects of both top-down and bottom-up approaches as valid perspectives for explaining social systems (Everton, 2012; Lane, 2006; Levin, 1998; McKelvey, 2002; Monge & Contractor, 2003; Root, 2020; Sawyer, 2005; Tasselli et al., 2015). Adherents to this viewpoint assume that feedback occurs between levels so that micro level interactions may shape global structures, yet the macro level then constrains future interactions, and so on (Rickles et al., 2007).⁵¹ One can see how this view applies to insurgent warfare in which interactions among individuals give rise to larger structures, while at the same time structure constrains individuals' behaviors and actions. For instance, a civilian may share information with government forces, but is less likely to continue to do so if close family members become deeply embedded in an active and violent insurgency. Padgett and Powell (2012, p. 2) take a similar perspective about the evolution of actors and their relations, so much so, that their mantra is, "in the short run, actors create relations; in the long run, relations create actors." In the case of a civilian sharing information with government soldiers, the authors would likely suggest the civilian's decision to form a collaborative relationship with the government in the short-term may ultimately shape the civilian's allegiances and actions in the long-term.

The concept of "hierarchy" is inherently tied to the notion of levels. Like the concepts of complexity and emergence, hierarchy is a topic about which little consensus exists. Lane (2006), for example, outlines four different types of hierarchy as they relate to complexity, namely order,⁵² control,⁵³ level, and inclusion. The last two are particularly relevant for the MTML framework. The author describes "level hierarchy" as a form of ontological organization of entities (Lane, 2006, p. 82). This view accounts for both bottom-up and top-down determination and appears in several social contexts, such as economic hierarchies comprising of individuals who make up departments, which then

⁵¹ The point here is not to make a "chicken and egg" claim about which comes first. Rather, this perspective suggests both top-down and bottom-up effects have impacts.

⁵² An order hierarchy, according to Lane (2006, p. 84) is "an ordering induced by the values of a variable defined on some set of elements."

⁵³ Lane (2006, p. 85) defines this as a "who gives orders to whom" type of hierarchy. For example, the U.S. Army reflects a control system such as the Army.

make up firms, and so on. Inclusion hierarchies, on the other hand, refer to Simon's (1962) views on complex systems that they are organized into "Chinese boxes." This position holds that each "box," or hierarchy, contains other boxes, and that entities interact primarily with entities on the same level. In other words, this is a top-down point of view in which systems are nested within larger systems, a perspective that appears to have inspired others using the notion of "systems of systems" (Capra, 1996). Critics of this perspective, however, have pointed out that complex system hierarchies are not clearly defined or as nested as they are often portrayed (Cilliers, 2001; Padgett & Powell, 2012; Walby, 2007).

Guided by Monge and Contractor (2003), this aligns more with the final perspective on structural emergence: heterarchy (Kontopoulos, 1993). In this sense of the term, heterarchies are far more complex than Simon's notion of fully nested hierarchies. These "tangled composite structures," or partially nested ones, have "multiple overlapping, relations across levels" (Kontopoulos, 1993; McKelvey, 1997; Monge & Contractor, 2003, p. 15). This perspective accounts for both top-down constraints and bottom-up influence, as well as feedback processes driving dynamics internal to each level (Monge & Contractor, 2003, p. 13). For example, two insurgents may share information reciprocally, thereby driving structure at a dyad level. Yet, they may also have information sharing relationships with many others that create local structures at "higher levels" (e.g., triad level), all of which occur within a larger existing structure that constrains behavior. Finally, because social networks are open systems connected to others, and thereby import and export material and non-material goods (e.g., information, recruits, and money) with one another, this perspective accounts for the possibility of "external" influences on one or more levels. This framework, therefore, suggests that internal, self-organization and co-evolutionary processes, such as in the case of interconnected, competing networks, can influence a system's dynamics (Contractor et al., 2006).

E. SOCIAL PROCESSES AND SELF-ORGANIZATION IN THE MTML FRAMEWORK

Self-organization is a central concept of complex adaptive systems research, as well as to the MTML framework (Kauffman, 1993; Keller, 2005; Levin, 2002; Monge &

Contractor, 2003). While various definitions exist, it generally comprises of a broad range of pattern-formation processes that attempt to explain the emergence of stable patterns and structure from the interactions of a system's constituent parts, whether they be chemical elements, social actors, or other system entities (Haken & Portugali, 2016; Kauffman, 1993; Monge & Contractor, 2003; Prigogine et al., 1988). A foundational element of self-organizing behavior is that patterns emerge spontaneously from nonlinear dynamics and without the intervention and direction of a "central controller."⁵⁴ Leading scholars and ideas within biology and complexity science, such as Haken's (1977) "synergetics," Varela's (1980) concept of "autopoiesis," Bak's (1996) notion of "self-organized criticality," as well as others (Ashby, 1962), have made substantial contributions to the body of work and inspired scientists in other fields.

In particular, Stuart Kauffman's (1993) renowned work is a commonly referenced example in the study of self-organizing behavior in complex social systems (Lansing, 2003; McKelvey et al., 2013; Monge & Contractor, 2003; Stacey, 1995).⁵⁵ In fact, Monge and Contractor (2003) illustrate self-organizing behavior in organizational networks largely from Kauffman's perspective. While an exhaustive summary of his work and contributions is beyond this dissertation's scope, one of his central claims is that self-organization, in addition to Darwinian natural selection, produces order in living systems through simple processes/rules. Using the notion of "fitness landscapes"⁵⁶ to study genes' evolutionary behavior, he argues that the fitness of any trait is likely determined by neighboring genes

⁵⁴ Hence, the "self" in "self-organization." Unlike "chaotic" structures, self-organized patterns emerge from complexity, rather than the other way around (Allen et al., 2011; Anderson, 1999).

⁵⁵ As Lansing (2003, p. 183) and others (Mitchell, 2009; Monge & Contractor, 2003) explain, Kauffman's work has offered important insights for biology, such as that "natural selection is not the sole source of order" in living systems, as well as for mathematics and physics, namely the notion that complexity is present within simple systems. Yet, it also has inspired the study of social systems in the sense that complex global patterns may emerge spontaneously from local interactions (Lansing, 2003).

⁵⁶ He describes "fitness" from an evolutionary biologist's perspective. He states an organism's fitness has components, such as fecundity and fertility, that lead to reproductive success. He states (1993, p. 37), "These include complex issues such as the frequency of each genotype variant of the organism in the population, the density of each genotype variant in a region, and even the entire ecosystem with which each organism interacts." Fitness values are assigned to each gene and the fitness of the genotype is the average of all traits that make up the genotype. Assigning these values generates a fitness landscape, which can be smooth or rugged, showing the fitness of all possible combinations of genetic traits. Populations of genes "attempt to optimize their fitness by finding, selecting, and retaining the best genotypes" (Monge & Contractor, 2003, p. 265)

through epistatic connections, which impose constraints on the adaptability of the linked traits.

Kauffman formalized this notion with the NK model (and an NK(C) model for co-evolution) and explored the association between genes' average connectedness and an organism's ability to evolve (Lansing, 2003). In this model, the number of elements ("N"), such as genes, are connected through some number of links (the average across the system is "K"), like epistatic connections. The latter is a measure of complexity and can range from $K=0$, whereby no genes are connected, to $K=N-1$, when all genes are connected. Using random NK Boolean networks,⁵⁷ each element (think strings of Christmas tree lights) in the network has two possible states (on or off), which is determined in accordance with its neighbors' states and implemented in a model as simple rules. For instance, a basic rule might be that if all of one element's (or node's) neighbors are in an "on" state, it will turn "on" too. The networks are random in the sense that element connections, element states, and decision rules are assigned randomly throughout the network. Consequently, a system's global behavior depends on the way it is wired (Mitchell, 2009; Stacey, 1995).

Ultimately, Kauffman's simulations found that the networks exhibited three "regimes" of behavior: ordered, chaotic, and complex. In ordered regimes, when K is small (e.g., $K=1$), simple and stable behavior emerges as the majority of elements' behaviors "freeze" (e.g., stay "on") and form a large, connected cluster while leaving some isolated elements whose activities fluctuate. Self-organization is difficult, if not impossible, in these cases because many elements and links in the system are largely fixed (Monge & Contractor, 2003, p. 270). In chaotic regimes, where K is large ($K = N-1$), there is no cluster of frozen elements and small changes in the system's initial conditions can cause behavioral "avalanches" across the system whereby patterns do not repeat; that is, it exhibits random behavior in which element states change chaotically (e.g., lights switch each other on and off). In this regime too self-organization is difficult, yet in this case, it is because there is no order in the system. The final regime—or complex one ($K=2$)—is a

⁵⁷ As Mitchell (2009, p. 283) states, "A Boolean rule is one that gets a number of inputs, each equal to 0 or 1, and from those inputs it produces an output of 0 or 1."

“transition region” between ordered and chaotic regimes in which clusters of stability (i.e., frozen behaviors) emerge but rather isolated elements unleash avalanches of change (Kauffman, 1993). In other words, he discovered that system behavior is largely dependent on K and neither ordered nor chaotic networks transmit information and therefore cannot adapt; however, the complex networks—that is, those at the “edge of chaos”—can do both. It is in the complex regime that self-organized behavior emerges (Lansing, 2003; Mitchell, 2009; Stacey, 1995).

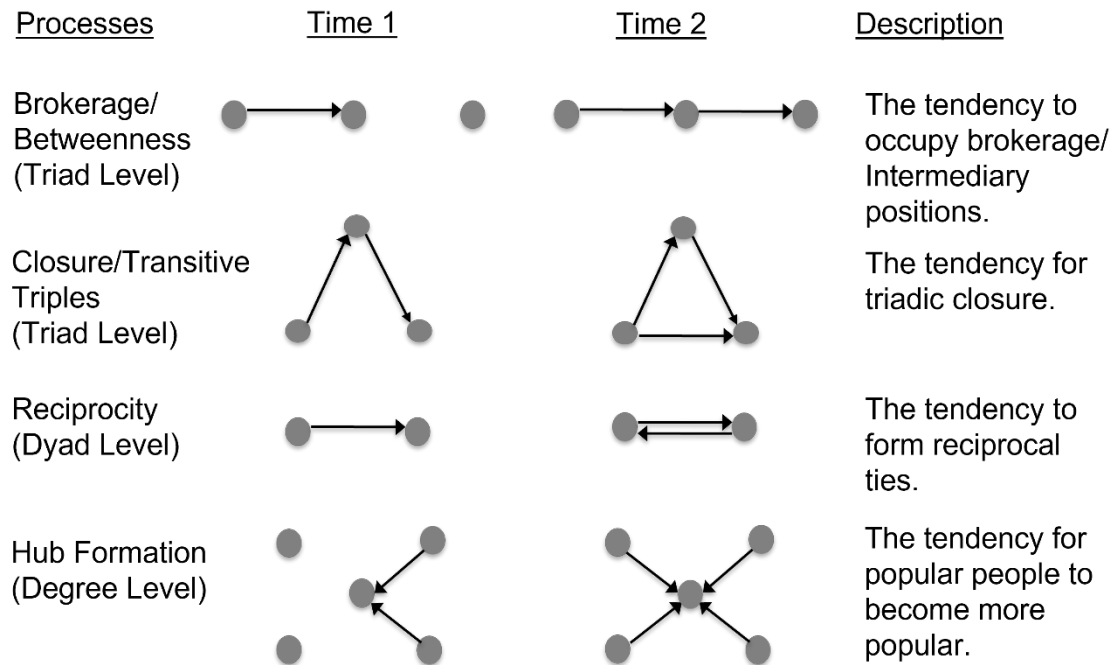
Because not all systems are thought to self-organize (e.g., some may be chaotic), extant literature has sought to outline self-organizing system characteristics. Prior to Kauffman’s work, Prigogine and Glansdorff (1971) offered criteria for describing such systems, such as autocatalysis,⁵⁸ mutual causality among parts, matter and energy exchanges with its environment (i.e., open systems), and far-from-equilibrium characteristics (Monge & Contractor, 2003, p. 89). Similarly, Cilliers (1998, p. 91), a prominent complexity scholar, described them as open systems that adapt to their environment, emerge without a priori design, are non-linear in nature, consist of components operating on local information, possess “memory,” and become increasingly complex over time. As Haken and Portugali (2016) explain, self-organization requires exchanges of information, matter, and/or energy with a surrounding environment.⁵⁹ Understandably, several foundational works have incorporated the concept of self-organization into the study of open, social systems that meet many of these characteristics, such as organizations (Monge & Contractor, 2003; Stacey, 1995; Volberda & Lewin, 2003) and ecological systems (Keller, 2005; Levin, 2005). More recently, Root (2020) has

⁵⁸ Monge and Contractor (2003, p. 95) describe it as, “the capabilities of the parts of a system to self-create and self-renew independent of the forces from the outside.” Drawing from its chemical origins of study, Padgett and Powell (2012, p. 8) define it as, “a set of nodes and transformations in which all nodes are reconstructed through transformations among nodes in the set.”

⁵⁹ Specifically, the authors illustrate how self-organizing processes are linked to Shannon, pragmatic, and semantic information, as well as information adaptation, or the interplay of Shannon information and the other two forms. As outlined in Chapter 1, they describe Shannon information “capacity of a channel through which a message passes,” whereas pragmatic information is the “impact of a message on recipients,” and semantic information is, “the meaning conveyed by a message” (Haken & Portugali, 2016, p. 1)

described economics systems, specifically in Europe and China, as self-organizing, complex systems.

The work of several renowned network scholars has inspired a shift in the study of self-organizing social systems from system regimes to empirical social processes that drive structural changes (Barabási, 2002, 2016; Burt, 1992; Granovetter, 1973, 1983; Watts & Strogatz, 1998). Building on these works, recent social network research has focused self-organization on how empirical social networks constitute emergent structural patterns built upon underlying social processes, or micro patterns of interaction, within the constraints of existing structure and devoid of a central “controller.” In his insightful book, Robins (2015, p. 34) encapsulates this domain’s more precise, structural view of self-organization by defining it as structural processes “where the presence of some network ties sustains the ongoing presence of other network ties, or encourages them into existence.” Such processes are considered “purely structural” and “internal” to a network (Lusher et al., 2013; Robins, 2015). From this perspective, common examples of self-organizing behavior are reciprocity, triadic closure, and preferential attachment, all of which are dynamic and may occur simultaneously to produce complex structures. Beyond identifying such processes in empirical networks, the challenge is explaining the extent to which each one is present. Recent developments in ERGMs (Lusher et al., 2013) and SAOMs (Snijders et al., 2010) have provided researchers with the means to do just that. Thus, this dissertation updates Monge and Contractor’s (2003) application of self-organization to incorporate this perspective and these advances. Figure 4 depicts several examples of self-organization processes.



Examples of structural, “micro configurations” that reflect dynamic self-organizing, social processes. While such processes can occur at “higher levels,” this figure depicts a selection of basic examples only at two levels: dyad and triad.

Figure 4. Examples of Self-Organizing, Social Processes

Existing literature offers little guidance about self-organizing behavior in insurgent warfare. Using Robins’s (2015) definition of self-organization, however, this study contends that self-organization is likely prevalent in insurgent warfare as combatants and noncombatants exchange information. The mixture of these actors in overlapping networks suggests many relations are informal rather than formal ones. Informal ties, which are naturally forming ties often created to complete tasks and access information and resources, are far more likely to define spontaneous interactions and self-organizing behavior than formal ties, even though they often overlap, embed, are constrained by, and serve the same goals of formal ties (Biancani et al., 2014; Brennecke & Rank, 2016; Goldstein, 1999; Kadushin, 2012; Monge & Contractor, 2003). While military and many insurgents, as well as civilians, tend to maintain formal organizational memberships, they are rarely, if ever, members of the same organizations during active conflict; instead, they appear to develop informal, information-sharing ties when they interact with others outside their formal

structure, which is often built on local information rather than from “order” imposed on them from a “central controller.”⁶⁰

Furthermore, the bottom-up and competitive nature of information collection in operational environments is likely to facilitate self-organizing behavior (Astley, 1985; Cilliers, 1998; Monge & Contractor, 2003; Pirnie & O’Connell, 2008). Unlike conventional warfare, information collection in insurgent warfare is primarily a bottom-up process based on reporting from units operating in the field who maintain contact with noncombatants in competitive public spaces, such as during patrols, and in private settings, like key leader engagements, to name just a few (Pirnie & O’Connell, 2008). In such cases, individuals who exchange information often help connect the competing, open social networks, and serve as conduits of information inputs into their respective “side.” Moreover, some scholars contend that competition is a precondition for self-organizing behavior (Cilliers, 1998), which is likely when the demand for resources (e.g., information) exceeds supply (Astley, 1985; Monge & Contractor, 2003). Actionable information is in high demand in insurgent warfare and the consequences of failing to acquire and disseminate information successfully can be disastrous (e.g., injury and death). One can expect, therefore, self-organizing behavior within such competitive contexts in which actors develop informal relations to exchange information and meet their operational objectives.

F. EVOLUTION, CO-EVOLUTION, AND SOCIAL SYSTEMS

Like the concepts of emergence and self-organization, co-evolution has drawn interest from various research domains and is a foundational aspect of the MTML framework. Ehrlich and Raven (1964), the biologists who some have credited with coining the term co-evolution (McKelvey, 1997; Porter, 2006), described it as genetic change of one species in response to the evolution of another. Others have outlined various forms of

⁶⁰ Volberda and Lewin (2003, pp. 2126–2127) make a similar point about self-organization in formal organizations, like businesses. They state that self-organization does not mean “that managers are not necessary or that they have demised roles. It means that no central controller is necessary, and it requires a fundamental departure from command-and-control philosophy of traditional hierarchical bureaucratic organizations.”

co-evolution (Benbya & McKelvey, 2006; McKelvey, 2002), such as “predator/prey,” and “symbiotic” co-evolution.⁶¹ Initially envisioned for biological applications, such as dynamic interactions between plants and herbivores and the study of genetic evolution (Kauffman, 1993), organization scientists and social network researchers have applied the concept to examine how various types of social systems evolve mutually with their environments. This perspective places its attention on systems’ micro adaptive changes within and between system levels in response to an environment and how such dynamics give rise to emergent macro patterns (Benbya & McKelvey, 2006; Dooley, 1997; Lichtenstein, 2000; McKelvey, 1997; Porter, 2006; Robins, 2015; Snijders et al., 2007). As such, co-evolution has become a central concept to complex adaptive systems and social network research and scholars have applied it to various social system settings, whether it be firms and/or alliances and organizational networks (Baum & Singh, 1994; Koza & Lewin, 1998; Lewin et al., 1999), organizational strategy (Dooley, 1997), or social networks (Amati et al., 2021; Choi et al., 2001; Fujimoto et al., 2018; Huitsing et al., 2014; Steglich et al., 2006).

Co-evolution extends evolutionary theory, which is essentially a theory of change (Abatecola et al., 2016; Kauffman, 1993; McKelvey, 1997; Monge & Contractor, 2003). While an exhaustive review of evolutionary theory is beyond this study’s scope, its foundations and application to organizations and organizational networks—especially among population ecology theorists—serves as a useful background for co-evolution research (Aldrich & Ruef, 2006; Lee & Monge, 2011; Lewin et al., 1999; McKelvey, 1997, 2002). It contends that basic mechanisms driving organizational evolution occur through random and intentional variation, which it can select and then retain through institutional procedures in efforts to improve survivability in the face of competition. Specifically, three broad categories of processes, which often occur simultaneously, serve as the basis for evolutionary systems in organizational contexts: namely variation, selection, and retention.

⁶¹ McKelvey (McKelvey, 2002) lists eight forms of co-evolution. For instance, “predator/prey” co-evolution could be tit-for-tat increases in a prey’s speed, which in turn, requires the predator to run faster, and so on. The “symbiotic” form occurs through symbiotic, sometimes mutually beneficial, relations.

A fourth process, competition for resources, drives organizational evolution as well (Aldrich & Ruef, 2006; Monge & Contractor, 2003).

According to Aldrich and Ruef (2006), *variation* is the counterpart to stability and in an organizational context it is any departure from routine or tradition. It can be intentional or unintentional (i.e., blind, or random). The former are variations that are the result of organizations trying to solve problems, whereas the latter occur via chance and without preplanning (Monge & Contractor, 2003). For instance, an example of intentional variation could be when an insurgent organization, through imitation of other organizations and/or trial and error, realizes improvised explosive devices (IEDs) slow down a militarily superior government and inflict casualties, which may lead them to pay large sums of money to individuals willing to plant them on highways that authorities use frequently. Blind variation may result from insurgents obtaining new information sources without planning it, such as segments of the population who offer them information after experiencing government oppression. Certainly, organizations need not benefit from one or the other; they can profit from both types simultaneously.

Evolutionary *selection*, not to be confused with social selection, is an organization's attempt to choose variations that provide it benefits and minimize harm. Some variations, for example, help insurgent organizations acquire legitimacy and resources, while others may degrade their operational effectiveness. An insurgent group's successful use of IEDs, which they can plant in secret and thereby reduce the risk of bodily harm to its members, may lead to influxes in external resources, while leadership infighting after re-organization may lead to a decline in performance and resources. Beneficial variations may then transfer to other organizations through mimicry or vicarious learning (Monge & Contractor, 2003, p. 289). Certainly, organizations may select harmful variations in the short term because in many cases it is impossible to know what will benefit them and what will not (Monge & Contractor, 2003).

According to Monge and Contractor (2003, p. 249), *retention* is the process by which a "selection variant becomes an integral part of the organization, an accepted routine, an innovative competency, or a new trait." Continuing with the IED example, an insurgent organization's continued success of paying locals to implant IEDs on highways may

replace more risky confrontations with militarily superior government forces and lead them to develop an organizational-wide procedure for local insurgent cells. Retention, like the other evolutionary processes, occurs within the context of competition for scarce resources within organizations, between them, and between populations⁶² (Aldrich & Ruef, 2006; McKelvey, 1997). Like Cilliers (1998), Monge and Contractor (2003, p. 251) explain that organizations compete with one another over resources in order to survive, as well as flourish, in times during which resources become scarce. They must evolve within this competitive context to succeed.

