Computational Social Sciences

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Computational Conflict Research

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Computational Social Sciences

Computational Social Sciences

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Computational Conflict Research

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Advancing Conflict Research Through Computational Approaches

Emanuel Deutschmann, Jan Lorenz, and Luis G. Nardin

Abstract Conflict, from small-scale verbal disputes to large-scale violent war between nations, is one of the most fundamental elements of social life and a central topic in social science research. The main argument of this book is that computational approaches have enormous potential to advance conflict research, e.g., by making use of the ever-growing computer processing power to model complex conflict dynamics, by drawing on innovative methods from simulation to machine learning, and by building on vast quantities of conflict-related data that emerge at unprecedented scale in the digital age. Our goal is (a) to demonstrate how such computational approaches can be used to improve our understanding of conflict at any scale and (b) to call for the consolidation of *computational conflict research* as a unified field of research that collectively aims to gather such insights. We first give an overview of how various computational approaches have already impacted on conflict research and then guide through the different chapters that form part of this book. Finally, we propose to map the field of computational conflict research by positioning studies in a two-dimensional space depending on the intensity of the analyzed conflict and the chosen computational approach.

Keywords Conflict research · Computational social science · Agent-based models · Geographic information systems · Advancement of science

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1 Introduction

From small-scale, non-violent disputes to large-scale war between nations, conflict is a central element of social life and has captivated the collective consciousness for millennia. In the fifth century B.C., Greek philosopher Heraclitus famously argued that "war is the father and king of all" and that conflict and strife between opposites maintains the world (Graham, 2019). Many centuries later, sociologist Georg Simmel would, in a similar vein, state that a society without conflict is "not only impossible empirically, but it would also display no essential life-process and no stable structure." Social life, he posited, always "requires some quantitative relation of harmony and disharmony, association and dissociation, liking and disliking, in order to attain to a definite formation" (Simmel, 1904, p. 491). Many related assertions could be listed: From Marx's depiction of all past history as class struggle (Marx and Engels, 2002) to Dahrendorf's conflict theory, which put clashing interests between conflict groups at the heart of questions of social stability and change (Ritzer and Stepnisky, 2017), conflict is seen as *the* fundamental principle that shapes society and history: "Because there is conflict, there is historical change and development," as Dahrendorf (1959, p. 208) put it.

Between societies, too, conflict has long been recognized as an essential force. In history and political philosophy, many of the classic works are centered on clashes and contentions: From Thucydides' *History of the Peloponnesian War* and Caesar's *De bello Gallico* to Machiavelli's *Prince* and Hobbes's *Leviathan*, the issue of violent struggle for power between cities, states, and empires of all kinds has been key. From psychology to international relations, conflict is one of the central fields of inquiry, with classic work searching for the root causes of conflict at various levels of analysis, from individual human predispositions and behavior to the spread of ideology and structural relations between states to the anarchic international system (Waltz, 2001; Rapoport, 1995). In short, it is hard to imagine human life without conflict. Rather, conflict can be seen as a "chronic condition" (Rapoport, 1995, p. xxi) we have to live under. Consequently, it is unsurprising that efforts to understand conflict have been abundant. The statement that "more has been written on conflict than on any other subject save two: love and God" (Luce and Raiffa, 1989, as cited in Rapoport, 1995, p. xxi) puts this impression into words.[1]

While this centrality of conflict for the human condition may be justification enough for the continued attempts of a range of scientific fields to better understand conflict in its manifold forms, another central motivation is, of course, the search for ways to control, reduce, or even prevent conflict. "Are there ways of decreasing the incidence of war, or increasing the chances of peace? Can we have peace more often in the future than in the past?" asks, for instance, Waltz (2001, p. 1). This

[1]Luce and Raiffa (1989, p. 1) actually talk specifically about "conflict of interest" and mention "inner struggle" as a third topic that has received "comparable attention" apart from "God" and "love." Rapoport may have misremembered the exact quote or he deliberately subsumed "conflict of interest" and "inner struggle" under "conflict."

desire to contribute to a saver, less conflictual world became most urgent in the face of total annihilation during the Cold War. As Rapoport (1995, p. xxii) put it, talking about nuclear war: "understand it we must, if we want a chance of escaping what it threatens." An entire field, peace science, now aims at understanding the conditions for conflict resolution. Improving our understanding of the causes, structures, mechanisms, spatio-temporal dynamics, and consequences of conflict is thus an important goal of social science research.

Recently, computational social science has set out to advance social research by using the ever-growing computer processing power, methodological innovations, and the emergence of vast quantities of data in the digital age to achieve better knowledge about social phenomena. The central thesis of this book is that such computational approaches have enormous potential to advance conflict research. Our goal in this introductory chapter—and the book as a whole—is (a) to demonstrate how such computational approaches can be used to improve our understanding of conflict at any scale and (b) to call for the consolidation of *computational conflict research* as a field of research that collectively aims to gather such insights.

We argue that computational conflict research, i.e., the use of computational approaches to study conflict, can advance conflict research through at least three major innovative pathways:

1. The identification of spatio-temporal dynamics and mechanisms behind conflicts through simulation models that allow to track the interaction of actors in conflict scenarios and to understand the emergence of aggregated, macro-level consequences.
2. The availability of new, fine-grained datasets of conflict events at all scales from the local to the global ("big data") that have become available through digitization together with novel techniques in the computer age to collect, store, and analyze such data.
3. The combination of these simulation and other advanced computational methods with this vast, fine-grained empirical data.