Over time, co-evolution has become a prominent focus in the study of organization and organizational network evolution (Abatecola et al., 2016; Porter, 2006). Like with the concept of self-organization, Kauffman's (1993) inspirational work extends evolutionary theory to include co-evolution as a source of order. While his NK model considers the evolution of a single population or species, his NK(C) model addresses the co-evolution of multiple populations. As with his NK model, co-evolving systems can behave in ordered, chaotic, and complex regimes. The "N" (i.e., number of genes) and "K" (average connectedness/complexity) parameters remain defined the same in his model extension, yet it also accounts for the number of interconnected species (i.e., "S" parameter) as well as number of links between them (i.e., "C" parameter). This model, therefore, connects different species' fitness landscapes (Kauffman, 1993; McKelvey et al., 2013; Monge & Contractor, 2003). These inter-species links constrain populations and have consequences for them, such as producing local optima for the interlinked systems but not necessarily for each species. He contends that when internal complexity (or K) is greater than between population complexity (i.e., $S \times C$), the interconnected populations may reach an optimal level rather efficiently, but they may not reach one for a long time when the opposite is true (i.e., $K < S \times C$). When species co-evolve into a system-wide optimal level, the entire co-evolving ecosystem attains the edge of chaos. Thus, his NK(C) model extends to the

⁶² Monge and Contractor (2003, p. 252) describe populations, such as a set of organizations, as those that share common features (e.g., communication nets across a set of organizations) or specializations (e.g., breweries). For instance, they give an example of how telephone companies in the early 1900s collaborated and made up a population.

principle that systems at the edge of chaos can adapt and sustain the highest level of fitness (Kauffman, 1993, pp. 279–280).

While his innovative work has well-known limitations for the study of social systems,⁶³ it appears to have inspired the study of co-evolving social systems from various perspectives (Lansing, 2003; McKelvey, 1999; McKelvey et al., 2013; Monge & Contractor, 2003; Snijders et al., 2007). One example is the community ecology perspective,⁶⁴ which frames co-evolution as a means to explain how organizations compete and cooperate with each other for scarce resources at various levels, such as between organizational populations and communities (Aldrich & Ruef, 2006; Astley, 1985; N. Contractor & Monge, 2002; Monge & Contractor, 2003). At one “level,” organizations within the same population (e.g., Federal Bureau of Investigation (FBI) joint task forces) compete and cooperate for resources (e.g., funding) to “survive” in a shared “niche” (e.g., federal law enforcement). At another level, they compete with other populations for resources too (e.g., other intelligence agencies), whereby they become interconnected and make up a broader community (e.g., “intelligence community”). Ultimately, this community interacts and competes with others (e.g., telecommunications and social media companies) (Contractor & Monge, 2002; Lee & Monge, 2011). A major focus of these interactions has been on two forms of relations that drive dynamics: namely, ties of commensalism and symbiosis (Aldrich & Ruef, 2006; Monge & Contractor, 2003). The former refers to cooperation (often known as mutualism) to outright competition for resources between similar entities, whereas symbiotic relations refer to mutual interdependence between dissimilar entities, often based on functionality.⁶⁵

⁶³ For example, one commonly reference limitation is that the NK(C) model assumes K is a constant value, which is highly unlikely in social systems (Monge & Contractor, 2003). McKelvey (1999) offers a section discussing additional issues with “translating” Kauffman’s model to social systems.

⁶⁴ Community ecologists examine multiple populations of different organizations. Various definitions exist for both populations and communities. Monge and Contractor (2003) suggest populations refer to types of organizations and communities may refer to populations joined by ties of commensalism and symbiosis through some geographical and temporal boundary. Community ecology essentially subsumes population ecology by adding community level evolutionary mechanism and connects populations with their environments (Monge & Contractor, 2003, pp. 256–257) .

⁶⁵ Aldrich and Ruef (2006, p. 244) go further in their description of organizational relations by offering eight possible types commensalism, symbiosis, and dominance between organizational populations.

Drawing from evolutionary biology, several organizational scientists have made substantial contributions to the advancement of the co-evolution perspective since the 1990s (Abatecola et al., 2016; Baum & Singh, 1994; Benbya & McKelvey, 2006; Choi et al., 2001; Dooley, 1997; Koza & Lewin, 1998; Lichtenstein, 2000; McKelvey, 1997, 1999, 2002; Porter, 2006; Tasselli et al., 2015; Volberda & Lewin, 2003; Wycisk et al., 2008). Like Kauffman's (1993) work, this domain contends that one cannot understand organizational evolution without accounting for connectivity and simultaneous evolution of environment, which depending on one's perspective, can consist of individuals and groups within an organization and/or external organizations (McKelvey, 1997, 1999; Volberda & Lewin, 2003). According to Lichtenstein (2000, p. 13), the essential goal of co-evolution research is to understand "adaptive changes within and between all levels of organizational and environmental interactions," whereby shifting micro interactions produce macro patterns. For instance, employees within an organization may form networks and mutually influence one another as they interact, and as that happens over time, groups may emerge that establish norms and rules, which, in turn, influence the individuals. In addition to such "horizontal" co-evolution, so-called "vertical" co-evolution may arise when emergent groups become subsumed under another group (or manager) with a new set of rules and norms (McKelvey, 2002). Moreover, these types of co-evolution occur within larger systems of interconnected organizations. Others have examined co-evolution as the interplay of the individual, operational, and strategic levels in organizations (Benbya & McKelvey, 2006; Monge & Contractor, 2003), while some have explored how individuals in organizations shape networks through their characteristics and cognitions, which in turn influence and affect them (Schulte et al., 2012; Tasselli et al., 2015).

In addition to multiple levels, scholars have argued that co-evolutionary social systems possess certain traits. Porter (2006) offers six defining characteristics in an effort to translate co-evolution from a biological context to an organizational one: namely, specificity, reciprocity, simultaneity, genetic fixing/permanent structural change, boundary crossing, and organic. In short, co-evolution takes place when evolution is mutual and concurrent between organizations. Volberda and Lewin (2003) make a similar claim in the

sense that there must be interconnected, heterogenous agents in systems with the ability to learn and adapt. Additionally, system components must be motivated to co-evolve (i.e., facing some sort of constraint) and some event must initiate or trigger co-evolutionary processes. Other related traits include competition among entities, multi-directional causality, non-linearity, feedback and interdependence, and history dependence (Benbya & McKelvey, 2006; McKelvey, 1997, 1999; Volberda & Lewin, 2003).

While many of these insightful works have been qualitative, many scholars argue that both complex adaptive systems and social network research offer useful approaches for studying co-evolution in computational contexts (Dooley, 1997; Lichtenstein, 2000; McKelvey, 1999; Monge & Contractor, 2003). These approaches are relevant, because as Monge and Contractor (2003) and Porter (2006) contend, co-evolutionary studies require multilevel, multi-theory, and multi-method approaches. For instance, Monge and Contractor (2003, p. 273) illustrate Kauffman's NK(C) model by looking at the emergence of co-evolving belief systems and strategic practices among competing organizations. Yet, however insightful, many complex adaptive system principles and model assumptions, including those like "fitness landscapes," are difficult to apply and measure in empirical social systems (Anderson, 1999; Eidelson, 1997). In fact, while Monge and Contractor (2003, pp. 294–295) explore co-evolving organizational networks from a complex adaptive systems perspective and employ Kauffman's approach, they recognize these limitations and argue that several "emerging" social network research models, such as ERGMs and SAOMs, enable researchers to leverage their framework. At the time of the MTML framework's introduction, however, these models were in their infancy and not widely available.⁶⁶

G. SOCIAL NETWORK RESEARCH: EVOLUTION AND CO-EVOLUTION

Perhaps inspired by organizational and complex systems research, social network researchers have examined the evolution of empirical social networks (Breiger et al., 2003; Robins, 2015; Snijders et al., 2010). Specifically, social network researchers have

⁶⁶ Interestingly, their use has begun to appear in organization scientist journals to study co-evolution, such as team members' perception and their ties (Schulte et al., 2012).

increasingly applied longitudinal network models, especially SAOMs, to explore which social processes undergird social networks. With an emphasis on social structure, such studies typically examine how individual level mechanisms (e.g., homophily) and multilevel self-organizing processes (e.g., reciprocity and triadic closure) drive network dynamics rather than focus on evolutionary mechanisms such as variation, selection, retention, and competition for resources (Aldrich & Ruef, 2006; Snijders et al., 2010). Cunningham et al. (2015), for example, examine the evolution of the Noordin Top Terrorist network using SAOMs. The authors hypothesize about several self-organizing and individual level factors driving the social network's structural evolution, including transitive ties, alter degree, and selection processes based on similar roles and nationalities. Others have used SAOMs to study topics ranging from the evolution of drug trafficking networks (Bright et al., 2019) to corporate interlock networks (Withers et al., 2018). However, few social network evolution studies have employed the MTML framework explicitly and scant research has incorporated the notion of competitive networks in such models.

Social network researchers have increasingly examined the concept of co-evolution as well. Like complexity and organization sciences, social network co-evolution studies focus on how networked actors mutually evolve with their social environments, which is defined as other actors and relations (Kadushin, 2012; Lazega & Snijders, 2016; Snijders et al., 2010; Walby, 2007). Such empirical studies commonly frame co-evolution as the interplay of actor behaviors (e.g., drug use) and a single type of relationship (e.g., friendships). The goal of such analyses is to untangle, and assess the extent to which, social influence, social selection, and self-organizing processes (i.e., purely structural) at multiple levels drive an empirical network's dynamics. Snijders et al. (2006) examine the degree to which social influence and selection account for the co-evolution of alcohol consumption and tobacco use among adolescent friends, while simultaneously considering self-organizing dynamics, such as reciprocity (i.e., dyad level) and preferential attachment (i.e., individual level). Others have applied this approach to other contexts, such as co-evolving tastes in entertainment (e.g., music, books, and movies) and friendships (Lewis et al., 2012).

However, many real-world, social networks are comprised of multiple, overlapping relations; that is, they are multiplex or multirelational. For instance, two insurgents in the same operational cell may share information because they trust each other (i.e., shared “affiliation,” “information sharing,” and “trust” ties). Several studies have taken this perspective and have looked at multiplex insurgent, terrorist, and criminal networks for various purposes (Bright et al., 2015; Diviák et al., 2019; Everton & Cunningham, 2013, 2015; Papachristos & Smith, 2014; Roberts & Everton, 2011; Stys et al., 2020), including internetwork associations (Campana & Varese, 2013; Faulkner & Cheney, 2013). In fact, social network research has long recognized that overlapping relations, such as informal and formal systems, interact and often shape one another (Kadushin, 2012; McKelvey, 2002). The key point is to identify which relations are relevant and help define an “environment” in a given context.

The presence of overlapping relations has implications for system emergence and dynamics, including co-evolution (D’Agostino & Scala, 2014). Padgett and Powell (2012) make a substantial contribution to this topic. The authors examine how the emergence of macro-outcomes, especially innovation, is a product of feedback and transformative processes among social networks. Drawing from the concept of “autocatalysis,”⁶⁷ they look at co-evolution among interacting self-organizing social systems. While illustrating many empirical case studies, Padgett and Powell (2012, p. 3) contend “interaction among autocatalytic networks is the key to generating novelty,” and that connected networks transform one another rather than merely transmit material and non-material goods (e.g., information) through relations. For instance, they describe how information is transformed through communication protocols; that is, they explain that information injected from one overlapping network to another can transform organizations. To illustrate such transformational processes, they outline eight network “folding mechanisms,” such as transposition and re-functionality whereby “relations and relational protocols developed in one autocatalytic network are inserted into another and reproduced there” (Padgett &

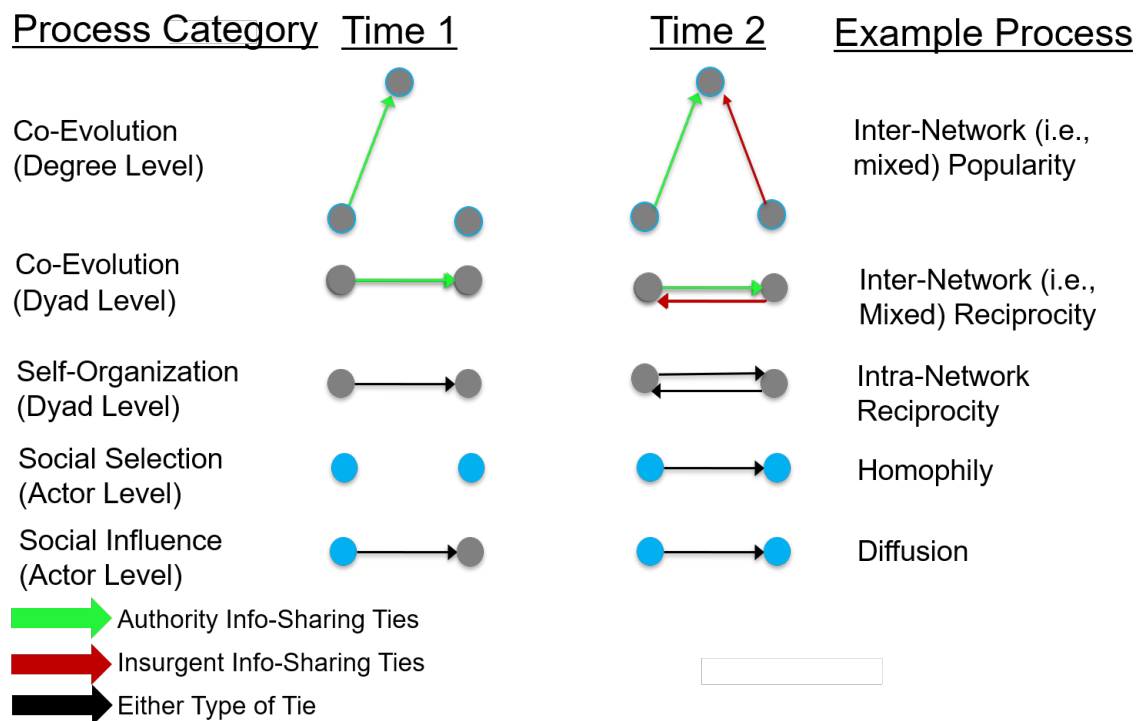
⁶⁷ While the authors describe it as self-referencing behavior, they claim that resource exchanges with the outside can take place. In fact, Padgett and Powell (2012, p. 8) describe “autocatalytic networks” as those of transformation in which multiple self-referencing networks connect and transform one another.

Powell, 2012, p. 12). Hence, Padgett and Powell's emphasis on multiple, self-organizing and interacting networks in evolutionary processes aligns well with the MTML framework, as well as with the increasingly popular domain of multilayer systems that often describes cascades and percolation within and across networks, including how a system's level of connectivity is positively related to information flows (Aleta & Moreno, 2019; Boccaletti et al., 2014; D'Agostino & Scala, 2014; De Domenico et al., 2015; Dickison et al., 2016; Kivela et al., 2014; Pandit et al., 2013; Root, 2020).

The multirelational nature of social networks, as well as their open nature in which they intertwine with others, also suggests micro social processes can involve multiple networks (Porter, 2006; Snijders et al., 2013). In fact, existing research has demonstrated that social relations can interact at many network levels to produce structures by influencing the formation, maintenance, or dissolution of another (Amati et al., 2021; Fujimoto et al., 2018; Gould, 1991; Granovetter, 1973; Huitsing et al., 2014, 2014; Lee & Monge, 2011; Monge & Contractor, 2003; Rambaran et al., 2015; Ripley et al., 2021). For example, Gould (1991) analyzed insurgency in a seventh century Paris Commune and demonstrated substantial interplay between formal and informal relations in mobilization processes. Several practical publications have offered similar insights by recognizing how multiple social networks can interact to produce outcomes in operational settings (Department of the Army, 2017; U.S. Marine Corps, 2017).

Interestingly, as statistical models for the study of empirical networks have become more sophisticated, as Monge and Contractor (2003) foretold, researchers have begun to consider multiplex dynamics as a form of co-evolution in which different networks are mutually constitutive at multiple network levels (Amati et al., 2021; Ellwardt et al., 2012; Fujimoto et al., 2018; Htwe et al., 2020; Huitsing et al., 2014; Rambaran et al., 2015; Ripley et al., 2021; Stadtfeld et al., 2020; Warren, 2016). Like the interplay of behaviors and ties, this approach seeks to untangle inter-network, self-organizing processes (or "uniplex") from co-evolutionary ones; however, this perspective characterizes co-evolution as multilevel social processes between overlapping, multiplex social ties/networks in which the presence of one type can influence the presence, maintenance, or dissolution of another. For example, Rambaran et al. (2015) leveraged SAOMs to examine the structural interplay

of friendship and antipathy relations among adolescents in two U.S. middle schools. Controlling for self-organizing processes underlying each network, the authors incorporated several “between-network”—or co-evolutionary effects—at dyad and triad levels, and found support for several of them, such as “sharing a common enemy promotes friendship” and “sharing the same friend may result in antipathy” (Rambaran et al., 2015, p. 174). This approach to co-evolution, therefore, focuses on inter-network dynamics rather than the interplay of behavior and a single network. Figure 5 depicts a sample of multilevel social processes, including examples of self-organizing and co-evolutionary processes, that may undergird the emergence and dynamics of social systems comprised of authority and insurgent-information sharing networks in insurgent warfare.



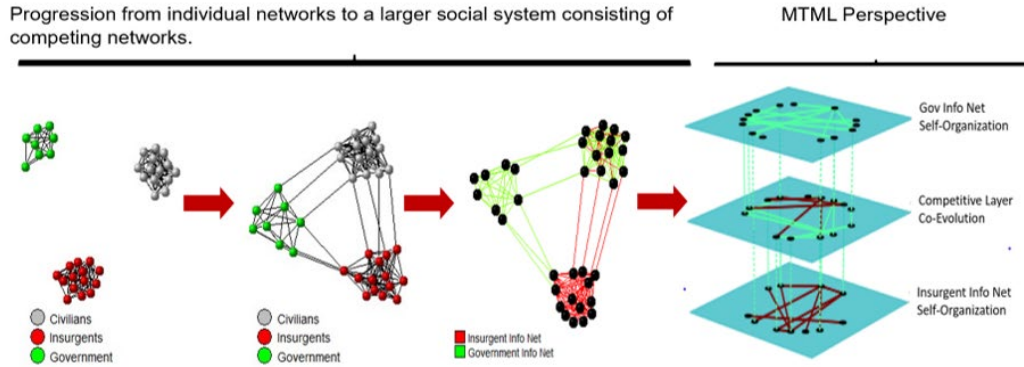
This figure depicts only a few examples of multilevel social processes, including intra- and inter-network processes; that is, self-organizing and co-evolutionary processes.

Figure 5. Examples of Multilevel, Social Processes

Consistent with the MTML framework, this dissertation views co-evolution from the multiplex perspective for at least two reasons. The first is that it focuses on modeling

empirical social network dynamics, which fills an important gap in extant insurgent warfare literature. The second is that it enables the analysis of social systems comprised of multiple relations/networks. As previously described, one can observe at least two interconnected structures competing for control and legitimacy over a populace during an insurgency: namely *authority information-sharing* and *insurgent information-sharing* networks. When considered in isolation, both social networks consist of cooperative,⁶⁸ information sharing ties among combatants and noncombatants on one side of a conflict (i.e., intra-network ties). This study contends that self-organization, as defined by Robins (2015), is prevalent in these networks because of the bottom-up and informal nature of many information exchanges in insurgent warfare. The competitive context in which each network operates is only likely to enable self-organizing behavior further (Astley, 1985; Cilliers, 1998; Monge & Contractor, 2003; Pirnie & O’Connell, 2008). However, the networks’ open nature and the presence of ties between the competing sides (i.e., inter-network ties), such as when a civilian provides information to both networks, suggests they are interconnected through individuals embedded in both structures. When taken together, and consistent with co-evolution studies in across domains (Benbya & McKelvey, 2006; Kauffman, 1993; Lichtenstein, 2000; Monge & Contractor, 2003; Porter, 2006; Snijders et al., 2007), these characteristics suggest each network, which combine into a larger social system, contains intra-network, self-organizing processes and inter-network, co-evolutionary processes at multiple network levels. By accounting for both categories of processes, this perspective offers a realistic depiction of the structural emergence of social systems in insurgent warfare. Figure 6 depicts the progression from the analysis of individuals networks to the examination of a larger social system consisting of competing networks.

⁶⁸ I recognize that individuals “on the same side” can compete with one another too but the act of sharing information is a cooperative action.



The last network represents a more realistic depiction of social networks in insurgent warfare in which they intertwine and compete through shared nodes whose affiliations do not fit into neat categories. The dotted lines between layers correspond to the same node in different networks.

Figure 6. Progression from Distinct Networks to MTML Perspective

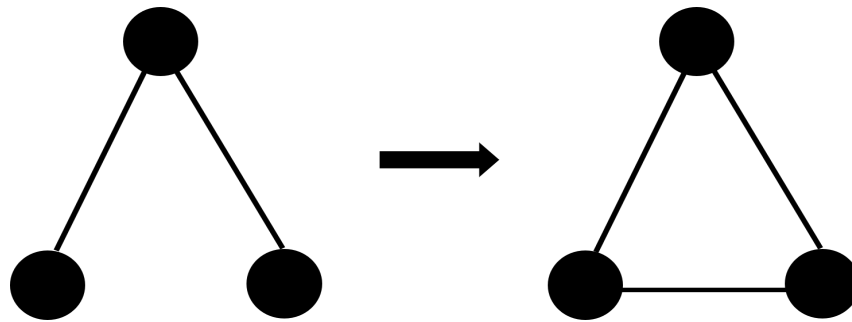
H. MULTILEVEL HYPOTHESES: SELF-ORGANIZATION AND CO-EVOLUTION IN INSURGENT WARFARE

Existing literature offers little guidance about how social network co-evolution can occur within insurgent contexts. Nevertheless, several prominent theoretical mechanisms, as well as empirical interactions described in insurgency literature, offer some direction about the types of processes that may drive network dynamics at the individual/degree, dyad, triad, and other levels. For instance, theories pertaining to network “closure” (Granovetter, 1973, 1983) and the emergence of “hubs” (Barabási, 2002, 2016; Capra, 1996; Kadushin, 2012; Robins, 2015; Root, 2020) appear, in part, to help frame many observed social interactions in variety of insurgent warfare contexts (Kuehl, 2009; Montgomery & McWilliams, 2009; Wilson, 2006). The key is to hypothesize which intra- and inter- network processes or tendencies might be at play in a struggle between authority and insurgent information-sharing networks. Therefore, while this study primarily attempts to unravel associations underlying co-evolutionary patterns between competing networks, it will offer several hypotheses about intra-network processes as well.

1. Self-Organizing, Intra-Network Processes

It is likely that several multilevel, social processes will help drive the creation and maintenance of cooperative information-sharing among individuals within both competing

networks. Granovetter’s (1973) well-known notion of a “forbidden triad” captures the role that strong ties can play in the emergence of new relations at a triad level. It suggests strong ties among two pairs of actors in a triad are likely to lead to network “closure.” For instance, if individual A in a triad maintains an enduring information-sharing relationship with individual B, and the latter has a strong contact in actor C, it follows that individuals A and C will end up sharing information eventually (Everton, 2012).⁶⁹ Put simply, individuals are likely to form ties with “a friend of a friend.” This process can lead to dense, local substructures that can amplify and transmit information efficiently (Kadushin, 2012), which can be beneficial in competitive contexts like insurgent warfare. Evidence in places like Iraq and the Philippines suggests counterinsurgents have developed close relations, including information-sharing ones, with segments of local populations and host governments in efforts to improve relations between the two over time (Kuehl, 2009; Montgomery & McWilliams, 2009; Wilson, 2006).⁷⁰ Thus, the first hypothesis is that “closure” will occur within each information-sharing social structure (*information closure hypothesis*). This hypothesis pertains to the triad level (Figure 7).



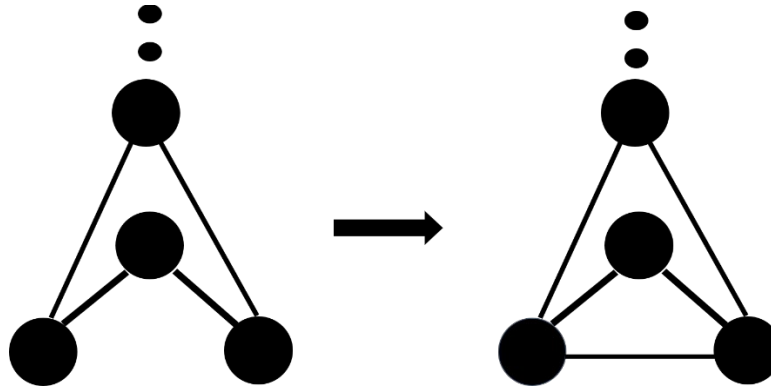
A shared between contact between two individuals leads to a direct tie between them in the same network (“closure”).

Figure 7. Information Closure Hypothesis

⁶⁹ Many forms of local clustering can emerge if one is able to capture the direction of relations. Papachristos et al. (2013), for example, accounts the emergence of such “dominance hierarchies” in his study of inter-gang violence.

⁷⁰ Certainly, one may question if such ties can persist over the long term in many insurgent contexts. Relationships among U.S. troops and some tribal leaders in Iraq, for example, did not endure and may be described better as relationships of convenience (Cordesman, 2007; Montgomery & McWilliams, 2009).

Similarly, closure can occur at “higher levels” in which individuals could share multiple contacts before establishing an information-sharing relationship directly. Extant literature has offered useful examples demonstrating the important role that preexisting relations and trust play in people’s participation in high-risk activities, such as social movements and covert networks (McAdam, 1986; Pye, 1950; Sageman, 2004). While little attention has been paid to the number of ties required to engage in such activities, it is likely that multiple shared contacts can help “vet” others before establishing a relationship with them, especially when violence helps define one’s environment. In the context of the FARC in Colombia, for example, both the government and insurgents were concerned about potential “collaborators” with their adversaries. As official demobilization reports indicate, the FARC were concerned about operational security so much so that they regularly resorted to violence against those who even knew people who collaborated with the government. The government was explicitly concerned about “collaborators,” too. Officials who interviewed demobs asked them repeatedly about their knowledge of government personnel who might have collaborated with insurgents. In other words, rather than relying on a single “friend,” as with closure at a triad level, it may benefit individuals to form ties with others if they are “a friend of friends.” When closure occurs at such “higher levels,” it offers an additional benefit in the sense that information can transmit efficiently within larger clusters beyond the triad level (Kadushin, 2012). Thus, the second hypothesis is that “higher-order” closure (i.e., cluster level) will occur within each information-sharing network (*information cluster hypothesis*). Figure 8 depicts such closure.

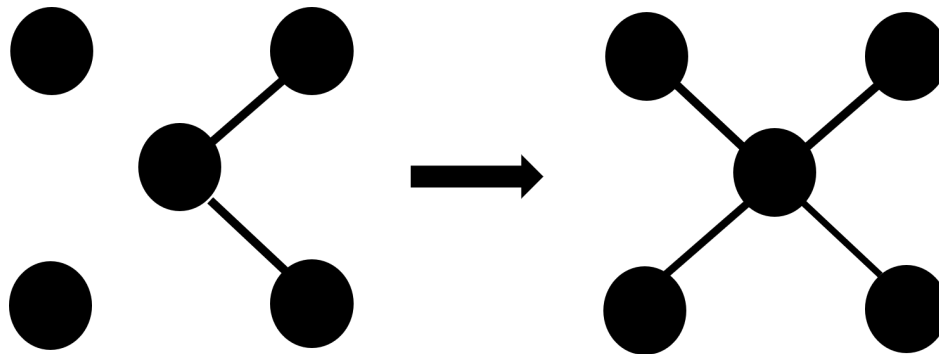


Individuals who share multiple contacts in the same network will share information (higher-order closure). Note the two dots at the top of each diagram indicate the potential presence of 3 or more shared contacts.

Figure 8. Information Cluster Hypothesis

Because information is critical to outcomes in insurgent warfare (Berman et al., 2018; Guevara, 2007; McCormick, Forthcoming; Tse-Tung, 1989; United States Government, 2018a), it is likely individuals will seek to establish as many information-sharing relationships within their network as possible. Insurgents, counterinsurgents, and civilians require information for numerous purposes, many of which overlap, such as survival and intelligence gathering and analysis. The development of information-sharing ties, through in-person interactions, can take place in a variety of situations, ranging from spontaneous ones, such as civilians approaching soldiers, to planned yet informal interactions, such as key leader engagements. However, individuals often gravitate toward others who already maintain many social ties and who may already possess attractive skills, information, and resources (Barabási, 2002, 2016; Barabási & Bonabeau, 2003; Capra, 1996; Kadushin, 2012; Robins, 2015; Root, 2020). One can expect, therefore, some form of this “preferential attachment” in information-sharing networks in which “the rich get richer;” that is, well-connected individuals, or “hubs,” attract others to form ties with them (Barabási, 2016; Robins, 2015). The famous “80/20 Rule” (i.e., Pareto Principle) in which 20% of nodes maintain approximately 80% of the relations reflects the essence behind this commonly observed process (Barabási, 2016; Capra, 1996). Therefore, the final self-organizing hypothesis is that information-sharing hubs will emerge in each network

(*information hubs hypothesis*). This hypothesis relates to the degree or actor level (Figure 9).



Well-connected individuals will continue to acquire new contacts.

Figure 9. Information Hubs Hypothesis

2. Co-Evolutionary Processes Between Insurgent and Authority Networks

Authority and insurgent networks compete over the control of a populace (Galula, 2006; Kilcullen, 2010; Nagl, 2005). Consequently, the two sides often attempt to establish contacts with civilians and other individuals who can provide them with information critical to their objective of understanding and controlling a population (Department of the Army, 2014; Galula, 2006; Guevara, 2007; Tse-Tung, 1989). When the two sides compete over the same populace in the same geographic area, they can come into close “social distances” of one another whereby only a few individuals separate them, ultimately leading the social systems to exhibit a “small world” effect (Travers & Milgram, 1969; Watts, 1999b, 2003). Going a step further, the two networks can intertwine directly through shared information contacts, such as when people “play both sides” during a conflict (Department of the Army, 2014, 2017; Kilcullen, 2010; Montgomery & McWilliams, 2009; U.S. Marine Corps, 2017; Wilson, 2006). For instance, civilians may share information with insurgents and authorities out of fear or for opportunistic reasons, whereas insurgents might provide a government information to acquire some benefit while maintaining contacts with insurgents. While it is almost unheard of for U.S. personnel to support an adversary, authorities in several contexts have played and switch sides (Department of the Army,

2017; Kilcullen, 2013; Kuehl, 2009; Wilson, 2006). Thus, in the competitive space for information in insurgent warfare, the first co-evolutionary hypothesis is that an information-sharing relationship in one network will lead to a tie in the other network (*information multiplexity hypothesis*). This hypothesis pertains to the dyad level (often called dyadic entrainment) (Figure 10).

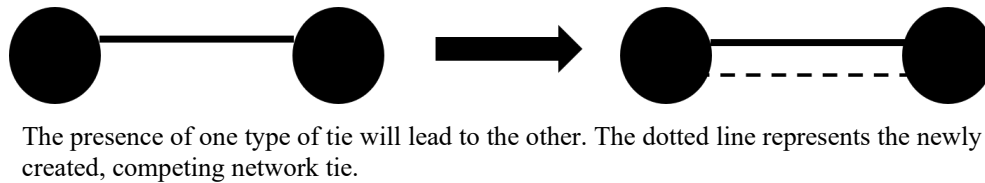
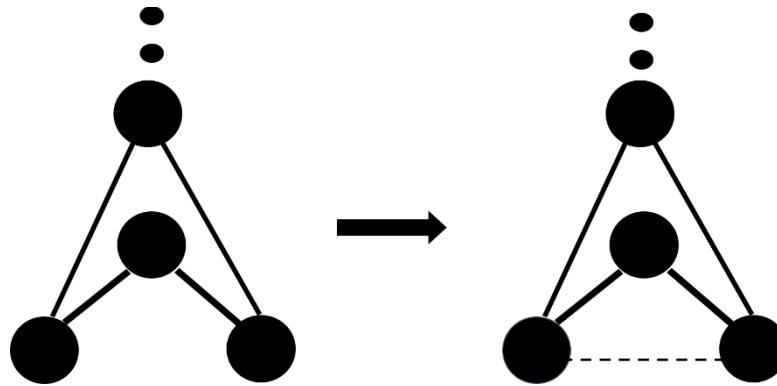


Figure 10. Information Multiplexity Hypothesis

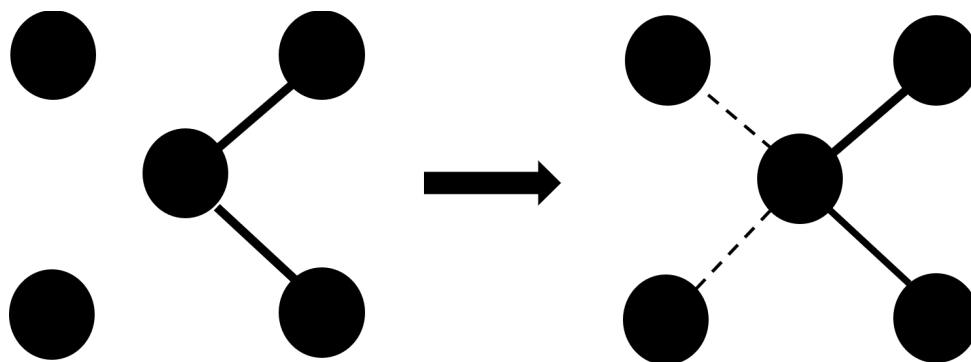
As with intra-network closure, it is likely that closure will occur between the competing networks. However, the potential motivations for closure between two competing networks are likely different than what would occur within each network. In the case of competing networks, it would serve each side well to infiltrate the other because establishing a single information sharing contact in an adversary's network could offer value insight into their operations, personnel, weaponry, etc. Because dense networks can transmit information efficiently (Kadushin, 2012), establishing an information source embedded in dense portions of an adversary's network could offer additional benefit than doing so with peripheral actors. In a broad sense, infiltration and recruitment of enemy personnel has been observed in many insurgent warfare contexts (Pirnie & O'Connell, 2008; Trinquier, 2006), including recent examples of "green on blue" violence in Afghanistan where Taliban insurgents posed and trained as Afghan government personnel (e.g., Afghan Police) to inflict government and U.S. casualties. While trust and internal control mechanisms (e.g., operational security procedures) will be present in both authority and insurgent networks to prevent infiltration and defection, it is likely both sides will try to infiltrate the other anyway (United States Government, 2007). Thus, the next hypothesis is that closure will occur between the competitive networks at the cluster level (*mixed information cluster hypothesis*) (Figure 11).



Mixed closure whereby one network “closes” the other. The dotted line represents the newly created, competing network tie.

Figure 11. Mixed Information Cluster Hypothesis

Due to insurgent warfare’s nature, competition for the allegiance of hubs is likely to occur between insurgents and authorities. As previously described, prominent insurgents and COIN theorist have described the importance of the populace in a conflict’s outcome (Galula, 2006; Guevara, 2007; Taber, 2002; Trinquier, 2006; Tse-Tung, 1989). It is likely insurgents and authorities will seek out well-connected individuals embedded in the populace, especially if they believe those individuals have relations with key individuals or groups and can exchange information with many others (Department of the Army, 2017; United States Government, 2007, 2016; U.S. Marine Corps, 2017). For instance, in 2007, U.S. forces successfully initiated informal agreements with well-connected tribal leaders in several key provinces, sometimes called “handshake agreements,” to establish information-sharing ties, stop violence between the two, and fight al-Qaeda and other extremists (Cordesman, 2007; Kuehl, 2009). In doing so, tribal members joined the authority information-sharing network even if they maintained ties with segments of the insurgency. Who engages well-connected individuals can vary, too. As previously described, various types of actors (e.g., civilians, insurgents, and militia) can exchange information in insurgent warfare. Hence, it is hypothesized that individuals from both networks will attempt to exchange information with well-connected individuals, or hubs, who maintain many connections with their adversaries (*competitive hubs hypothesis*). This hypothesis pertains to the degree/actor level (Figure 12).



Well-connected individuals in one network will be sought out by their competitor. The dotted line represents the newly created competing network tie.

Figure 12. Competitive Hubs Hypothesis

IV. DATA, MODELS, AND OPERATIONALIZATION

A. INTRODUCTION

To examine the co-evolution of social networks in insurgent warfare, this study analyzes competing social networks in the conflict between the Colombian Government and the Revolutionary Armed Forces of Colombia (FARC). This context serves as a useful case study to examine co-evolution in insurgent warfare given its historical significance as an insurgency, as well as the embedded nature of networks comprised of insurgents, government, and noncombatants. Like in other contexts, social relations served as important conduits of information for the FARC during its years as an active insurgency. The FARC's semi-distributed command system enabled it to create informal ties and establish political, informant, recruitment, criminal, and other networks throughout Colombia. While the group drew much of its recruits, information, and resources from rural populations over the years, it also established clandestine networks and militias throughout the country, corrupted politicians, and worked with urban criminal and other illicit organizations (International Crisis Group, 2005; Jane's World Terrorism and Insurgency Centre, 2020; Metelits, 2010; Stanford University, 2019).

To investigate the dynamic interplay between authority and insurgent information-sharing networks, this study applies a complete network design based on information exchanges at an operational level in the southern Colombian geographic area during the January 2002-April 2003 timeframe. This context is interesting in that the FARC's Southern Bloc, a historically prominent FARC command, operated heavily in the southern Colombia; nevertheless, while during this period of time the FARC remained relatively powerful, it faced several, substantial setbacks (International Crisis Group, 2005, 2008; Jane's World Terrorism and Insurgency Centre, 2020; Stanford University, 2019). Guided by the MTML framework, this research leverages SAOMs to test hypotheses about multilevel co-evolutionary dynamics of the two competing networks. Specifically, it uses a multiplex, or multivariate, model extension to test hypotheses about both intra-network, self-organizing and inter-network, co-evolutionary social processes. The data set was built from a unique set of archival records from official, unclassified Colombian Government

reports on demobilized FARC members, which offer rich data on informal relationships among demobilized individuals, then-active FARC members, militia members, local leaders, government, and other actors.

This chapter continues with a brief overview of the FARC beginning with its emergence in the 1960s through its transition into a political party in 2016. This section's goal is to establish this study's empirical setting, rather than provide an exhaustive summary of the FARC's history. The following section describes the role of information and social networks as it pertains to the FARC's insurgency. Next, this chapter describes this study's relational data and network boundaries. This section defines relational ties and networks, as well as outlines how this study handles the multiplex nature of these two competing networks. The following section provides an in-depth description of SAOMs, the modeling procedures, and explains the multivariate extension used to test the hypotheses outlined in the previous chapter. Finally, this chapter closes by addressing issues regarding informant accuracy, inter-coder reliability, and external validity for the study of social networks.

B. BRIEF HISTORY OF THE FARC

Founded in 1964, the Revolutionary Armed Forces of Colombia (or Las Fuerzas Armadas Revolucionarias de Colombia [FARC]) is a now defunct insurgent organization that until 2016, was one of the oldest, and at some points in its history, the largest, insurgent organizations in the world (Cunningham et al., 2013). Beginning as a Marxist-Leninist group in southeastern Colombia, it evolved into a violent, narcotics trafficking organization that coerced the peasant population it promised to protect (Cunningham et al., 2013; Metelits, 2010). FARC was rooted in self-defense organizations that emerged from the period of violent conflict known as, "La Violencia" (1948-1958). As the government increasingly targeted these groups in early-1960s, the core remnants coalesced into the Bloque Sur (Southern Bloc), which changed its name to the FARC in 1966. The FARC, which served as the Communist Party of Colombia's armed wing, acted as an alternative governing authority in portions of the country by collecting taxes, providing social services, and establishing police and judicial systems. This status gave them the power to

address local disputes and social conflicts, as well as investigate criminal activities (Metelits, 2010).

By the early-1980s, the FARC began engaging in “strategic kidnapping,”⁷¹ and the illegal drug trade by taxing traffickers and producers in exchange for protection and other guarantees (Metelits, 2010). At their seventh conference in 1982,⁷² however, the FARC made a strategic decision to expand its offensive military capabilities in the context of a severe economic downturn in Colombia. This new plan pushed them deeper into the drug trade. As Metelits (2010, p. 102) points out, drug-related income allowed the FARC to expand from twenty-seven fronts (i.e., geographic units) in 1989, to sixty by 1999. However, relations between the FARC and many traffickers soured throughout the decade and gave rise to other so-called self-defense groups (e.g., MAS-Muerto a los Secuestros) that often fought alongside the Colombian military against the FARC. One such group, founded in the late-1990s, the Autodefensas Unidas de Colombia (United Self-Defense Forces of Colombia—AUC), expanded throughout the country, and like the FARC, became involved heavily in narcotics trafficking and committed human rights abuses against civilians (International Crisis Group, 2005; Stanford University, 2019).

Several other important events in the FARC’s history occurred during the 1980s. In 1982, the FARC began exploratory peace talks with the Government of Colombia under President Belisario Betancur (1982-1986). Along with several other groups, such as the Popular Liberation Army (EPL), the 19th of April Movement (M-19), and the National Liberation Army (ELN), FARC agreed to a ceasefire and condemned kidnapping, terrorism, and blackmail in exchange for government commitments to improve education and address other socioeconomic issues. The 1984 agreement, known as the Uribe Accords, created the space for the FARC to form the Union Patriótica (Patriot Union [UP]) political

⁷¹ The FARC kidnapped ranchers and farmers who it considered “ideologically illegitimate.” Eventually, they began kidnapping government officials and other prominent individuals to fund its expansion into urban areas (Metelits, 2010, p. 97).

⁷² Though this analysis uses the acronym, FARC, throughout this summary, the FARC changed its name in 1982 to the Revolutionary Armed Forces of Colombia – People’s Army (FARC-EP) to emphasize its renewed objectives. The group changed it again to the Fuerza Alternativa Revolucionaria del Común (Common Alternative Revolutionary Force [FARC]), after agreeing to demobilize and become a political party.

party and address long-lasting issues affecting rural populations, such as land reform. The UP had many notable electoral successes⁷³ during the latter half of the decade and expanded its reach into urban areas through unions and student groups; however, conservative paramilitary and allied security forces elements assassinated and kidnapped thousands of its members (Jane's World Terrorism and Insurgency Centre, 2020; Metelits, 2010; Stanford University, 2019).

Throughout the 1990s, the FARC became increasingly powerful within the country, as well as formalized its international outreach to foreign audiences (The International Institute for Strategic Studies, 2011). The FARC's strength and lethality improved during the decade, as indicated by a ballooning membership and bold attacks on military bases, to the point that then-President Pastrana (1998-2002) granted it a 42,000 square kilometer demilitarized zone in 1998. During this time, the FARC expanded its involvement in drug trade activities, worked more closely with groups such as the Provisional Irish Republican Army (PIRA), and became increasingly coercive toward local populations by committing human rights abuses (e.g., extrajudicial killings, forced recruitment of child soldiers, and kidnappings⁷⁴) (Cunningham et al., 2013; Metelits, 2010; Stanford University, 2019). The FARC's International Front (or International Committee - COMINTER), established in 1993, simultaneously portrayed its guerrillas as freedom fighters, enabled it to improve its transnational trafficking systems, and disseminated propaganda to foreign entities that highlighted the government's human rights abuses. Ultimately, COMINTER helped the FARC establish presence in approximately two-dozen Latin American (e.g., Ecuador and Colombia) and European countries over the next two decades (The International Institute

⁷³ The UP won 350 local council seats, 23 deputy positions, 9 seats in the House, and 6 seats in the Senate. The party reemerged but lost its legal status in the early-2000s (Metelits, 2010; Stanford University, 2019).

⁷⁴ While they increasingly become involved indiscriminate kidnapping, they continued kidnapping prominent estate owners, businesspeople, and politicians.

for Strategic Studies, 2011). Most notably, FARC built upon existing relations with Cuba, and solidified relations with regimes in Ecuador and Venezuela.⁷⁵

However, the FARC began facing military and political setbacks in the late-1990s and early-2000s, both internationally and domestically. In 1997, the U.S. Government placed the FARC on the list of Foreign Terrorist Organizations (FTO), thereby setting the stage for further involvement in Colombia. The U.S. initiated Plan Colombia a few years later, in 2000, with the goal of injecting substantial resources to combat the Colombian-based drug trade and reestablish government control over the country. That same year, approximately a quarter of the Colombian population protested the FARC and its violence against civilians in the “No Más” protests, which drew substantial international media coverage. In 2002, Alvaro Uribe ran successfully for the presidency on an aggressive platform to confront the FARC. The Uribe administration’s (2002-2010) military operations, as well as paramilitary operations by groups like the AUC, reduced the FARC’s territorial control, depleted its ranks, and killed several members of its leadership council, or “Secretariat,” including Tomás Media Caracas (aka Negro Acacio) in 2007, who oversaw its drug trade, and its second-in-command, Luis Edgar Devia Silva (aka Raul Reyes) in 2008⁷⁶ (International Crisis Group, 2008; Stanford University, 2019). Furthermore, the FARC’s use of terrorism, continued involvement in the drug trade, and numerous civilian kidnappings, such the Southern Bloc’s kidnapping of then-Presidential candidate, Ingrid Betancourt, shed its popular support, as indicated by a subsequent wave of “No Más” protests in 2008.

In 2010, President Uribe’s Minister of Defense, Juan Manuel Santos (2010-2018), became the newly elected president and restarted exploratory peace talks with the FARC.

⁷⁵ The FARC reportedly made financial contributions to Ecuadorian President Rafael Correa’s campaign in 2006 and Venezuela began providing it with funding, arms, safe havens, and other resources during the early-2000s, so much so, that it ultimately became a proxy of Hugo Chavez’s Bolivarian movement and an asset to his regime who maintained adversarial relations with Colombia (The International Institute for Strategic Studies, 2011).

⁷⁶ The FARC lost two other important leaders in 2008. Manuel Jesús Muñoz (alias Iván Ríos) was killed by one of his own bodyguards in 2008, and its founder, Manuel Marulanda died of a heart attack. Just two years later, under the Santos Administration, the Colombian military killed the FARC’s military commander, Briceño Suárez Rojas (aka Mono Jojoy).

After years of negotiations, as well as several setbacks, the final agreement between the two came to fruition in 2016. Following the agreement, more than 11,000 fighters demobilized (Jane’s World Terrorism and Insurgency Centre, 2020), and the group became a political party and renamed itself the Fuerza Alternativa Revolucionaria del Común (Common Alternative Revolutionary Force—FARC). The accord’s main points focused on land reform, political participation, cessation of hostilities, reintegration of FARC members into civil society, reparations, and formalizing verification mechanisms (Stanford University, 2019). As of mid-2020, the party’s president, Rodrigo Londoño Echeverri (aka Timochenko), remains committed to the peace accord. However, several members have rejected the accords, such as Luciano Marín Arango (aka Iván Márquez), and a few thousand former fighters who have remained active in drug trafficking activities or formed splinter groups.⁷⁷

C. FARC’S ORGANIZATIONAL STRUCTURE DURING ITS INSURGENCY

As an active insurgency, the FARC’s maintained a formal, hierarchical command structure across Colombia, in both rural and urban portions of the country (Cunningham et al., 2013). The FARC’s executive command consisted of a seven-person Secretariat, which commanded its approximately thirty-member Estado Mayor Central (EMC) (General Staff). Both bodies shaped strategies and operational policies, as well as coordinated and directed the activities of subordinate commands (Jane’s World Terrorism and Insurgency Centre, 2020; Stanford University, 2019). It had five geographical blocs, or commands (i.e., Eastern, Southern, José María Córdoba, Caribbean, and Middle Magdalena), as well as two joint commands (i.e., the Joint Central and Joint Western Commands). Each bloc and joint command, which had a commander who served on the EMC, consisted of several fronts. The number of fronts across all blocs ranged from sixty to seventy-seven (Jane’s World Terrorism and Insurgency Centre, 2020). Finally, the FARC maintained a series of specialized mobile columns, such as the Southern Bloc’s Teófilo Forero Mobile Column (TFMC), that focused on specific tasks, such as regaining territory and serving as the

⁷⁷ For example, one group is “Segunda Marquetalia” (<https://insightcrime.org/colombia-organized-crime-news/segunda-marquetalia/>).

FARC’s special operations units (Cunningham et al., 2013; International Crisis Group, 2009; Stanford University, 2019). Figure 13 depicts the FARC’s approximate geographical distribution of its blocs around the mid-to-late 2000s timeframe.⁷⁸

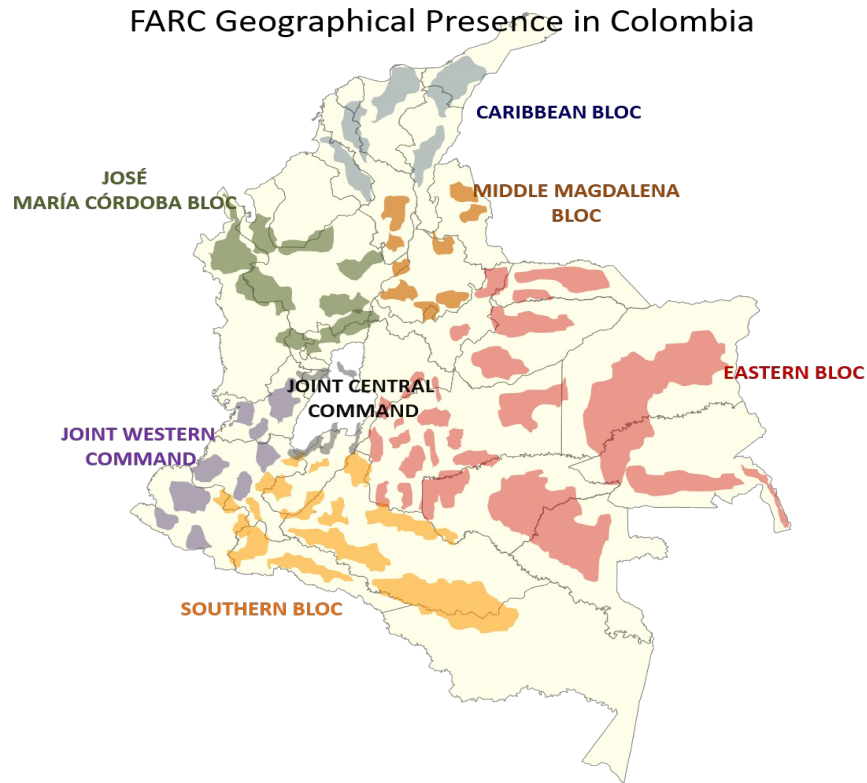


Figure 13. Southern Bloc’s Area of Operation. Source: Colombian National Police (2012)

D. THE FARC’S INFORMATION AND INFORMAL SOCIAL NETWORKS

The FARC, both as an active insurgency and a political party, has used various means to communicate to Colombian and international audiences. As an insurgency, it used illegal radio stations, published newspapers and websites, printed pamphlets, produced handbooks, and released videos to disseminate propaganda (Jane’s World Terrorism and

⁷⁸ The Colombian National Police provided this map and information. The “ink spots” are not meant to suggest the FARC maintained complete control over those areas; rather, they were suspected to have a presence in those areas.

Insurgency Centre, 2020). COMINTER's efforts, as well as close relations with Hugo Chavez and other governments, bolstered (and often diminished) the group's efforts abroad (The International Institute for Strategic Studies, 2011). Today, the FARC, as a political party, continues to use a combination of traditional and modern means to disseminate its views, such as hosting websites, releasing videos, and leveraging social media. For instance, Iván Márquez, a former commander who served as a negotiator in the 2016-peace process, released a video in mid-2019 calling on his followers to take up arms against the government.⁷⁹ The FARC party, to which Márquez belonged since its inception, has adapted, and maintains social media accounts, as well as several "sister" accounts, on platforms such as Twitter and YouTube, where they communicate their political platform to domestic and international audiences. Their President, Rodrigo Londoño Echeverri (aka Timochenko), also has separate profiles on various social media platforms, such as Facebook and Twitter, to communicate the party's political and social positions.

Like in other contexts (Haim, Forthcoming; McAdam, 1986; Pye, 1950; Sageman, 2004), in-person social relations (i.e., non-digital) served as critical conduits of information for the FARC during its insurgency. Its semi-distributed command system enabled the FARC to create informal, information-sharing ties in both urban and rural areas through political, informant, recruitment, and other networks. Though the extent to which the FARC embedded in local, rural populations varied over the years, it largely drew most of its recruits, information, and other resources from this segment of the population, whether it be voluntarily or through coercion (Metelits, 2010). It sought to establish a presence in Colombia's cities during its existence as well. For instance, following the wave of targeted assassinations of UP members in the late-1990s, the FARC created the Clandestine Colombian Communist Party (PCCC) and the Bolivarian Movement for the New Colombia (MBNC) to establish militant presence in urban areas through which it could recruit members and informants, carry out operations, and espouse their organization's ideas (Cunningham et al., 2013; International Crisis Group, 2009). The FARC also had worked

⁷⁹ See BBC article titled, "Colombia ex-FARC Rebel Iván Márquez Issues Call to Arms," (Accessed May 20, 2020) <https://www.bbc.com/news/world-latin-america-49508411>

with urban gangs and criminal organizations (e.g., bandas criminales - BACRIM⁸⁰), including those comprised of minors, to cooperate in the drug trade and serve as informants (Metelits, 2010).

The way with which the FARC interacted with local populations, and acquired information, varied during its existence as an insurgent organization. Metelits's (2010) insightful work contends the FARC shifted from a largely contractual relationship with civilians through the mid-1990s, to a more coercive one in its later years. Initially, the FARC relied on its deep roots in rural parts of Colombia to access food, shelter, protection, and information from peasant communities. She claims the FARC's behavior toward noncombatants, however, changed with the emergence of paramilitary forces during the late-1990s, namely the AUC. While not entirely new FARC behavior, the AUC's emergence led it to increasingly commit human rights abuses, stop enforcing judicial processes, kidnap civilians indiscriminately, extort noncombatants, and corrupt civilians and politicians. Moreover, the FARC forged on-and-off relations with other insurgent organizations such as the ELN, collaborated with criminal organizations, and associated with several militias (e.g., MBNC), which made up large portions of their support networks, helped them run their drug trade, and embed in local populations to serve as informants and extort noncombatants (Jane's World Terrorism and Insurgency Centre, 2020; Metelits, 2010; Stanford University, 2019).

E. DATA AND BOUNDARIES

This study is based on official, unclassified Colombian Government reports on demobilized FARC fighters.⁸¹ The approximately 200 "Demobilization Reports," which were provided by the Colombian National Police's Intelligence Directorate (DIPOL) and cover the 2000–2011 timeframe, offer unique insight into relations among various types of actors in areas in which active competition took place between the FARC and the government. They include information about former FARC members who entered the

⁸⁰ For more information, see Insight Crimes' website, <https://www.insightcrime.org/investigations/inside-colombias-bacrim/>.

⁸¹ This study followed all institutional review board (IRB) protocols and received approval.

government's demobilization program prior to the 2016-accords, which was designed to enable FARC members to leave the organization's ranks and enter civil society. The documents contain relevant attribute data about demobilized fighters, as well as other FARC members, noncombatants, and government personnel (e.g., police and military), such as the city from which they came, the FARC unit they left (if applicable), and other attribute data, such as physical characteristics (e.g., height and weight). More importantly, they offer information about the formal hierarchy of many FARC units along with rich data on informal relationships among demobilized individuals, FARC members/leaders, militia members, civilians/local leaders (e.g., mayors and governors), as well as government actors (e.g., police, military, and government civilian employees).

To investigate the dynamic interplay of competing networks, this study applies a longitudinal complete network design. Several criteria guided the choice of network boundaries.⁸² Specifically, this study focuses on the operational level interactions in the Southern Bloc's geographic area of operations during the January 2002-April 2003 timeframe. The operational level is defined as the level of COIN that sits between strategic and tactical levels and is the level at which practitioners employ forces and assets to accomplish strategic goals through operations. While the lines between the three levels are often blurred, the operational level is conceptualized as below the strategic level, which focuses on defining and supporting national policy, and above the tactical level, where individual battles, engagements, and interactions take place (United States Government, 2018b). Because operational environments encompass tactical activities⁸³ across several areas of operation, the network data includes actors and ties from geographically dispersed units, such as FARC fronts and Colombian Army battalions, operating within and across departments (i.e., states) in southern Colombia. These boundaries, therefore, stop short of directly capturing national level—that is, strategic networks—spanning multiple FARC blocs, and as a result, the data set does not include high level government officials or

⁸² This study applies an etic/nominalist perspective to defining network boundaries whereby I define them, as opposed to an emic/realist approach whereby members of a population of interest define them (Cunningham et al., 2016).

⁸³ The tactical level is where the actions of Soldiers, civilians, insurgents, and other actors, at a local level, such as in an area of operation, have immediate effects in an area of responsibility.

members of the FARC's Estado Mayor or Secretariat unless they participated in operational level activities.

The FARC's Southern Bloc, a historically prominent command, operated heavily in southern Colombia during the timeframe, which is period when the FARC remained relatively powerful, yet faced several, substantial setbacks (International Crisis Group, 2005, 2008; Jane's World Terrorism and Insurgency Centre, 2020; Stanford University, 2019). Several of the FARC's prominent leaders, such as Joaquin Gomez and Milton de Jesus Toncel Redondo, commanded the Southern Bloc and some of FARC's deadliest fronts, such as the Teofilo Forero Mobile Column (TFMC), fell under the command. The timeframe encompasses when the FARC started facing considerable pressure as a newly designated, foreign terrorist organization while large sums of U.S. dollars began targeting the Colombian drug trade, of which the FARC played a considerable part. Competition between the Colombian Government and the FARC ratcheted up, too, following the group's latest peak in the late-1990s. The Uribe administration, for example, increased military operations against the FARC, including against the Southern Bloc and its networks during this time (International Crisis Group, 2008; Jane's World Terrorism and Insurgency Centre, 2020).

This study examines the co-evolution of two competing, intertwined networks: authority information-sharing and insurgent information-sharing networks. The former is comprised of several types of actors, including government personnel, civilians, militia members, and then-active and demobilized FARC members, who exchanged information to serve the Colombian Government's COIN efforts, such as offering actionable and "insider" information about the FARC. The latter network consists of similar types of actors, including government personnel (e.g., local police), who exchanged information to support the FARC's objectives, such as conducting intelligence operations on its behalf. As described in the next chapter, many individuals embedded in both networks simultaneously, and at different times.

Drawing from Monge and Contractor's (2003, p. 3) description of communication networks, as well as Kadushin's (2012, pp. 39–42) notion of informal ties, this analysis defines information-sharing relations as *informal connections created by the flow of*

messages among individuals.⁸⁴ It is important to note three points about this definition. First, it is consistent with extant COIN literature's emphasis on the importance of in-person relations in insurgent warfare (Cleveland et al., 2018; Department of the Army, 2017; Department of the Navy, 2017; Kilcullen, 2010; McAdam, 1999; Pye, 1950; Sageman, 2004). Second, and related to the first point, is that these ties should not be confused with online, social media interactions. While social media is often used to disseminate narratives to larger audiences, mobilize populations, and can serve as a place where recruitment begins for nefarious networks (Benigni et al., 2017; Hassanpour, 2014), additional research is needed to examine its role in operational level social networks, as well as online and offline relational dynamics in insurgent warfare (Kane et al., 2014; Robins, 2015). For instance, there is no evidence that social media played a role at the operational level in this particular case study.⁸⁵ In fact, all interactions take place in face-to-face contexts or through other traditional means of sharing information, such as through the passing of intelligence reports from one person to another.⁸⁶ Third, because this is archival research, this study is unable to assess the veracity of information passed through interactions as well as capture message quantity (i.e., Shannon information), impact (e.g., pragmatic information), and meaning (i.e., semantic information) (Haken & Portugali, 2016). It does, however, consider the frequency and duration of interactions (i.e., how many times two individuals shared information and for how long) to attempt to model "enduring" patterns

⁸⁴ This definition does not incorporate *what* happens with the information (e.g., processing, exploiting, and disseminating), but simply establishes a tie between two individuals if the interaction meets this definition.

⁸⁵ No evidence suggests the FARC used social media platforms during this time frame for operational purposes. For instance, the FARC's Twitter page states it joined the platform in 2012. Future studies, however, may want to incorporate online, digitally based relationships with offline networks in operational environments.

⁸⁶ The demobilization reports included identifiable information about the demobs, report authors, and recipients of the information extracted from demobilization interviews. For example, government interviewers would write and address demobilization memos and reports containing information that could have intelligence value, such as FARC members exchanging information, operating together, etc. Government personnel would send documents to other government personnel (e.g., military, police, civilian) who often responded with their own reports containing pertinent information, thus creating a mutual information exchange. The reports, therefore, offered granular information about government information-sharing networks.

of ties and address issues pertaining to informant accuracy (Bernard et al., 1984; Robins, 2015).

Like with Monge and Contractor (2003, p. 3), the term “messages” is used in a broad sense here to refer to data, information, knowledge, and facts about the conflict that move from one person in a network to another. While the exact content of most messages is often indiscernible in the reports, they offer enough description and context to categorize interactions into insurgent, authority, or both networks. For instance, the reports describe information exchanges between FARC members and civilians in small towns during FARC patrols in which the latter provided actionable information about government troop movement to insurgents, in which case, all actors and relations were coded as part of the insurgent network. The coding procedure does not attempt to understand an individual’s intent for sharing information.

As indicated in the reports, appearing with many information-sharing relations are interactions among family members, and other relations one could define as formal ties, collaborators, close friends, and co-membership ties. This natural “bundling” of various type of relations is related to both role and content multiplexity, whereby one or more actor roles, such as “superior” and “subordinate,” or “FARC member,” creates opportunities for a number of different “flows,” including information exchanges (Kadushin, 2012, pp. 35–36). However, this research did not infer the presence of an information-sharing tie based on the presence of another type; that is, this study only recorded a tie between two individuals when the interaction met the definition outlined above. For example, many low-ranking FARC members (e.g., guerrillas) within Southern Bloc fronts had little, to no contact with front and bloc leadership.⁸⁷ In other words, this study did not purposely capture formal military, insurgent, or civilian structures, but sometimes includes overlapping formal ties based on the opportunities they create for information exchanges.

⁸⁷ Another common example is demobilized members who describe their family members (e.g., names, locations) in their demobilization report, but who have not seen or communicated with their family for years, or since they joined the FARC. By including family members, especially family ties among large families, the data would be biased towards them.

The network data set is comprised of 357 actors and an average of 471 information-sharing ties per time wave, as well as attribute data, such as an individual's department (i.e., state), gender, and micro affiliation (e.g., FARC Front, Military Unit). The networks were coded as unweighted (i.e., binary) and nondirected relational data over four, four-month time waves from January 2002-April 2003.⁸⁸ In terms of actors, the data structuring procedure assigned time codes to each individual based on the month in which they first appeared in a network during the January 2002-April 2003 time frame. Many individuals entered a network (e.g., insurgent) well before January 2002. However, no individuals left the network permanently (e.g., died) during the time frame and in cases when people switched sides, the individuals were coded as remaining in the larger, social system. In terms of ties, this analysis assigned time codes to each interaction in the data set to indicate when information exchanges took place between pairs of individuals. The coding procedure considered the duration of each relationship as the time from when two individuals first shared information, to the last time they did in the reports, which permitted the analysis to capture "enduring" ties rather than one-time interactions.⁸⁹ Finally, this study supplemented the demobilization reports with open-source data to fill in important information gaps and provide context about FARC fronts.

F. STOCHASTIC ACTOR ORIENTED MODELS (SAOMS)

SAOMs are models designed to represent network dynamics and evaluate them based on the paradigm of statistical inference (Ripley et al., 2021; Snijders et al., 2010; Snijders, 1996, 2005; Steglich et al., 2006). Like other stochastic network models, such as

⁸⁸ While the reports made many details about authority network-based interactions available (e.g., who initiated an interaction), they did not offer the same level of granularity for insurgent-based ties.

⁸⁹ As Chapter 5 explains, because SAOMs model network evolution (and co-evolution), the RSiena manual recommends users ensure that actor and tie "turnover" are not too high. Consequently, it recommends that networks maintain Jaccard index, which is a measure of stability, of at least .20 between waves (Ripley et al., 2021). A few examples of one-time interactions appear in the data, but all of this analysis' Jaccard indices were well above the recommended threshold. The four waves were January-April 2002, May-August 2002, September-December 2002, and January-April 2003.

ERGMs,⁹⁰ a common way to employ SAOMs is to treat observed networks as dependent variables and incorporate network dynamics, as driven by different tendencies, into models as independent variables (e.g., structural effects reflecting social processes, actor variables, and dyadic (or tie-based) variables). This approach captures how the network itself helps explain its own dynamics through interdependent ties and feedback processes; that is, it accounts for self-organizing processes that, along with actor characteristics and behaviors (e.g., attitude, performance), help drive evolutionary processes and undergird emergent structures. Actor characteristics can serve as dependent variables in both model classes too, such as with diffusion studies. Both model classes, therefore, permit researchers to test hypotheses about underlying network tendencies, while controlling for others (Lusher et al., 2013; Snijders et al., 2010).

However, while both SAOMs and ERGMs offer advantages over each other depending on the study (Block et al., 2019; Leifeld & Cranmer, 2018), this research employs SAOMs to model multilevel co-evolutionary dynamics for the FARC case study for two reasons. The first is that SAOMs more explicitly focus on actors, whereas ERGMs, which are still valid for modeling social structures in which agency is important, are best characterized as tie-based models. This difference means that for SAOMs, one interprets parameters as tendencies of actors, whereas in most cases with ERGMs, researchers interpret parameters as tendencies conditioned on the rest of the graph (Block et al., 2019; Leifeld & Cranmer, 2018).⁹¹ For instance, ERGMs calculate network statistics, such as reciprocity, as the count of the effect over all dyads in a network, while SAOMs would compute it from the perspective of each vertex (Leifeld & Cranmer, 2018, p. 5). The

⁹⁰ Interestingly, Monge and Contractor (2003) argue that P* models, from which ERGMs developed, can be useful for testing theories from a MTML framework. In simple terms, the ERGM is a probabilistic model for networks that researchers can use for link prediction and testing theories regarding tie formation in empirical networks. For more information, see Lusher et al.'s (2013) excellent book on ERGMs, which offers both technical and non-technical descriptions of ERGMs.

⁹¹ There are debates about this, however. The difference between the models in terms of the primacy of actors is less of a major difference than the names of the models suggest. While Block et al. (2019, p. 233) contend that SAOMs are more appropriate for actor-based hypotheses and theories, Leifeld and Cranmer (2018, p. 7) argue that ERGMs, namely the temporal extension known as temporal exponential random graph models (TERGMs), remain compatible with actor-based theories even though they do not assume “per se that actors make these decisions.” They both agree that ERGMs are likely more suited for networks in which agency does not play a role.

second, and more important reason, is that SAOMs, unlike ERGMs, enable the estimation of multiple interdependent network processes for longitudinal network data. While ERGMs have variants designed to examine either multiplex or temporal networks (e.g., TERGMs and STERGMs⁹²), they have not yet been extended to model longitudinal, multiplex networks (Leifeld & Cranmer, 2018).

The goal of SAOMs is to model empirical data on patterns of ties and behaviors and to identify a set of social processes that most likely reflect actor decisions. However, the authors are explicit that, “actor oriented does not imply the assumption that the actors make decisions in any real sense,” nor do they “reflect a commitment to any particular theory of action elaborated in the scientific disciplines” (Ripley et al., 2021, p. 9). Rather, this model class’s objective is to help researchers explore and develop theories of networks at multiple network levels, recognizing that, like other regression models, SAOMs do not solve casual questions to modeling alone (Ripley et al., 2021). A major distinction between SAOMs and other forms of “agent-based” models often used in complex adaptive systems research is the former is designed to model empirical network data.

Researchers use RSiena (Ripley et al., 2021) to try to reproduce features from one observation to the next. The process begins by designing models comprised of aspects of structure and behavior based on theoretically derived and/or empirical observations, such as triadic closure and homophily. Analysts represent empirical, social networks and attributes as dynamically changing variables over discrete time waves, whereby the statistical modeling, using method of moments, seeks to minimize the differences between expected values and observed values (Snijders, 1996, 2005; Warren, 2016).

Because one cannot obtain expected values directly, SAOMs leverage the Robbin’s Monro Markov-chain Monte Carlo algorithm (MCMC) to run simulations about tie

⁹² Both TERGMs and separable temporal ERGMs are meant for modeling relational dynamics using the ERGM framework.

changes between time points.⁹³ This approach simulates data between two observations by interpreting an empirical network as the culmination of a series of unobserved changes based on the decisions of actors (Elmer et al., 2017; Snijders et al., 2010; Warren, 2016). At discrete time moments between waves, each actor assesses (i.e., controls) all possible potential changes of an outgoing tie and an attribute to evaluate if they should create, drop, maintain the tie, or whether they should increase, decrease, or keep an attribute at a previous level (Elmer et al., 2017).⁹⁴ The change process occurs in two, stochastic sub-processes determined by two functions. The rate function indicates the frequency by which actors execute a “mini-step” (i.e., how many changes), whereas the objective function represents the probability that an actor will change a tie given a chance (i.e., what changes) (Elmer et al., 2017).⁹⁵ The actors are myopically rational in the sense “that they maximize utility with stochastic error,” as well as “that they condition their choices on the current network structure rather than attempting to make predictions about the future structure of the networks” (Warren, 2016).

One can test hypotheses about actor tendencies while controlling for others. The simulations identify models that minimize the divergences between the simulated data and observed data by establishing parameter values as weights for each factor across all waves. This approach permits analysts to evaluate network statistics built into the model by taking the parameter weights from the simulations and by running additional simulations. During

⁹³ A dynamic network can be interpreted as the result of a Markov process. This assumption means “that at any point in time, the state of the network determines probabilistically its further evolution, and there are no additional effects of the earlier past” (Snijders et al., 2010, p. 45). All relevant information is included in the current state. This assumption seems to have implications for the study of networks as “complex adaptive systems,” which are non-Markovian by nature (Rickles et al., 2007). Snijders et al. (2010, p. 45) argue that this assumption can be made “more plausible by choosing meaningful independent variables that incorporate relevant information from the past.”

⁹⁴ A few points are worth noting here about assumptions regarding actors and tie dynamics. First, SAOMs assume that “actors have full information about the network and the other actors” (Snijders et al., 2010, p. 46). Second, “no more than one tie can change at any moment” between panels; that is, tie changes are not coordinated, and depend on each other only sequentially, via the changing configuration of the whole network (Snijders et al., 2010, p. 46). Finally, ties “are not brief *events*, but rather *states* with a tendency to endure over time” (Snijders et al., 2010, p. 45) in other words, ties gradually change and do not resemble events such as a meeting at a single point in time.

⁹⁵ The objective function can be expressed in a similar manner as a generalized linear model in which the probability an actor will change a tie is expressed in a combination of effects. The probability of a tie change is calculated as the sum of a set of effects each with a corresponding weight. The effects may be endogenous, exogenous, or a combination (Cunningham et al., 2016)

the latter step, parameters are held constant to estimate covariance among the factors as well as uncertainty associated with each parameter estimate (Warren, 2016).

Subsequently, researchers can assess a model's fit using goodness of fit (GOF) tests. This process helps one assess the extent to which observed data is compatible with the models developed and fitted for a study. The GOF test uses common structural tendencies in social networks, implemented as a menu of "auxiliary statistics," to evaluate a model's ability to account for them "in general" (Lospinoso & Snijders, 2019; Ruth M. Ripley et al., 2021). Examples of such tendencies include degree distributions, various forms of triads (i.e., triad census), and geodesic distances.⁹⁶ This procedure takes one of these auxiliary statistics, which are not explicitly included in a model, and compares its observed value in a network with its estimated conditional distribution generated by the simulations during analysis.

While there is no "rule" as to what an auxiliary statistic's p-value should be, it is recommended that they should be near or above 0.05.⁹⁷ When an auxiliary statistic's p-value is well below 0.05, it suggests the constructed model is of poor fit in the sense that it does not account well for certain patterns or tendencies that it should and that one should consider revising the model (e.g., extending the model with certain triads). Conversely, when an auxiliary statistic's p-value is above that threshold, it suggests the model is not ignoring potentially important network patterns that reflect social processes.⁹⁸ RSiena permits analysts with the ability to plot the simulated auxiliary statistics versus the observed ones to get an idea about where the fit is poor (see Chapter 5). Finally, the GOF procedure offers a Mahalanobis distance (lower is better) for each auxiliary statistic to give researchers an idea about which model extensions/changes could produce a better fit (Lospinoso & Snijders, 2019; Ruth M. Ripley et al., 2021).

⁹⁶ Lospinoso and Snijders (2019) describe degree distributions as the count of nodes with n ties. Triad census is used to account for 16 (for directed data) possible subgraphs containing three nodes and edges between them, while geodesic distance accounts for the lengths of the shortest paths between all nodes.

⁹⁷ For instance, Ripley et al. (2021, p. 59) state, "The customary value of $p=0.05$ may be used as a threshold determining whether fit is adequate, but this threshold is of even less importance here than it is in the case of regular hypothesis testing."

⁹⁸ As described in Chapter 5, for instance, the isolates and anti-near isolates variables were included after initial model procedures to improve fit for degree distributions in one or both networks.

Two broad types of co-evolution models exist within the SAOM framework: one meant to enable the analysis of a network (or networks) co-evolving with actor behaviors, and another, designed to examine multiple, co-evolving social networks (Snijders et al., 2007, 2013; Steglich et al., 2006). Many researchers use the first extension to untangle, and assess the extent to which, social influence, social selection, and purely structural processes drive an empirical network's dynamics (Snijders et al., 2007). This approach incorporates the same framework as "traditional" SAOMs by modeling actor choices in terms of tie and behavioral dynamics through a series of micro steps, yet integrates structural and behavioral models in a subsequent phase (Steglich et al., 2006). The second approach, or the co-evolution of multiplex networks, is relatively new in which a model represents the internal dynamics of each network as well as dependencies between networks. Snijders et al. (2013) used this approach to examine how a network of MBA students, comprised of friendship and advice relations, co-evolve with employment preferences (e.g., organizations). They find that friendship relations mediate the tendencies of reciprocation and homophily in advice relations. Fujimoto et al. (2018) take a similar approach to study generative mechanisms linking sports activities to friendship dynamics. While these studies have focused on the joint dynamics of two-mode⁹⁹ and one-mode networks, the models permit the study of co-evolving one-mode networks, such as authority information-sharing and insurgent information-sharing networks (Snijders et al., 2013).

This study leverages the multiplex SAOM to examine dependencies between competing networks in insurgent warfare. This analytic approach produces three categories of parameters: uniplex ones for each network that reflect intra-network, self-organizing processes in each network; actor level, or covariate parameters to show effects for actor characteristics on individual networks; and, multiplex parameters that represent co-evolutionary, social processes between the two competing networks (Fujimoto et al., 2018; Huitsing et al., 2014; Rambaran et al., 2015; Ripley et al., 2021; Snijders et al., 2013). As with standard SAOMs, the models treat the networks as dependent variables, while

⁹⁹ Two-mode network data consist of two types of actor/node classes. For instance, a network comprised of individuals *and* organizations is a two-mode network. One-mode network data are relations among a single type of actor, for example, friendship relations among individuals.

structural processes at various levels (e.g., actor, dyad, triad) and covariate effects serve as independent variables for estimating intra-network, self-organizing effects. One can obtain the multiplex parameters after combining the networks into a multiplex system, and subsequently testing for one network's effects on the creation, maintenance, or dissolution of ties in the other.¹⁰⁰

G. OPERATIONALIZING THE MODEL

1. Network Evolution Effects—Self-Organization and Attribute-Based Processes

This analysis considers the combined, authority and insurgent information-sharing ties as a co-evolutionary system consisting of two dependent networks in Colombia. It designed two models that are outlined in the following section and in Chapter 5. Model 1 consists of uniplex effects to test hypotheses related to self-organizing, as well as includes actor covariate effects as control variables.¹⁰¹ Model 2 builds upon Model 1 by incorporating multiplex effects to test for co-evolutionary-based hypotheses. The *density* effect is the most basic one and controls for the tendency for individuals to form ties.¹⁰² While it may give some information about such a tendency, it is similar to a constant (a.k.a., intercept) term and is often not interpreted on its own (Ferriani et al., 2013; Warren, 2016). To test the information closure hypothesis in both networks, the models include a *transitive triads* effect to account for the proclivity of pairs of individuals to share information when they share a mutual contact. The geometrically weighted edgewise shared partners, or *GWESP* effect, is included to test the information cluster hypothesis, whereby individuals who share multiple contacts ultimately share information with one another. Finally, the models include the *Activity + Popularity* effect to test the information hubs hypothesis whereby well-connected individuals continue to acquire new contacts.

¹⁰⁰ This study focuses on the creation and maintenance of ties, which is a standard approach for using SAOMs (Ripley et al., 2021).

¹⁰¹ For effect equations, see Ripley et al. (2021).

¹⁰² Note that all effect terms in italics are common SNA terms and are those that RSiena uses in its menu of possible network effects.

This analysis includes several actor covariates to control for various forms of homophily and spatial effects. The *Same Gender* covariate controls for the propensity of individuals with the same gender to form and maintain ties with one another. *Same Geography* controls for the role of geography in the likelihood that pairs will form and maintain connections (i.e., propinquity effect), whereas *Same Affiliation* controls for individuals' primary affiliation on tie formation. This analysis considers seven types of affiliations, including Colombian Armed Forces, Civilians, FARC members, Government Civilians, Justice Department personnel, FARC Militia members, and Colombian National Police personnel (see the appendix for definitions). Lastly, the *Same Demobilization Status* covariate controls for the tendency of individuals who participated in the Colombian Government's Demobilization Program to form ties with other individuals who did the same.

2. Network Co-Evolution Effects

To test the information multiplexity hypothesis, this analysis includes the *Insurgent-> Government* effect, which is formally RSiena's *crprod* effect (Ripley et al., 2021, p. 153). The model contains a *GWESP-mixed* effect to test the mixed information cluster hypothesis, whereby one network "closes" the other. To test for the competitive hub hypothesis, this analysis includes three versions of the *Mixed Activity + Popularity* effect, which is officially known as RSiena's *InPopIntnX* effect (Ripley et al., 2021, p. 160). This effect weights the Activity + Popularity effect by three covariates, implemented here as to whether individuals were *civilians*, *insurgents*, or *militia*.¹⁰³ The three versions of this effect, when used for nondirected data like in this study, consider the extent to which these types of actors establish connections with well-connected individuals in one network, who in turn, become well-connected in the other. Table 1 summarizes the effects, their graphic expression, related hypothesis, and interpretation.

¹⁰³ As Chapter 5 highlights, the models had to drop the government version, as well as several other effects, due to convergence issues.

Table 1. Summary of Model Effects and Hypotheses

Effect	Graph Representation	Hypothesis	Interpretation
Density			
Transitive Triads		Information Closure	A shared contact leads to an information-sharing tie between two individuals in the same network (closure).
GWESP		Information Cluster	Individuals who share multiple contacts in the same network will share information (higher-order closure).
Activity + Popularity		Information Hubs	Well-connected individuals in a network continue to acquire new information-sharing contacts the same network.
Within-Network (Covariates)			
Same Gender			Tendency for individuals with same gender to establish information-sharing relations.
Same Geography (Dept.)			Tendency for individuals located in same geographic location to establish information-sharing relations.
Same Affiliation			Tendency for individuals with same affiliation to establish information-sharing relations.
Same Demob. Status			Tendency for pairs of demobs to establish information-sharing relations.
Co-evolution			
Insurgent -> Government		Information Multiplexity	The presence of one type of tie leads to the other.
GWESP - Mixed		Mixed Information Cluster	Individuals who share multiple contacts in one network share information for the other, too (mixed higher-order closure)
Mixed Act. + Pop. (Civilian)		Competitive Hubs	Individuals with many civilian connections in one network become well-connected in the other network.
Mixed Act. + Pop (Insurgent)		Competitive Hubs	Individuals with many insurgent member connections in one network become well-connected in the other network.
Mixed Act. + Pop. (Militia)		Competitive Hubs	Individuals with many militia member connections in one network become well-connected in the other network

H. RELIABILITY AND VALIDITY

Two types of reliability are particularly important for this study and the identification of relational ties from one actor to others: informant accuracy and inter-rater (or inter-coder) reliability. Informant accuracy refers to the association between what people do and their recollection of those actions, which has implications for the reliability of information contained in the demobilization reports (Bernard et al., 1984; Robins, 2015). In a series of studies throughout the 1970s and 1980s, Russ Bernard, Lee Sailer, and Peter Killworth (commonly referred to as the “BKS studies”) made several claims about the unreliable nature of communication-based ties, including that informants’ recollections are often inaccurate when compared to their actual behaviors, even with the maintenance of personal logs or notes (Robins, 2015). To address this issue, this study draws from Freeman

and Romney (1987) by focusing on recurring or “enduring” patterns of interaction, rather than event-based (i.e., one-time), information exchanges. As previously described, the coding and modeling procedures focused on interactions among individuals that, from the first time pairs interacted to the last, often spanned several months. This study, as described in Chapter 5, uses the Jaccard index to assess the “stability” of networks across time waves. All indices are above RSiena’s recommended threshold of .20 for both networks.¹⁰⁴

The second issue regarding reliability is inter-coder/inter-rater reliability. This form assesses the degree to which coders classify relations and attributes consistently. While this study does not leverage multiple coders, and therefore cannot obtain an inter-coder reliability statistic, the principle remains the same for single coder studies. To ensure consistent coding, this research followed strict definitions for categorizing relational and attribute data (see appendix), as well as conducted periodic “spot checks” throughout the coding process.

In social network research, generalization (i.e., external validity) is not straightforward in large part because the notion of a population is poorly defined (Robins, 2015). While there are social network designs, namely ego network studies, that consist of randomly sampled participants from a given population whereby one can make inferences to a population, many studies, including this one, use complete network designs. This dissertation’s focus on social processes underlying co-evolving, competing networks in insurgent warfare means the “population” for this study consists of the nodes and ties that make up the system comprised of the two competing networks. By testing for social processes using SAOMs, this analysis can make claims about tendencies within and between the two networks (Lusher et al., 2013; Robins, 2015). This point means that this study’s findings cannot be generalized to the FARC’s network outside of the chosen

¹⁰⁴ As previously stated, many of these relations bundle with information exchanges. This approach, therefore, aligns with the notion of “social structure,” which refers to enduring patterns of interaction, as well as aligns with the models used here that assume ties are enduring states rather than brief events (Snijders et al., 2010; Steglich et al., 2006). The ties are binarized for modeling purposes, though they may represent more than one interaction. Finally, as Robins (2015) points out, there remains much research to be done regarding the measurement of social ties, especially as it pertains to reliability. He states (2015, p. 119), “We do not have methods akin to a network factor analysis that can aggregate multiple name generators in a compelling way.”

boundaries, nor can they be generalized to other insurgencies. Similarly, the identification of co-evolutionary social processes in social systems in insurgent warfare is not intended to make causal claims about them, in large part, because of dependencies and feedback within such systems. It is important, therefore, to reemphasize those social processes reflect “tendencies” of network dynamics within existing structure, rather than suggest casual claims about social systems in insurgent warfare. Nonetheless, the results here may inform hypotheses in future studies about other competitive contexts.

V. ANALYSIS

A. INTRODUCTION

This chapter presents descriptive statistics and the results of two models that offer insights into the co-evolutionary processes that can undergird competing social networks in insurgent warfare. Using standard SNA statistics, such as density and average degree (definitions offered in the next section), the descriptive section highlights the insurgent and authority information-sharing networks' global patterns during each time period. Though both networks remained relatively decentralized and sparse, they followed contrasting evolutionary patterns at a macro level. For instance, the insurgent network progressively decentralized while the authority network did the opposite. The descriptive section illustrates that the competing networks formed a larger social system via overlapping relations among a variety of actors, including when “demobs” shared information with both sides and government personnel shared information with insurgents. As a result, the combined social system took on unique global characteristics from the individual networks, such as the extent to which it centralized around information brokers.

The findings in the modeling section describe the evolution of each network via self-organizing processes and actor attributes, as well as how the competing networks co-evolved. While the insurgent and authority networks exhibited contrasting macro patterns over time, similar self-organizing social processes helped drive their evolution. For example, “hubs” emerged in both networks whereby well-connected individuals continued to acquire new information-sharing contacts. More importantly, and consistent with co-evolutionary research, the modeling results demonstrate that the dynamics in one network help drive dynamics in the other and at multiple network levels (Benbya & McKelvey, 2006; Lusher et al., 2013; Monge & Contractor, 2003; Porter, 2006; Ripley et al., 2021). Specifically, the insurgent network had a direct effect on the authority network at the dyad level, whereas the latter had a direct effect on the former at a degree level.

B. DESCRIPTIVE ANALYSIS—GLOBAL PATTERNS

1. Authority and Insurgent Information-Sharing Networks

Table 2 provides several, global descriptive statistics for the two networks during each time period.¹⁰⁵ *Density* is a measure used to reflect the extent to which a network is interconnected. Formally, it is the proportion of observed ties to the number of potential ties among actors in a network.¹⁰⁶ *Average degree* is another measure often used to indicate a network's interconnectedness (Wasserman & Faust, 1994). This measure is calculated as the sum of ties in a network divided by the number of actors in it (Everton, 2012). For instance, the average degree of a network consisting of 50 communication links among 25 individuals is 2 (50/25), which indicates that, on average, each individual communicates with two other people. While average degree can be misleading when social networks are locally dense and globally sparse, it offers a useful glance into global interconnectedness. As indicated by both measures in Table 2, the authority network became increasingly dense over time (from 0.001 to 0.004), whereas the insurgent network followed an opposite trend (from 0.006 to 0.004). Both networks, however, were sparse throughout the waves.

The next measures in Table 2 reflect forms of *network centralization*. It is the ratio of the actual differences in all actor centrality scores from the highest score divided by a theoretical maximum¹⁰⁷ for a network of that size and number of connections (Wasserman & Faust, 1994). The index ranges from 0.0 to 1.0 and attempts to capture the extent to which a network is “dominated” by a single actor, several individuals, or nobody. An index of 1.0 indicates a centralized network in which a single actor scores highly in a selected centrality measure when others do not. The assumption is that relatively central individuals are likely to maintain some form of relative advantage over others. An index of 0.0 implies a decentralized network in which all actors are relatively equal in terms of their centrality scores, suggesting no single actor possesses unique structural advantages over other actors.

¹⁰⁵ As described in Chapter 4, this analysis treated all networks as dichotomized (i.e., binary) and symmetric networks.

¹⁰⁶ See Appendix for all statistic formulas.

¹⁰⁷ The theoretical maximum is the maximum possible sum of differences in actor centrality for a network of that size and number of ties (Wasserman & Faust, 1994).

Certainly, what it means to “dominate” a network depends on the centrality measure on which the index is calculated. Many forms of centrality exist, and thus many centralization indices do too, so one has to be explicit about how centralization is measured and interpreted. This analysis leverages *betweenness* and *degree centralization*, which reflect variation in actor betweenness centrality¹⁰⁸ and degree centrality scores, respectively. Conceptually, the former implies the distribution of information brokers throughout a network, while the latter highlights whether a few individuals maintain relatively more information sharing connections than others. Both provide context about the distribution of potential influence over the flow of information in each network (Borgatti & Halgin, 2011).

The authority network, as both centralization indices show, appears to have become increasingly centralized over the time. The indices suggest a handful of individuals became progressively more connected (i.e., degree centralization increased from 0.031 to 0.118) as well as strengthened their positions as information brokers (i.e., betweenness centralization increased from 0.004 to 0.095). However, the authority network remained fairly decentralized throughout the waves whereby no single actor, or “central controller,” dominated the network. The opposite trends emerged in the insurgent information-sharing network. It decentralized over time whereby actors became increasingly more equal in terms of their potential positional advantages regarding the flow of information in the network. Specifically, degree centralization decreased from 0.079 in the first wave to 0.061 in the last, while betweenness centralization decreased from 0.093 to 0.044 over time. It too was decentralized to begin with at the first wave.

¹⁰⁸ Betweenness centrality “measures the extent to which each actor lies on the shortest path between all other actors in a network” (Everton, 2012, p. 13). The assumption is that actors who sit directly between many others are in a structural position that gives them the opportunity to control the flow of information and resources flowing through a network. Degree centrality is simply the count of each actor’s connections. Individuals with many connections may possess advantages in a network (Everton, 2012; Robins, 2015; Wasserman & Faust, 1994).

Table 2. Descriptive Statistics of Insurgent and Authority Networks

	Authority Info Network				Insurgent Info Network			
	W1	W2	W3	W4	W1	W2	W3	W4
Social System (N = 357 Actors)								
Density	0.001	0.002	0.003	0.004	0.006	0.006	0.005	0.004
Average Degree	0.381	0.723	1.053	1.35	2.078	1.989	1.787	1.406
Degree Centralization	0.031	0.057	0.065	0.118	0.079	0.068	0.063	0.061
Betweenness Centralization	0.004	0.029	0.054	0.095	0.093	0.097	0.081	0.044
Number Ties	68	129	188	241	371	355	319	251
# Created	83	119	85		27	12	24	
#Dissolved	22	60	32		43	48	92	
#Stable Ties	46	69	156		328	307	227	
Jaccard Index	0.305	0.278	0.571		0.824	0.837	0.662	

Note: W1-W4 in the columns reflect the four-month time slices/waves from January 2002–April 2003.

The next few statistics in Table 2 capture tie changes in the two networks over time. The *number of ties* reflects how many information-sharing relations existed in each network during each wave, while the various types of tie changes provides greater detail about how many ties were created, dissolved, or stable (i.e., maintained) for each network between waves. The *Jaccard index* is the proportion of “stable” relations compared to the total number of newly created, dissolved, and maintained ties (Huitsing et al., 2014; Ripley et al., 2021). Because SAOMs model network evolution (and co-evolution), the RSiena manual recommends a Jaccard index of at least 0.20 between waves to ensure that “turnover” is not too high and that networks evolve gradually rather than change from rapid, event-based dynamics (Ripley et al., 2021). As Table 2 shows, these data meet this standard (all indices are greater than 0.27). The insurgent network, in particular, maintained high Jaccard indices (or structural stability) despite individuals leaving through the demobilization program (indices range from 0.662 to 0.837).

1. Global Social System Descriptive Statistics

Table 3 provides descriptive statistics for the social system comprised of both authority and insurgent information-sharing networks. The measures for global interconnectivity indicate that the larger social system was sparse (i.e., density ranges from 0.07 to 0.08) and that, on average, individuals only maintained approximately two to three information sharing contacts during the January 2002-April 2003 time frame (i.e., average degree). Like the individual networks, the overall system was relatively decentralized in terms of the number of information sharing contacts (i.e., degree centralization ranges from 0.060 to 0.114); however, it was far more centralized in terms of information brokers than the individual networks (i.e., betweenness centralization increases from 0.132 in the first wave to 0.260 in the final wave), suggesting that progressively a handful of individuals became better positioned as information brokers.¹⁰⁹ Finally, the overall system remained “stable” (Jaccard indices >.2) across the four time slices in the sense that many relations endured between waves.

Table 3 contains an additional set of statistics to illustrate actor diversity and dynamics in the combined social system. Specifically, the affiliation statistics indicate the percentage of actors in each wave whose primary affiliation meets the definition of one of seven attribute categories.¹¹⁰ The FARC, representing a range of 32–40% of actors across waves, and the Colombian Armed Forces, maintaining 20% of the individuals over time, accounted for the majority of people in the social system. Government Personnel (i.e., civilian, government employees) (6%), Justice Department staff (10%), Police (7%), FARC militia (7-9%), and Civilians (8-18%) represent smaller proportions of actors. Table 3 also shows that while many individuals’ affiliations remained constant (e.g., Armed Forces,

¹⁰⁹ Interestingly, only a single demob ranks in the top-ten for betweenness centrality throughout the four waves, whereas most of the highly ranked individuals were FARC leadership and military personnel.

¹¹⁰ As discussed in Chapter 2, individuals may serve the interests of both insurgent and government networks even though they may have a primary affiliation, such as civilian, insurgent, or government personnel. This attribute indicates each individual’s primary, or most obvious affiliation. For example, several Colombian police officers who shared information with the FARC were coded as police officers even though they might be law enforcement *and* supporting insurgents. The code book appendix provides definitions for all categories.

Government Personnel, Justice, and Police), many others changed over time. For instance, civilians made up 8% of all actors in the first wave, but 18% in the fourth.

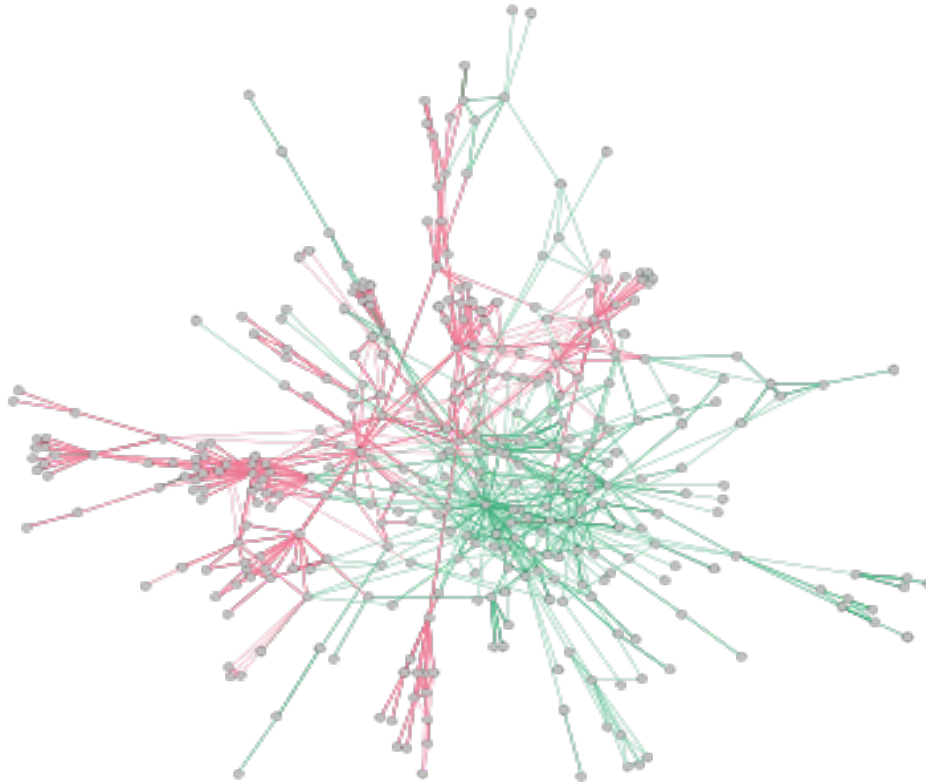
Table 3. Descriptive Statistics of Social System—Combined Authority and Insurgent Networks

	W1	W2	W3	W4
Density	0.007	0.007	0.008	0.008
Average Degree	2.392	2.639	2.768	2.745
Degree Centralization	0.078	0.066	0.060	0.114
Betweenness Centralization	0.132	0.221	0.151	0.260
#Ties	427	471	494	490
#Created	109	130	107	
#Dissolved	65	107	111	
#Stable	362	364	383	
Jaccard Index	0.675	0.606	0.637	
Affiliation				
Armed Forces	20%	20%	20%	20%
Gov. Personnel	6%	6%	6%	6%
Justice	10%	10%	10%	10%
Police	7%	7%	7%	7%
FARC	40%	39%	35%	32%
Militia	9%	8%	8%	7%
Civilians	8%	10%	15%	18%

To supplement the descriptive statistics, Figure 14 depicts a composite visualization of the competing networks from January 2002-April 2003. While the insurgent (red) and authority (green) information-sharing networks remain modular (i.e., separated) and had relatively little overlap, the networks intertwined through the actions of various actors.¹¹¹ Examples of such actions include civilians (e.g., local politicians) offering information to competing actors/networks; FARC insurgents or self-identified militia members demobilizing and giving information to authorities; FARC members operating and acquiring

¹¹¹ Using the quadratic assignment procedure (QAP) test, the correlation between the networks was very weak (0.036) and statistically significant (Everton, 2012; Robins, 2015).

information on behalf of the government; and government personnel sharing information with the FARC or members of its militias.



Note the gray nodes reflect individuals ($n=357$) and the lines represent insurgent (red) and authority (green) information-sharing ties.

Figure 14. Colombia: FARC and Authority Social System

The Venn diagram in Figure 15 depicts the number of actors who established ties in each network, or both. It shows that 150 actors (42%), who were mostly FARC and militia members, formed and maintained only insurgent information-sharing relations. Likewise, 149 actors (~42%) established and kept authority information-sharing ties only, most of whom were government personnel (e.g., members of armed forces). Most importantly, the diagram shows that 58 individuals (16%) formed information-sharing relations with both

social networks, which offers empirical evidence that competing social networks intertwine in insurgent warfare and, in part, make up each other’s social environment.

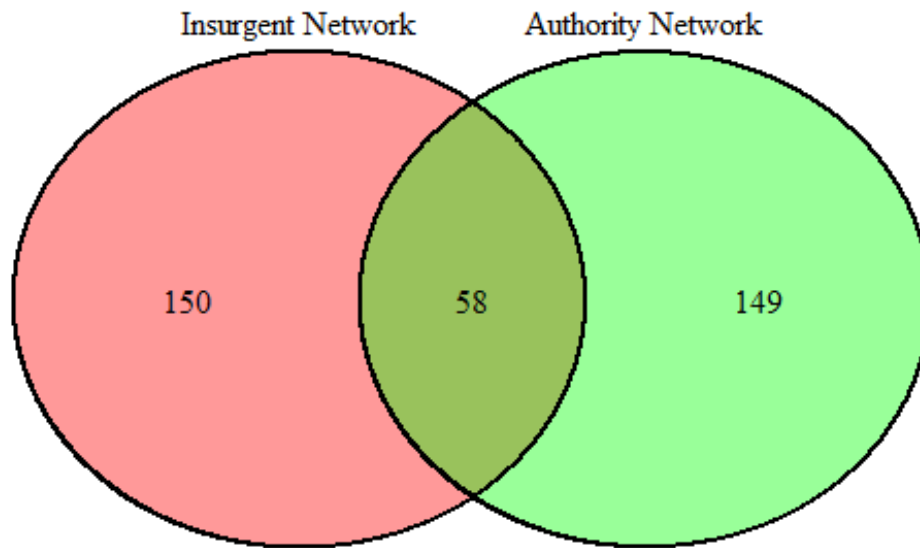


Figure 15. Venn Diagram—Insurgent, Authority, and Both

C. INTRODUCTION TO MODEL RESULTS - SAOMS

As described in Chapter 4, the modeling of multilevel, social networks can be sorted into uniplex, covariate, and multiplex effects (Fujimoto et al., 2018; Huitsing et al., 2014; Rambaran et al., 2015; Ripley et al., 2021). The first category, or *uniplex* structural effects, reflect self-organizing processes in which changes in a network depend on itself at various network levels (Huitsing et al., 2014; Ripley et al., 2021; Robins, 2015; Snijders et al., 2010). The effects outlined in Table 3 include the tendency for individuals to form ties and share information (i.e., *density*); the propensity of triadic closure whereby individuals who share a *single* contact begin sharing information (i.e., *transitive triads*); the formation of “higher-order” clusters (i.e., beyond triad level) whereby individuals who share multiple contacts begin sharing information (i.e., geometrically weighted edgewise shared partners, or

GWESP); and the inclination for well-connected individuals to continue to acquire additional information sharing contacts (i.e., *Activity + Popularity*).¹¹²

The second category, or *covariate* effects, model how changes in a network depends on the characteristics or attributes of the individuals within it. Both models include these effects to control for various forms of homophily on tie formation, which is a well-documented category of processes in which individuals with “similar” characteristics (e.g., same gender or affiliation) are more likely to form and maintain a tie than not (Lawrence & Shah, 2020; McPherson et al., 2001). Similarly, the models also include a geographic-based effect to account for a “propinquity effect,” which, when in reference to spatial distance, suggests geographic location plays an important role in the likelihood that two individuals will form a connection (Adams et al., 2012; Daraganova et al., 2012).¹¹³ Finally, the *multiplex* effects show *co-evolutionary* social processes and account for how changes in one network depend on the other at different network levels (Ripley et al., 2021). While these effects are this chapter’s focus, it will describe self-organizing and covariate results to illustrate intra-network evolutionary processes and to offer a baseline with which to compare the role of co-evolutionary processes. Model 1 reflects the baseline model, whereas Model 2 incorporates co-evolutionary effects.

A few points are worth noting before proceeding to the results. First, both models converged appropriately (Ripley et al., 2021). This assessment is based on observing independent variable t-ratios and a model’s overall maximum convergence ratio, both of which RSiena provides for users during modeling. Together they are designed to help assess whether a model fits the data appropriately. The t-ratio for each independent variable is a combination of the average deviation and standard deviations of the deviations between the observed values (e.g., closed triads) and the simulated values of statistics (Ripley et al., 2021). RSiena recommends that t-ratios for each independent variable (e.g., Transitive Triads, Activity + Popularity) are below 0.1. The overall maximum convergence ratio is the

¹¹² RSiena offers users the ability to include many types of network effects like these. This list is not exhaustive but reflects those relevant to this research.

¹¹³ This effect can refer to social proximity, too. However, this study uses it to capture spatial distance.

maximum value of the average deviation divided by the standard deviation. RSiena's states that overall maximum convergence ratios should be ≤ 0.25 (Ripley et al., 2021, p. 66).

Also, problems with model fit and convergence, in part, informed the models' variable selection. Note the differences in independent variables for each network in Models 1 and 2. This analysis attempted to maintain the same theoretically-driven variables for both networks but had to add some based on GOF tests that suggested models did not account well for degree distributions in one or both networks. Specifically, the models include effects to account for the proclivity of isolated individuals in the authority network to remain that way by avoiding information sharing with others (i.e., *isolates*¹¹⁴), and the tendency for those who have few connections ($n=2$) in both networks to keep few contacts (i.e., *anti near-isolates*).

In other cases, this analysis had to drop some variables to get the models to converge appropriately. For instance, both models do not include several effects for the insurgent information-sharing network that reflect potentially relevant evolutionary and co-evolutionary processes (e.g., no isolates variable in the insurgent network models). While convergence issues are broadly the culprit for their exclusion, the reasons behind the omitted variable's role in convergence depends on several factors, including extreme correlations with other variables or the fact that some were not observed frequently (or at all) in the data set.¹¹⁵ This challenge was particularly noticeable for the insurgent network whereby only a single multiplex effect (i.e., *Mixed Activity + Popularity (Civilian)*) could be modeled to permit convergence.

¹¹⁴ This effect and the anti near-isolates effects were included only after initial goodness of fit (GOF) tests indicated that isolates existed and for which models should account.

¹¹⁵ For instance, Model 1 does not include a homophilous effect for "demobilization" in the insurgent network because pairs of demobs in this context did not establish insurgent information-sharing ties once they had left the FARC or their militias. Put simply, one cannot model networks based on patterns that do not exist in the empirical data set.

D. SELF-ORGANIZATION AND ACTOR ATTRIBUTES—UNIVARIATE AND COVARIATE EFFECTS

1. Authority Information-Sharing Networks

The results for Model 1 in Table 3 reflect effects related to self-organizing social processes and actor attributes (i.e., covariates) that help drive each network's evolution without accounting for co-evolutionary processes.¹¹⁶ Odds ratios (OR) are provided in the text for many estimates to support interpretation. Beginning with the authority information-sharing network,¹¹⁷ it appears actors within it largely avoided establishing and maintaining information-sharing ties with others (i.e., *density*). This result (Est. = -5.991, $p < 0.01$) suggests that while individuals acting on behalf of the government had the potential to form information sharing ties with a variety of other individuals (e.g., government employees, military, civilians, militia, FARC), often they did not. However, it is important to keep in mind two points when interpreting the density effect. The first is that statistical procedure considers all types of actors (e.g., insurgents) as potential information-sharing partners, so the likelihood is low that deeply embedded government personnel would form ties with adversaries. The second, and arguably more important point, is that density essentially acts as a control variable for all other effects and is often not all that meaningful (Pasquaretta et al., 2016; Warren, 2016).

The tendency for closure-related processes (i.e., *transitive triads* and *GWESP*) within the authority network depends on the level of analysis. At the triad level, individuals had an aversion to sharing information with others who maintained only a single contact with them (Est. = -2.239, $p < 0.01$). While triadic closure is common in a variety of contexts (Kadushin, 2012), *the results here do not provide support for the information closure hypothesis*. However, the authority network exhibited a tendency for “higher-order” closure processes (i.e., *GWESP*) whereby pairs of actors were far more likely to share information with others when they shared multiple contacts (Est. = 4.692, $p < 0.01$). In fact, when holding all other

¹¹⁶ All p-values were calculated using Wald-type tests. RSiena offers functions to enable this step (Ripley et al., 2021, pp. 90–94).

¹¹⁷ The column titled, “Authority Network,” indicates results for the authority network as the dependent variable, whereas the “Insurgent Network” column shows results for the insurgent network as the dependent variable.

variables constant, these individuals were 109 times more likely ($OR = 109.07$) to form a direct tie than those who did not share multiple contacts. *The positive and statistically significant result provides support for the information cluster hypothesis.* Interestingly, when considered together, the results for these multilevel, “closure” related processes may say something about the importance of trust and “extra vetting” when it comes to sharing information with others in insurgent warfare.¹¹⁸

Related to the notion of clustering is the potential presence of network “hubs.”¹¹⁹ Table 3 shows that the *Activity + Popularity* variable is positive and statistically significant ($Est. = 0.124, p < 0.01$), *which offers support for the information hubs hypothesis.* This result suggests that well-connected individuals continued to acquire and maintain new information sharing contacts, albeit only slightly more likely do so than those who were not well-connected ($OR = 1.13$). The demobilization reports highlight that several, experienced military personnel (e.g., Colonels) and government civilians repeatedly engaged in information sharing with others about former insurgents, former militia members, and key civilians. This result aligns well with findings in other contexts regarding the presence of “hubs” developed through social processes, such as preferential attachment, as well as emergence of clusters in networks (Barabási, 2016; Barabási & Bonabeau, 2003; Capra, 1996; Robins, 2015).

The last two effects, which were included to obtain model convergence, offer details into the other side of spectrum on actor ties; that is, the tendency for individuals with few, to no contacts to remain that way. The *isolates* effect indicates that many actors did not share information on behalf of the authorities ($Est. = 3.962, p < 0.01$); that is, isolated individuals were almost fifty-three times ($OR = 52.56$) more likely to avoid forming a new tie than non-isolates. As stated before, the model considers insurgents and militia members, including deeply embedded ones who are less likely to share government information than others, as potential information sources or targets. Yet, when individuals maintained a single

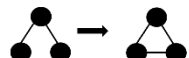
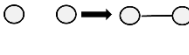
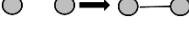
¹¹⁸ It is clear in the demobilization reports that Colombian government personnel were aware that some “played both sides.” In fact, several of the questions that interviewers asked demobs pertained to their knowledge of government personnel supporting the FARC.

¹¹⁹ Because these data are nondirected, a hub in this context is simply well-connected actors. The use of the term here is not the same as Kleinberg’s (1999) measure of “hubs and authorities.”

relationship through which information could flow, there was a high probability (*anti-near isolates*, Est. = 1.285, $p < 0.01$) they would establish an additional contact and become more embedded in the network over time—the odds of doing so, holding all other variables constant, were nearly four times (OR = 3.61) greater than not sharing information with additional people in the authority network. When considered together, these two outcomes could suggest that while there might have been barriers for individuals to engage the network initially (i.e., “get their foot in the door”), there were mechanisms to keep individuals sharing information once they did. Finally, there were several significant covariate effects that controlled for the role of homophily in the network. Specifically, operating in the same geographic area (Est. = 1.213, $p < 0.01$), maintaining the same affiliation (Est. = 0.333, $p < 0.05$), and participating in the demobilization program (Est. = 1.057, $p < 0.01$) enabled the formation of authority information-sharing connections.¹²⁰ Gender did not have an effect in the formation of ties in the authority network.

¹²⁰ In other words, the odds of two individuals in the same geographic area forming an authority information-sharing tie were three times (odds ratio = 3.36) greater than those who were not located in the same location. Those who shared the same affiliation were 1.40 times more likely to share information than those who did not, while those participating in the demobilization program were almost three times (odds ratio = 2.88) more likely exchange information for authorities than those who did not participate in it.

Table 4. Self-Organization and Actor Attributes—SAOMs Univariate and Covariate Effects

		Model 1	
Parameter	Graph Representation	Authority Estimate (SE)	Insurgent Estimate (SE)
Within-Network			
Density		-5.991(0.621)***	-10.070(0.670)***
Transitive Triads		-2.239(0.684)***	0.135(0.269)
GWESP		4.692(0.866)***	2.796(0.559)***
Isolates		3.962(0.561)***	
Anti-Near-Isolates		1.285(0.331)***	2.359(0.446)***
Activity + Popularity		0.124(0.028)***	0.115(0.020)***
Within-Network (Covariates)			
Same Gender		0.058(0.139)	-0.596(0.310)***
Same Geography (Dept.)		1.213(0.145)***	1.163(0.308)***
Same Affiliation		0.333(0.118)**	3.533(0.499)***
Same Demob. Status		1.057(0.292)***	
Overall Maximum Convergence		0.2456	

Note: Standard errors in parentheses, * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$ (two-sided)

2. Insurgent Information-Sharing Networks

The insurgent information-sharing network exhibited similar evolutionary, self-organizing social processes as its competitor. It too displays a strong propensity away from establishing information-sharing relations within the broader social system comprised of multiple types of actors (i.e., *density*, Est. = -10.070, $p < 0.01$). As described earlier, however, it is a challenging effect to interpret for several reasons. Keeping those in mind, it is interesting to note that several examples exist in which government personnel (i.e., armed forces, government civilians, justice, and police), who make up approximately 45% of networked actors, established and maintained insurgent information-sharing ties during the January 2002–April 2003 time frame. For instance, several police officers in one of the local police departments in southern Colombia provided information to the FARC for most of the time frame of interest.

Like the authority network, the insurgent information-sharing network's tendency for closure-related processes is mixed depending on the level of analysis. The *transitive triads* coefficient is positive (Est. = 0.135), but statistically insignificant, so *it does not provide support for the information closure hypothesis*. Yet, the *GWESP* result indicates the insurgent network displayed a tendency for "higher-order" closure whereby those acting on its behalf were far likely to share information with others when they had several, shared contacts between them (Est. = 2.796, $p < 0.01$). In other words, when holding all other variables constant, these individuals were sixteen times more likely (OR = 16.39) to establish and maintain a direct tie than those who did not share multiple contacts. Similar to the authority network, *this supports the information cluster hypothesis*. This finding also aligns with research on social movements and "dark networks" that emphasize the important role of preexisting connections and trust for individuals who consider engaging in high-risk activities (Lofland & Stark, 1965; McAdam, 1986; Sageman, 2004).

As with the authority network, it appears well-connected actors, or "hubs," continued to establish and maintain ties throughout the waves, which *offers support for the information hubs hypothesis (Activity + Popularity, Est. = 0.115, $p < 0.01$)*. The insurgent network's most well-connected actors across the waves included front leadership, well-connected militia members, and local politicians (e.g., city mayors). Though only slightly more likely to form additional contacts than those in different situations (OR = 1.12), preferential attachment is possibly an underlying process whereby well-connected individuals, who likely possess a lot of information, continue to acquire new contacts and information (Barabási, 2016; Robins, 2015). This model dropped the *isolates* variable for the insurgent network due to convergence issues. Yet, like the authority network, individuals were much more likely—about ten times more so than those in other social positions (odds ratio = 10.58)—to establish additional ties and become increasingly embedded in the network over time when they possessed at least one preexisting tie (*anti-near isolates, Est. = 2.359, $p < 0.01$*). Finally, the results for homophily are mixed. Table 3 shows evidence for the influence of geography (Est. = 1.163,

$p < 0.01$) as well as affiliation-based homophily (Est. = 3.533, $p < 0.01$),¹²¹ but a tendency away from homophily based on gender (Est. = -0.596, $p < 0.01$). The FARC's demographic composition in which male and female members often served in the same unit is a likely explanation for the negative and statistically significant effect for gender.

E. CO-EVOLUTIONARY SOCIAL PROCESSES—MULTIPLEX EFFECTS

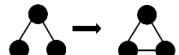
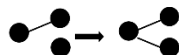
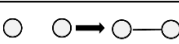
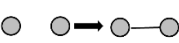
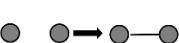
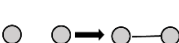
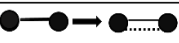
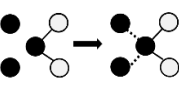
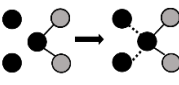
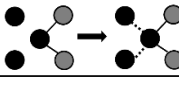
Table 4 depicts the results for Model 2, which incorporates multiplex, or co-evolutionary effects into a model. While the addition of these effects does not “explain away” any of the baseline evolutionary effects for either network, the results demonstrate that the dynamics in one network help drive the dynamics in the other. Like Model 1, however, the results depend on the level of analysis. Beginning with the authority network (i.e., dependent variable), there is a direct effect of insurgent ties on the formation and maintenance of government ties at the dyad level (*Insurgent* => *Government*, Est. = 2.643, $p < 0.01$). The results show that individuals involved in insurgent information-sharing ties were fourteen times (odds ratio = 14.05) more likely to establish authority-information sharing ties than who were not (e.g., isolates and authorities). *This supports information multiplexity hypothesis and indicates that the presence of insurgent ties between pairs of actors often led to government information-sharing ties.*¹²² Some of this result is likely due to the context in which a government-led demobilization program enticed FARC and militia members to lay down their weapons and reintegrate into Colombian society. It also fits into a broader pattern during the early-2000s in which the FARC became “weaker” from a high point in the late-1990s after facing several setbacks, such as diminishing popular support (e.g., “No Más” protests and backlash from kidnappings and killings), the creation of “Plan Colombia” in 2000, failed peace talks with Colombian Government, and the election of an aggressive, then-President Uribe (Jane’s World Terrorism and Insurgency Centre, 2020; Stanford University, 2019). Civilians engaged in insurgent information-sharing ties likely contributed to this

¹²¹ The odds of two individuals in the same location forming an insurgent tie were three times (odds ratio = 3.19) higher than those who were not, while those who shared the same affiliation were thirty-four times (odds ratio = 34.23) more likely to share information than those who did not.

¹²² Model 2 did not converge when accounting for the authority network's direct effect on the insurgent network at the dyad level (i.e., government => insurgent).

outcome, too. The demobilization reports illustrate that many civilians had tenuous ties to the FARC and their militias, often forced upon them via threats of violence, but who participated in the program in order to seek protection and benefits from the government.

Table 5. SAOM Results

Parameter	Graph Representation	Model 1		Model 2	
		Authority Estimate (SE)	Insurgent Estimate (SE)	Authority Estimate (SE)	Insurgent Estimate (SE)
Within-Network					
Density		-5.991(0.621)***	-10.070(0.670)***	-5.958(0.786)***	-10.502(0.876)***
Transitive Triads		-2.239(0.684)***	0.135(0.269)	-2.922(0.817)***	0.159(0.296)
GWESP		4.692(0.866)***	2.796(0.559)***	5.563(1.073)***	3.012(0.649)***
Isolates		3.962(0.561)***		3.416(0.643)***	
Anti-Near-Isolates		1.285(0.331)***	2.359(0.446)***	1.544(0.390)***	2.410(0.633)***
Activity + Popularity		0.124(0.028)***	0.115(0.020)***	0.112(0.039)***	0.114(0.035)***
Within-Network (Covariates)					
Same Gender		0.058(0.139)	-0.596(0.310)**	0.018(0.139)	-0.678(0.394)*
Same Geography (Dept.)		1.213(0.145)***	1.163(0.308)***	1.206(0.150)***	1.239(0.316)***
Same Affiliation		0.333(0.118)**	3.533(0.499)***	0.401(0.126)***	3.711(0.542)***
Same Demob. Status		1.057(0.292)***		0.989(0.292)***	
Between-Network					
Insurgent -> Government				2.643(0.635)***	
GWESP - Mixed				-0.803(0.508)	
Mixed Act. + Pop. (Civilian)				-0.309(0.285)	2.028(0.442)***
Mixed Act. + Pop (Insurgent)				-0.820(0.261)***	
Mixed Act. + Pop. (Militia)				-0.329(0.156)**	
Overall Maximum Convergence		0.2456		0.2209	

Note: Standard errors in parentheses, *p<0.10; **p<0.05; ***p<0.01 (two-sided)

The results for closure-related processes and several degree level effects indicate the insurgent network (i.e., independent variable) did not have direct effects on the authority network (i.e., dependent variable) at those levels. As shown in Table 4, Model 2 includes a *GWESP-Mixed* variable to capture the former. The coefficient is negative (Est. = -0.803) and statistically insignificant and therefore *does not lend support to the mixed information cluster hypothesis that the government would find ways to embed in insurgent clusters*. At the degree level, Model 2 includes three effects that account for competition over well-connected individuals. The three *Mixed-Activity + Popularity* effects reflect the tendency for *civilians*, *insurgents*, or *militia* members to have established ties with well-connected actors in the insurgent network who subsequently became well-connected, or share information with many others, in the authorities' network as well. In all three cases, the effects are negative but only the *insurgent* (Est. = -0.820, $p < 0.01$) and *militia* (Est. = -0.329, $p < 0.05$) coefficients are statistically significant. *These results do not support the competitive hub hypothesis* and rather indicate there was a tendency for insurgents and militia to have avoided well-connected individuals who could have put them at risk by sharing share information with the government. Viewed from a different perspective, it indicates that the government, outside of the demobilization program, did not compete effectively to establish contacts with well-connected people in the insurgent network.

The *Mixed-Activity + Popularity (Civilian)* coefficient in Table 4's last column indicates the authority information-sharing network (i.e., independent variable) exhibited a direct effect on the insurgent network (i.e., dependent variable) at the degree level.¹²³ The coefficient is positive and statistically significant (Est. = 2.028, $p < 0.01$) and *supports the competitive hubs hypothesis with respect to civilians*. This result implies there was a tendency for civilians in the authority network to establish ties with well-connected individuals who become attractive contacts for insurgents and their affiliates. Put differently, individuals in the authority network with many civilian contacts were eight times (odds ratio = 7.60) more likely to share information with insurgents than those without such characteristics. It suggests

¹²³ As previously stated, several explanatory variables included in the insurgent network model prevented it from converging. Many versions of this model were run to swap out the civilian version with militia and insurgent versions but were unsuccessful.

that insurgents tended to compete effectively for individuals who had many civilian contacts by establishing information-sharing relations with them. Compared to the authorities' efforts to compete for well-connected individuals, it appears the FARC and its affiliates placed more emphasis on competing for civilians outside their social circle than the Colombian authorities did at that time and location. The FARC's ideological roots (i.e., Marxist-Leninism) and emphasis on guerrilla warfare offer context for this perspective. This does not suggest, however, that the FARC were "nice" to populations in their interactions; in fact, the FARC's Southern Bloc threatened, kidnapped, and killed many civilians during that time who would not cooperate with them. Rather, it is important to recall that, at that time, the FARC faced several major setbacks in their competition with the government (Jane's World Terrorism and Insurgency Centre, 2020; Marks, 2010). This point suggests it is likely the FARC established ties with well-connected individuals within the authority network, specifically those with many civilian contacts, in order to acquire information in a competition with a government who had the momentum.

F. GOODNESS OF FIT (GOF)

This analysis assessed each model's fit using "goodness of fit" (GOF) procedure implemented in the RSiena package. As previously described, a model should be able to replicate features that are included in the model, as well as those that are not. To assess model fit, this analysis included GOF tests for degree distribution (i.e., indegree¹²⁴), triad census, and geodesic distances for both insurgent and authority networks.¹²⁵ As described in Chapter 4, the GOF test uses common structural tendencies in social networks, implemented as a set of "auxiliary statistics," to evaluate a model's ability to account for them (Lospinoso & Snijders, 2019; Ripley et al., 2021). RSiena's manual recommends an auxiliary statistic's p-value is near or above 0.05. While the analysis conducted GOF tests for both models, it will

¹²⁴ The indegree distribution is the distribution of ties that actors receive. Because this is nondirected data, this check helps account for simple degree distributions; that is, it ignores the direction of ties.

¹²⁵ Fitting each network separately rather than the larger social system is consistent with existing studies that have employed GOF tests for multiplex networks (Fujimoto et al., 2018; Huitsing et al., 2014; Rambaran et al., 2015).

focus on Model 2 because it includes self-organizing, covariate, and co-evolutionary effects.¹²⁶

The GOF results in Model 2 show the authority network fits degree distribution sufficiently ($p = 0.036$) and does much better with triad census ($p = 1$) and geodesic distances ($p = 0.573$). The insurgent network is a good fit for all three auxiliary statistics in the sense that all three p -values are greater than 0.05. Figure 16 depicts plots demonstrating GOF tests for Model 2 for the three auxiliary statistics and for each network. The red lines indicate the observed values, whereas the violin plots represent the simulated statistics. The dotted lines reflect the 95th percentile banks while the p -value is located at the bottom of the plot (Lospinoso & Snijders, 2019). For example, looking at the insurgent network, the model does an excellent job accounting for the distribution of actor connections (i.e., degree distribution), as well as for various types of triads commonly found in networks; however, simulated distributions for the number of pairs with geodesic distances between 4 and 5 are somewhat lower than the observed frequencies.

¹²⁶ In Model 1, the authority network is a good fit for all three auxiliary statistics (indegree p -value = 0.11; triad census p -value = 0.988; and geodesic distances p -value = 0.394), whereas the insurgent network is good for degree distribution (p -value = 0.599) and triad census (1.00) and satisfactory for geodesic distribution (0.044).

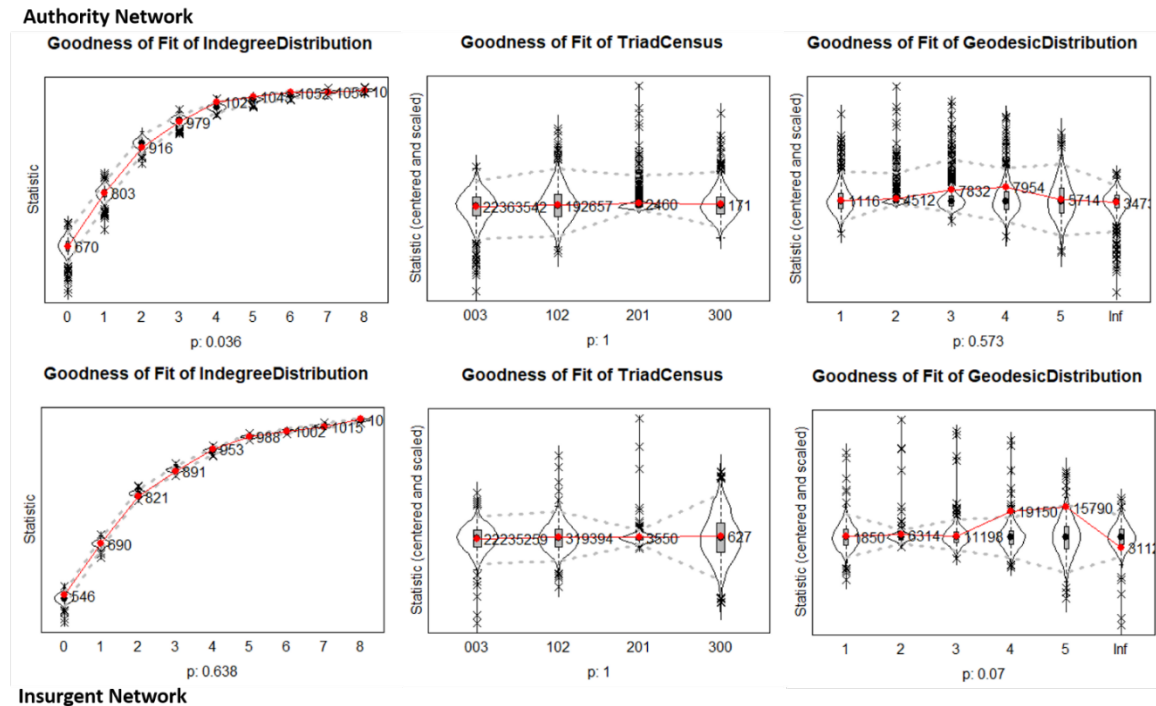


Figure 16. Model 2 Goodness of Fit

G. SUMMARY OF RESULTS

The empirical data show that the insurgent and authority information-sharing networks intertwined to make up a larger social system comprised of various types of actors, including civilians, insurgents, and government personnel. Consistent with COIN literature, they did not partition themselves into distinct networks (Department of the Army, 2017; Gventer, 2014; Herrington, 1982; Kilcullen, 2013; U.S. Marine Corps, 2017). The descriptive statistics, including those depicted in the Venn diagram (Figure 15), reveal that a choice of network boundaries based on affiliation categories would not have captured this key aspect of the social system. Moreover, the composite statistics for the larger system reflect that it had some unique characteristics from the individual networks, such as the extent to which it was centralized around brokers (i.e., betweenness centralization). While these are insights that can be found in multiplex networks in many contexts (Ferriani et al., 2013; Kadushin, 2012; Robins, 2015), they are points often ignored in the analysis of social networks in insurgent warfare. As COIN literature illustrates, the inability to create an

accurate depiction of an operational environment can have serious consequences (Cleveland et al., 2018; Department of the Army, 2014, 2017).

The two information sharing networks exhibited similar multilevel, evolutionary social processes despite differing global patterns. For instance, the insurgent network became increasingly sparse and decentralized over time, while the authority network did the opposite (albeit still decentralized). At the triad and cluster levels, individuals within each network tended to avoid sharing information with others in their social circles (i.e., closure) unless they shared multiple contacts. These results, which *provide support for the information cluster hypothesis but not the information closure hypothesis*, are insightful for the study of multilevel dynamics and nested patterns of interaction. They show that similar social processes can occur at one level but not another. Also, they may indicate the importance of trust in information sharing in insurgent warfare. Individuals in both networks might not have felt comfortable sharing information with others unless they had fully vetted them via multiple contacts. Many insurgent warfare contexts, including in Colombia at that time, are replete with examples of individuals “switching sides” or “playing both sides,” which is a pattern that poses serious risks for individuals sharing information with defectors (Kilcullen, 2013; Kuehl, 2009; Metelits, 2010; Montgomery & McWilliams, 2009; Wilson, 2006). This risk was not limited to one side of the conflict, either. The demobilization reports showed that *both* the FARC and the authorities were concerned about their affiliates offering information to their adversaries.¹²⁷ Interestingly, it was also highly likely that individuals would become increasingly integrated into each network over time once they had joined (i.e., anti-near isolates).

Hubs tended to emerge in both networks, too. In this context, hubs acquired information contacts and, in turn, established more contacts through which they could acquire or disseminate information through social interactions. *The results for both networks provide support for the information hubs hypothesis*. That is not to say these hubs “controlled” either network, let alone the larger social system comprised of the two

¹²⁷ For instance, the reports discuss many examples of FARC leadership who targeted rank and file members who they suspected of “collaborating” with the government. In terms of the government, the reports explicitly covered each demob’s knowledge of government personnel collaborating with insurgents.

networks. In fact, the combined system was decentralized even though it was relatively more centralized in terms of betweenness centralization than the individual networks. Finally, affiliation homophily and geography played a significant role in tie formation and maintenance in both networks.

The findings highlight underlying co-evolutionary effects between two competing, information-sharing networks in this insurgent warfare context. They show that individuals in the broader social system acted and/or reacted to local their social environments, which in part were comprised of competing structures. The outcomes are consistent with existing literature on co-evolution, as well as its multilevel nature (Benbya & McKelvey, 2006; Huitsing et al., 2014; Lusher et al., 2013; Monge & Contractor, 2003; Porter, 2006). In this study, the insurgent network had a direct effect on the authority network at the dyad level, whereas the authority network had a direct effect on the insurgent network at the degree level. The former result, which *provides support for the information multiplexity hypothesis*, illustrates that many of those embedded in the insurgent network often “played both sides,” at least temporarily, and helped intertwine the networks and contribute to the authority network’s dynamics when they joined it. Model 2, however, did not converge when accounting for the authority network’s direct effect on the insurgent network at the dyad level.

The latter co-evolutionary outcome *lends support for the competitive hubs hypothesis* and shows that civilians who were embedded in the authority network tended to establish contacts with well-connected hubs, who in turn, established many insurgent ties. Insurgents and militia members, however, did not have the same proclivity, which *does not offer support for the hypothesis*. This finding for civilians is interesting, though, in the context of information sharing in insurgent warfare. While many civilians established authority information-sharing ties with government-based hubs, it turns out this was risky in the sense that the latter often ended up sharing information with insurgent contacts. Taken together, the presence of the two multilevel, co-evolutionary effects highlight the importance of treating competing networks as part of the same social system, as well as illustrates the important role that hubs and civilians can play in the competition for information in insurgent warfare.

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VI. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

A. CONCLUSIONS

This study began by noting that extant literature has addressed empirical insurgent networks inadequately, insufficiently accounting for insurgent warfare's unique characteristics. Specifically, existing structural studies of insurgencies—those that seek to understand emergent social system patterns—have failed to capture the overlapping nature of competing, information-sharing networks in such contexts. This study addressed three bodies of relevant research, including COIN theory, complex adaptive systems, and social network research, all of which offer useful perspectives for understanding emergent social system patterns in insurgent warfare. Guided by Monge and Contractor's (2003) MTML framework, it identified several natural points of synthesis among these domains. This framework integrates complex adaptive systems and social network research around co-evolution and the two bodies' shared concepts closely related to it: namely, network emergence and self-organization. It argued that both self-organizing and co-evolutionary, social processes—the ways by which individuals form connections—help drive network dynamics at multiple network levels. It drew on longitudinal network data from official, Colombian demobilization reports, as well as leveraged multiplex SAOMs in order to examine how competing information-sharing networks can co-evolve in insurgent warfare.

This analysis uncovered empirical support for several, but not all, of the hypotheses outlined in Chapter 3. It tested several hypotheses about intra-network, self-organizing social processes, and inter-network, co-evolutionary ones. In particular, it found similar self-organizing social processes helped drive internal dynamics of both authority and insurgent networks at the degree and cluster levels. Both networks showed a tendency for information-sharing hubs to emerge (i.e., degree level), whereby well-connected individuals tended to continue to acquire new information-sharing contacts. Also, the two networks showed a proclivity toward closure at a cluster level in which individuals tended to share information with others when they shared multiple contacts. Interestingly, the two networks exhibited contrasting global evolutionary patterns in some regards (e.g., betweenness centralization), which aligned well with emergence literature that claims

global patterns are not the mere sum of patterns at lower levels (Corning, 2002; Goldstein, 1999; Holland, 1998; Lichtenstein, 2000; Monge & Contractor, 2003; Padgett & Powell, 2012; Wycisk et al., 2008).

It tested for dyadic multiplexity (i.e., the presence of one tie leads to another), multilevel closure (i.e., triad and cluster levels) and the emergence of hubs (i.e., degree level) between the competing networks. In this case study, the insurgent network had a direct effect on the authority network at a dyad level, whereas the authority network had a direct effect on the insurgent network at a degree level. The former co-evolutionary result illustrated that many of those embedded in the FARC network often “played both sides,” including demobs and civilians. The latter finding indicated that civilians who were embedded in the authority network tended to establish contacts with well-connected hubs, who in turn, established many insurgent ties.

The analysis extends previous research in at least four ways. First, it addressed empirical, insurgent networks explicitly, which the “dark network” literature has largely ignored. To date, much of this literature has focused on criminal and terrorist networks (Cunningham et al., 2016; Everton, 2012; Gerdes, 2015; Morselli, 2014), in part, due to a lack of access to relevant data on insurgent networks. For example, while researchers studying criminal networks have been able to access unclassified, closed source data (Bright et al., 2019; Diviák et al., 2019; Morselli, 2014; Papachristos et al., 2013; Papachristos & Smith, 2014), this has not been the case with insurgent networks. A consequence is that extant research has not examined social processes that can drive insurgent network dynamics at an operational level. To address this gap, this study built a unique data set from official, unclassified reports that offered rich data on informal relationships among a variety of actors, enabling the identification of social processes that contributed to network dynamics in Colombia. Moreover, this study captured detailed, operational level network data about the FARC’s competitor: the Colombian Government. Extant literature generally has not incorporated empirical, authority networks into analyses either, albeit a few exceptions exist for other types of “dark networks” (Diviák et al., 2019; Kenney, 2007; Papachristos & Smith, 2014; Stys et al., 2020).

Second, this study analyzed empirical insurgent networks from a perspective that is consistent with COIN and insurgency literature. It mapped and analyzed two, competing information-sharing networks at an operational level. Chapter 2 pointed out that lines between insurgent networks and other types of networks are often murky, in part, because they overlap with legitimate social circles (Department of the Army, 2014, 2017; Diviák et al., 2019; Herrington, 1982; Kilcullen, 2013; Papachristos & Smith, 2014; Stys et al., 2020; United States Government, 2016; U.S. Marine Corps, 2017). This characteristic, which brings the notion of open systems to the forefront, makes it difficult to classify individuals into neat network categories, such as insurgent, civilian, and government networks. While official U.S. publications on COIN (Department of the Army, 2014, 2017; United States Government, 2016; U.S. Marine Corps, 2017), as well as other related works (Cleveland et al., 2018; Gventer, 2014; Herrington, 1982; Kilcullen, 2013), offer some of the most useful descriptions of social networks in operational environments to date, in part, because the authors have real-life, practical experience, they have failed to pay explicit attention to the heart of the problem: boundary specification. This study addressed this gap by treating competing insurgent and authority networks as multiplex ties within the same social system. Consistent with COIN literature, the empirical data showed that individuals did not partition themselves neatly into distinct networks, suggesting that a choice of network boundaries based on affiliation categories (e.g., civilian, insurgent, government) would have missed important interdependencies between the networks.

Likewise, it focused on information-sharing networks. COIN and insurgency literature claim that forming personal relations with a populace, specifically through in-person information exchanges, is critical in determining a conflict's outcome (Cleveland et al., 2018; Department of the Army, 2014; Galula, 2006; Guevara, 2007; Kilcullen, 2010, 2013; Marighella, 2002; Taber, 2002; Tse-Tung, 1989). Yet, existing research has failed to focus on such networks in insurgent warfare contexts. This study demonstrated empirically that information-sharing among a variety of individuals (e.g., civilians and insurgents) ultimately intertwined two adversaries who competed for the same populace. Examples in this case study included civilians and local politicians offering information to competing actors/networks; FARC insurgents or self-identified militia members demobilizing and

providing information to authorities; FARC members operating and acquiring information on behalf of the government; and government personnel sharing information with the FARC or members of its militias. Interestingly, while the networks did not overlap substantially, information-sharing on one side of the conflict had an impact on the information-sharing structure in the other.

Third, this dissertation extended the application of the MTML framework to co-evolving social networks in insurgent warfare. As described in previous chapters, the framework synthesizes complex adaptive systems and social network research, which, in turn, helped address gaps in the study insurgent networks. The former perspective aided analysis from a standpoint on system boundaries that is consistent with insurgency and counterinsurgency literature: namely, social systems that encompass open and competitive, information-sharing social networks that are comprised of dynamic social beings, specifically combatants and noncombatants, who influence and react to their social environment. This perspective offered a more realistic depiction of social systems in insurgent warfare than existing social network literature on “dark networks.” Social network research’s central contribution was its emphasis on identifying social processes underlying *empirical* social systems. Also, guided by this domain, this study applied the MTML framework *explicitly* with the use of SAOMs to study insurgent networks, which have become a prominent model class in social network research; however, extant research leveraging the models has paid little attention to the framework.

Fourth, it identified the presence of *specific* multilevel, co-evolutionary effects between *empirical*, social networks in insurgent warfare. While complex adaptive systems and social network research have much to offer on co-evolution, they have largely ignored the concept in such contexts. Consistent with extant literature in several domains, it framed each network as part of the other’s social environment whereby co-evolution exists in the sense that there are mutual and concurrent effects on each other at various levels, often triggered by some need (e.g., information) (Huising et al., 2014; Monge & Contractor, 2003; Porter, 2006; Rambaran et al., 2015; Volberda & Lewin, 2003). In this study, information sharing interactions in one network had a direct effect on the structure of the

other, even while controlling for intra-network tendencies, such as self-organizing and other social processes (e.g., homophily).

The presence of co-evolutionary social process in an insurgent warfare context has important implications for practitioners, too. As *FM 3-24/MCWP 3-33.5* (Department of the Army, 2014, p. 20) states, “counterinsurgents must gather, analyze, and disseminate civil information pertaining to the population.” Information from noncombatants, which counterinsurgents can process into intelligence, is thought to help improve both offensive and defensive operational effectiveness because it helps them understand the identity, networks, and locations of insurgents (Galula, 1964; Kalyvas, 2006; McCormick, Forthcoming). This study’s results support existing literature that emphasizes the important role that civilians can play in insurgent warfare. They suggest that practitioners should continue to focus on information-sharing relations with civilians, as well as continue to emphasize the potential role that a variety of other actors (e.g., politicians, foreign partners) can play in insurgent warfare (Department of the Army, 2014, 2017; United States Government, 2016; U.S. Marine Corps, 2017).

Similarly, the study highlights practitioners must take extra care with boundary specification. Though it is almost certain that military leadership, as was the case with Colombians, considers how adversarial networks might intersect and compromise their own unit’s networks, including through foreign partners, civilians, and rouge government officials, they should frame competing social networks as part of the same system, rather than treat them as distinct from one another. Social system literature (Benbya & McKelvey, 2006; Cilliers, 2001; Lichtenstein, 2000; Monge & Contractor, 2003; Padgett & Powell, 2012; Porter, 2006; Sawyer, 2005), as well as some COIN literature (Cleveland et al., 2018; Department of the Army, 2014, 2017; Kilcullen, 2013; U.S. Marine Corps, 2017) and the co-evolutionary effects found in this study, demonstrate practitioners should not consider insurgent networks as completely external structures *onto which* they implement strategies. While it is clear that the removal of individuals from networks can affect an adversary’s network (Bakker et al., 2012; Carley et al., 2003; Everton, 2012; Roberts & Everton, 2011), co-evolutionary processes among information-sharing networks indicate that non-violent interactions can affect an enemy network’s structure, too. Though this perspective may

create more burden for practitioners (e.g., data collection), joint publications and other official documentation should, at a minimum, ensure personnel recognize the limitations of approaches that treat “friendly,” “threat,” and “neutral” structures as separate networks, such as the common practice of assigning color codes to networks (e.g., “blue,” “green,” “white,” and “red” networks).

Consequently, this analysis has implications for relational data structuring and storage as well. Some of the military’s commonly used enterprise systems, such as i2/Analyst Notebook¹²⁸ and Palantir,¹²⁹ should create ontologies and coding scheme options that encourage practitioners to embrace vague boundaries of social networks in competitive contexts rather than create rudimentary categories.¹³⁰ All too often technical systems force analysts into coding decisions that oversimplify some aspects of social systems in irregular warfare contexts, like insurgent warfare. For instance, some information systems obligate users to categorize entities based on affiliations and roles, such as “terrorist,” “politician,” or “law enforcement” categories. The fact that some individuals, as seen in this analysis, such as local Colombian law enforcement, can “play both sides” and maintain multiple roles and affiliations, suggests binary approaches can be problematic. As primary stakeholders, operational level decision-makers will have to adopt a more nuanced perspective about insurgent networks, as well as incorporate it into their guidance regarding collection, storage, and analysis of them.

B. LIMITATIONS AND FUTURE RESEARCH

This study is not without its limitations. An obvious limitation is that it is highly unlikely that the Colombian Government collected network data with informant accuracy in mind (Bernard et al., 1984; Freeman & Romney, 1987; Robins, 2015). This issue refers to the association between what people do and their recollection of those actions, which has implications for the reliability of information contained in the demobilization reports.

¹²⁸ For more information, see <https://www.ibm.com/products/i2-analysts-notebook-premium>.

¹²⁹ Like i2, Palantir has several products. See, <https://www.palantir.com/>.

¹³⁰ This point is anecdotal and based on my experience and conversations with many practitioners regarding several information systems.

Nevertheless, this study's emphasis on enduring patterns of ties, rather than event-based, information exchanges, as well as the timing of the interviews in which demobs were interviewed within days of their leaving the insurgent network, mitigated this limitation (Freeman & Romney, 1987; Robins, 2015). Similarly, the demobilization reports paid little attention to defining relational categories commonly seen throughout the reports, such as "associate" ties. Proper training on issues regarding network data coding and ensuring inter-coder reliability would have helped to overcome this limitation.¹³¹ This study's emphasis on two, information-sharing structures alleviated this concern in the sense that it did not intend to capture other, and often poorly defined, relational categories in the demobilization reports.

Another limitation is that it was unable to capture the type and veracity of the information exchanged through interactions. Many relations took place long before individuals participated in the demobilization program and most did not elaborate on what information they exchanged in past interactions. For instance, many demobs described that they exchanged information with their commanders during operations several months prior to leaving the FARC but did not elaborate on the details of their conversations. This gap means that it was impossible to assess if demobs provided accurate information to the government about their past relationships, or if they offered inaccurate or misleading information for reasons such as simply obtaining benefits from the demobilization program or for more nefarious reasons, such as collecting intelligence for the FARC. While the ability to assess individuals' motivations could have played an important role in coding decisions (i.e., if a tie should be coded as "authority" or "insurgent"), the demobilization reports and supplementary open source data did not offer that level of detail.

As noted in Chapter 4, self-organizing and co-evolutionary social processes may differ in other insurgent warfare contexts. Future research could be directed at other case studies in which insurgencies possess different characteristics than the FARC insurgency. This analysis pointed out that no two insurgencies are identical and several factors help

¹³¹ While it is possible government personnel received such training, it is highly unlikely based on engagements with them.

shape it, including its relationship with authorities it seeks to replace, whether it is rural or urban, its ideology, and the nature of the external and internal support it receives (Department of the Army, 2014; Galula, 2006). While this study's results may inform hypotheses in future studies, these factors suggest different social processes could be at play in other contexts.

Another contextual factor future research should consider is accounting for other types of relations that may co-evolve with information-sharing relations. It is possible that financial ties and/or trust-based relations, however defined, as well as digital (e.g., social media) networks, co-evolve with information-sharing ties as defined here. Future research should consider examining competition between three or more networks as well. This perspective may capture aspects of Gventer's (2014) notion of "honeycomb" conflicts whereby multiple insurgents networks compete with authorities and one another. These approaches might become more feasible as social network models, such as SAOMs, become more sophisticated.

Finally, future social network research should consider addressing co-evolution in at least two other competitive contexts in which adversarial networks may overlap. The first is competition between opposing social media networks. For instance, Russian activities on Twitter during the 2016 election included concerted efforts to capitalize on contentious issues in the U.S. (Mueller III, 2019), which begs questions about Russian-based accounts' roles in intertwining otherwise disconnected users and communities on the platform by "weaponizing" polarizing issues. The second context in which this study's framework could offer value is great power competition (GPC). For example, through efforts like its Belt and Road Initiative (BRI), the People's Republic of China (PRC) has gained leverage in key economic sectors, political networks, and regions across the globe, including in U.S. aligned countries (Lawrence & Sutter, 2021; Meia Nouwens, 2021; Office of the Secretary of Defense, 2020; Sutter et al., 2021). Future research could be directed at understanding how U.S. and Chinese aligned commercial networks intertwine and compete in key strategic areas, as well as co-evolve in response to each other's actions.

APPENDIX A. CODEBOOK

A. RELATIONS

Information-Sharing - informal connections that are created by the flow of messages among individuals.

B. ATTRIBUTES

Demobilized—This dynamic, dummy variable indicates the time wave(s) during which an individual was involved in the demobilization program.

Coding Scheme:

0. No

1. Yes

Affiliation—This dynamic variable indicates the waves during which an individual is a member of one of seven categories. Note this analysis treated some of these as binary variables for some effects (e.g., civilian hubs).

Coding Scheme:

1. Armed Forces—individuals employed by the Colombian Armed Forces (e.g., Colombian Navy, Army).

2. Civilian—individuals who did not meet any of the other definitions. Elected politicians were coded as civilians.

3. FARC—individuals who self-identified or who were explicitly stated as a member of the FARC.

4. Government Employee—individuals employed by the Colombian Government but who were not a member of the armed forces, police, or Justice Department.

5. Justice Department—individuals explicitly stated as an employee of Colombia's Justice Department.

6. Militia (FARC)—individuals who self-identified or were explicitly stated as member of FARC’s militia or community action boards.

7. Police—individuals employed by any law enforcement organization, with the exception of the Justice Department.

Gender—This categorical variable represents, as stated in the source documents, the socially constructed characteristics of an individual.

Coding Scheme

1. Male

2. Female

Department—The primary department (i.e., state) in Colombia in which an individual operated. Note some individuals operated in the Southern Bloc’s territory (hence, included in the analysis), but their primary area of operation was elsewhere.

1. Boyacá

2. Caquetá

3. Cauca

4. Choco

5. Cundinamarca

6. Huila

7. Meta

8. Nariño

9. Putumayo

10. Tolima

11. Valle de Cauca

APPENDIX B. RSIENA CODE

This dissertation leveraged and modified existing code from open source scripts at RSiena's website (<https://www.stats.ox.ac.uk/~snijders/siena/>). Due to IRB considerations, the data are not shown here.

C. LOAD PACKAGES

The first step is to load the necessary packages (assuming both are installed already).

```
library(RSiena)
library(network)
```

D. LOAD AND PREP DATA

The next step is to import your network data for each time wave. In this case, I have four time slices for both the “authority information-sharing network” and the “insurgent information-sharing network.” All files have been saved in Pajek format (.net) and are treated as non-directed networks. Also note that I have used “government” interchangeably with “authority” in the scripts below.

```
insurt1.net<-as.matrix(read.paj("TimeSlice1INS.net"), directed=FALSE)
insurt2.net<-as.matrix(read.paj("TimeSlice2INS.net"), directed=FALSE)
insurt3.net<-as.matrix(read.paj("TimeSlice3INS.net"), directed=FALSE)
insurt4.net<-as.matrix(read.paj("TimeSlice4INS.net"), directed=FALSE)

gov1.net<-as.matrix(read.paj("TimeSlice1GOV.net"), directed=FALSE)
gov2.net<-as.matrix(read.paj("TimeSlice2GOV.net"), directed=FALSE)
gov3.net<-as.matrix(read.paj("TimeSlice3GOV.net"), directed=FALSE)
gov4.net<-as.matrix(read.paj("TimeSlice4GOV.net"), directed=FALSE)
```

Use the `sienaDependent` function to establish each network as a dependent variable. The argument `dim` defines the dimensions of the networks (357 actors by 357 actors) and states how many time waves you have for each one (`n=4`).

```
insurgent <- sienaDependent(array(c(insurt1.net,
                                   insurt2.net,
                                   insurt3.net,
                                   insurt4.net),
                                dim=c(357,357,4)))

government <- sienaDependent(array(c(gov1.net,
```

```
gov2.net,
gov3.net,
gov4.net),
dim=c(357,357,4)))
```

Import attributes to represent actor covariates. Here, I began with the “time varying” attributes (i.e., those that change over time) and used `varCovar` to establish each one as a time varying covariate.

```
affiliation <- as.matrix(read.csv("Affiliation.csv," header=T)) # Affil
iation attribute.
aff<-varCovar (affiliation)

demobilization <- as.matrix(read.csv("Demob.csv",header=T)) # Demobiliz
ation attribute.
demob <- varCovar(demobilization)

civilian <- as.matrix(read.csv("Civilian.csv",header=T)) # Civilian att
ribute.
civ <- varCovar(civilian)

farc<- as.matrix(read.csv("FARC.csv",header=T)) # FARC attribute.
farc <- varCovar(farc)

militia<- as.matrix(read.csv("Militia.csv",header=T)) # Militia attribu
te.
militia <- varCovar(militia)
```

Next, I will bring in the constant covariates (i.e., those that do not change over time) and use the `coCovar` to define them as such (Note the “government” attribute is treated as constant because there were not any changes in the underlying data).

```
gender <- as.matrix(read.csv("Gender.csv," header=T)) # Gender attribut
e.
gen <- coCovar(gender [,1])

department <- as.matrix(read.csv("Department.csv," header=T)) #Location
/department attribute.
dep <- coCovar(department [,1])

gov_att <- as.matrix(read.csv("Government.csv," header=T)) # Government
attribute.
gov_att <- coCovar(gov_att [,1])
```

The next step is to create a composite data object comprised of network and attribute data.

```
comp_data <- sienaDataCreate(government,
                             insurgent,
                             aff,
                             demob,
                             gen,
                             dep,
                             civ,
                             farc,
                             militia,
                             gov_att)
comp_data #View your object with this command.
```

E. SETUP DATA FOR MODELING

You can get descriptive statistics for each time wave and examine your data to ensure it meets the recommended guidelines in **RSiena**'s manual (Ripley et al., 2021).

```
print01Report(comp_data, modelname="Multiplex-illustration(myModels - 4
Waves)")
```

The `getEffects` function identifies and describes which independent variables are available in your data (i.e., network configurations, such as triadic closure and between-network effects).

```
comp_effects <- getEffects(comp_data)
View(comp_effects)
```

F. SPECIFY MODEL

Now, establish the models with the `includeEffects` function. Note the `name=` argument indicates the dependent variable. Recall from the dissertation that some independent variables had to be dropped and added based on goodness of fit (GOF) checks and convergence issues.

```
#Model 1

#Self-organizing
comp_effects<- includeEffects(comp_effects,density,transTriads, gwesp,a
ntiInIso2, degPlus,name="insurgent")
comp_effects<- includeEffects(comp_effects,density,transTriads,gwesp,an
tiInIso2, isolateNet,degPlus, name="government")

#Actor covariates
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent",in
teraction1 = "gen")
comp_effects<-includeEffects(comp_effects, sameX, name = "government",i
```

```

interaction1 = "gen")
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent",in
interaction1 = "dep")
comp_effects<-includeEffects(comp_effects, sameX, name = "government,"
interaction1 = "dep")
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent",in
interaction1 = "aff")
comp_effects<-includeEffects(comp_effects, sameX, name = "government",i
interaction1 = "aff")
comp_effects<-includeEffects(comp_effects, sameX, name = "government",i
interaction1 = "demob")
comp_effects

```

Use the `sienaAlgorithmCreate` function to create an object with algorithm specifications.

```

ExampleAlgo <- sienaAlgorithmCreate(useStdInits = FALSE,
                                   projname="Mplex-illustr (four-month
)-M1 - atts," seed=123)

```

G. ESTIMATE MODEL

We can estimate the model now that we have set up everything. You can use `prevAns` if you do not get model convergence at first and `returnDeps` helps with GOF checks later. For more information, see Ripley et al. (2021).

```

mod1 <- siena07(ExampleAlgo,
                data=comp_data,
                effects=comp_effects,
                returnDeps=TRUE)
mod1
mod1<- siena07(ExampleAlgo,
                data=comp_data,
                effects=comp_effects,
                prevAns=mod1,
                returnDeps =TRUE)

```

You can check the model results using the `summary` function. Users can do a collinearity check here as well.

```
summary(mod1)
```

H. WALD TEST

To obtain p-values, users can divide the estimate by its standard error or use the `Multipar.RSiena` function to run a Wald test. Here, I have done the latter (though,

actually, I did both) and I have broken it out by each variable rather than combine them into a list.

```
Multipar.RSiena(mod1, 1)
Multipar.RSiena(mod1, 2)
Multipar.RSiena(mod1, 3) # and so on, for each variable. Here I've put only the first three.
```

I. GOODNESS OF FIT

Next, users can use the `sienaGOF` function to check if models do a good job capturing common tendencies of actors in networks (in general). I begin with degree distributions below for the insurgent network, followed by the authority network. My data are non-directed but `IndegreeDistribution` will still work for this assessment.

```
#Insurgent
gof1.deg_ins <- sienaGOF(mod1,
                        verbose=TRUE,
                        varName="insurgent,"
                        IndegreeDistribution,
                        join = T)

gof1.deg_ins
plot(gof1.deg_ins)

#Authority
gof1.deg_gov <- sienaGOF(mod1,
                        verbose=TRUE,
                        varName="government,"
                        IndegreeDistribution,
                        join = T)

gof1.deg_gov
plot(gof1.deg_gov)
```

Now, use the following code for triad census.

```
#First create the function (again, borrowed from RSiena's website)
TriadCensus <- function(i, data, sims, wave, groupName, varName, levls=
1:16){
  unloadNamespace("igraph") # to avoid package clashes
  require(sna)
  require(network)
  x <- networkExtraction(i, data, sims, wave, groupName, varName)
  if (network.edgcount(x) <= 0){x <- symmetrize(x)}
  # because else triad.census(x) will lead to an error
  tc <- sna::triad.census(x)[1,levls]
  # triad names are transferred automatically
  tc
}
```

```

#Insurgent network
gof.tc_ins <- sienaGOF(mod1,
                      verbose=TRUE,
                      varName="insurgent,"
                      TriadCensus)

gof.tc_ins
plot(gof.tc_ins, scale=TRUE, center=TRUE)

#Government network
gof.tc_gov <- sienaGOF(mod1,
                      verbose=TRUE,
                      varName="government,"
                      TriadCensus)

gof.tc_gov
plot(gof.tc_gov, scale=TRUE, center=TRUE)

```

Finally, consider geodesic distributions. Like much of the code in this appendix, this function is borrowed from **RSiena**'s website.

```

GeodesicDistribution <- function (i, data, sims, period, groupName,
                                varName, levls=c(1:5,Inf), cumulative
                                =TRUE, ...) {
  x <- networkExtraction(i, data, sims, period, groupName, varName)
  require(sna)
  a <- sna::geodist(symmetrize(x))$gdist
  if (cumulative)
  {
    gdi <- sapply(levls, function(i){ sum(a<=i) })
  }
  else
  {
    gdi <- sapply(levls, function(i){ sum(a==i) })
  }
  names(gdi) <- as.character(levls)
  gdi
}

```

Here is a GOF check for geodesic distribution pertaining to the insurgent network.

```

#Insurgent
gof.gd_INS <- sienaGOF(mod1,
                      verbose=TRUE,
                      varName="insurgent,"
                      GeodesicDistribution,
                      join=T,
                      cumulative=F,
                      returnDeps=TRUE)

```

```
gof.gd_INS
plot(gof.gd_INS, scale=TRUE, center=TRUE)
```

Now, check the authority network.

```
#Authority
gof.gd_GOV <- sienaGOF(mod1,
                        verbose=TRUE,
                        varName="government,"
                        GeodesicDistribution,
                        join=T,
                        cumulative=F,
                        returnDeps=TRUE)
gof.gd_GOV
plot(gof.gd_GOV, scale=TRUE, center=TRUE)
```

J. MODEL 2: CO-EVOLUTION MODEL

Begin by including effects into the model. Recall that the code below reflects the final effects after many iterations checking for multicollinearity, goodness of fit, etc. Again, the `name=` argument identifies the dependent variable/network.

```
#Self-organizing effects
comp_effects<- includeEffects(comp_effects,
                              density,
                              transTriads,
                              gwesp,
                              antiInIso2,
                              degPlus,
                              name="insurgent")

comp_effects <- includeEffects(comp_effects,
                              density,
                              transTriads,
                              gwesp,
                              antiInIso2,
                              degPlus,
                              isolateNet,
                              name="government")
```

Next, include the actor covariates.

```
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent",in
teraction1 = "gen")
comp_effects<-includeEffects(comp_effects, sameX, name = "government",i
nteraction1 = "gen")
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent",in
teraction1 = "dep")
comp_effects<-includeEffects(comp_effects, sameX, name = "government,"
```

```

interaction1 = "dep")
comp_effects<-includeEffects(comp_effects, sameX, name = "insurgent", interaction1 = "aff")
comp_effects<-includeEffects(comp_effects, sameX, name = "government", interaction1 = "aff")
comp_effects<-includeEffects(comp_effects, sameX, name = "government", interaction1 = "demob")

```

The code below includes between-network, or co-evolutionary effects.

```

#Insurgent effect on authority (insurgent==>authority)
comp_effects <- includeEffects(comp_effects,
                                crprod,
                                name="government",
                                interaction1="insurgent")#Gov effect on
insurgent

#Insurgent effect on authority (cluster-level)
comp_effects <- includeEffects(comp_effects,
                                gwespMix,
                                name="government",
                                interaction1="insurgent")# Insurgent effect on government at cluster level.

#Various hub-related processes
comp_effects <- includeEffects(comp_effects,
                                inPopIntnX,
                                name="government",
                                interaction1="insurgent",
                                interaction2 = "civ")

comp_effects <- includeEffects(comp_effects,
                                inPopIntnX,
                                name="government",
                                interaction1="insurgent",
                                interaction2 = "farc") #Note I use the term "insurgent" rather than "FARC" in the dissertation results section.
comp_effects <- includeEffects(comp_effects,
                                inPopIntnX,
                                name="government",
                                interaction1="insurgent",
                                interaction2 = "militia")

comp_effects <- includeEffects(comp_effects,
                                inPopIntnX,
                                name="insurgent",
                                interaction1="government",
                                interaction2 = "civ")

```

K. CO-EVOLUTION GOODNESS OF FIT

The final step is to re-run goodness of fit checks on the networks again (not depicted here).

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