To demonstrate the potential of these innovations for conflict research, this book brings together a set of (a) chapters that discuss these advances in data availability and guide through some of these computational methods and (b) original studies that showcase how various cutting-edge computational approaches can lead to new insights on conflict at various geographic scales and degrees of violence. Following Hillmann (2007, p. 432), conflict is understood in this book as opposition, tensions, clashes, enmities, struggles, or fights of various intensities between social units. This definition is deliberately broad: Social units can range from small groups of individuals without formal organization to institutions with differentiated organizational structure to large and complex units such as entire nation-states or even batches of countries. Examples in this book will include street protesters, terrorist organizations, rebel groups, political parties, and sets of parliaments.

Conflict, as understood here, can be non-violent or violent.[2] Some studies in this book will deal with the former, covering social, non-violent conflicts such as clashes between political parties in parliamentary debates or normative shifts in social networks, while others will deal with the latter, including the spatial structure of civil war violence or the extortion mechanisms rebel groups use to exploit enterprises.[3]

This chapter is structured as follows: We first give a short summary of the rise of computational social science for readers who are unfamiliar with this trend (Sect. 2). Next, we discuss how computational approaches have already enriched conflict research (Sect. 3). Finally, we give an overview of the contributions of this volume, laying out how they move the field forward. We also offer a visualization that allows to map the field of computational conflict research in a two-dimensional space (Sect. 4).

2 The Rise of Computational Social Science

The modern field of computational social science has emerged at the end of the first decade of our century starting with a “Perspective” article in *Science* (Lazer et al., 2009) mainly from scientists in North America, followed by a “Manifesto” (Conte et al., 2012) from scientists in Europe, leading to a great many books, conferences, summer schools, institutes, and novel job postings and titles all over the world in recent years.

The main driver of the popularity of computational social science in the past 10 years was clearly the new availability of large-scale digital data that humans now create by spending time online and by carrying mobile devices. This data accumulates in companies, government agencies, and on the devices of users. Just as a matter of business, engineers from the tech, internet, and information industries enabled, created, and processed increasing amounts of social and cultural data, and,

[2] Gleditsch, in the chapter “Advances in Data on Conflict” of this book, will identify too narrow definitions of conflict that focus on violent conflict alone as one major obstacle that prevents progress in the field. He gives the example of recent street protests in Venezuela and argues that it would be “absurd” not to treat this as a conflict due to the absence of organized armed violence in the sense of a civil war. By taking a broad perspective and combining research on non-violent and violent conflict, this book aims to contribute to overcoming this issue.

[3] When we use the term “violence” to classify the research conducted in this book, we use it to denote *physical* violence. Some definitions of violence, e.g., by the World Health Organization, also treat *psychological* and *emotional* violence as sub-types of violence (Krug et al., 2002). Sometimes *verbal* violence is described as another type of violence (Nieto et al., 2018). In that sense, words—and thus, for instance, also the analyses of parliamentary speeches analyzed in Part II of the book, which we titled “Computational Research on *Non-Violent* conflict” could also be seen as potentially dealing with violence, if such a broader definition of violence were used. Yet we deem the distinction between conflict based on physical force (=violence) and that carried out without the use of physical force (=non-violently) meaningful and thus decided to stick to it. In principle, computational conflict research could of course cover any kind of violence.

as a consequence, they interfered more and more with large-scale societal processes themselves. Business development in this situation requires not only technical skills but also skills in the interpretation of social data, leading to the emergence of the jobs as data scientists or social data scientists that have combined knowledge in statistics, computer science, and—in particular—social sciences.

While the "social data scientist" is to a large extent an invention of the business world, the term "computational social science" comes from academia—somewhat surprisingly, however, not so much from within the social sciences themselves. Many authors of the two seminal papers (Lazer et al., 2009; Conte et al., 2012) did not obtain their undergraduate training in a social science. They often conducted research in fields such as complex systems, sociophysics, network science, simulation, and agent-based modeling before the term computational social science appeared. Research on complex systems and related fields typically aims at a fundamental understanding of dynamical processes with many independent actors (Simon, 1962). The mode of computation is usually computer simulation (Gilbert and Troitzsch, 2005) and the relation to data is often focused on the explanation of large-scale empirical regularities: the *stylized facts*, with fat-tailed distributions as the seminal example (Price, 1976; Gabaix et al., 2003).

Due to the focus on universal mechanisms and the interdisciplinarity of contributors also from outside of the traditional social sciences, computational social science represents an integrated approach to the social sciences, where the traditional social and behavioral sciences serve as different perspectives for modeling how people think (psychology), handle wealth (economics), relate to each other (sociology), govern themselves (political science), and create culture (anthropology) (Conte et al., 2012), or operate in geographical space (Torrens, 2010) to gain quantitative and qualitative insight about societal questions and real-world problems (cf. Watts, 2013; Keuschnigg et al., 2017). These aspects can be subsumed under the current, broad definition by Amaral (2017, p. 1) that understands computational social science as an "interdisciplinary and emerging scientific field [that] uses computationally methods to analyze and model social phenomena, social structures, and collective behavior." Following this definition, *computational* refers to at least three very different aspects of computing: the retrieval, storage, and processing of massive amounts of digital behavioral data; the development of algorithms for inference, prediction, and automated decision-making based on that data; and the implementation of dynamic computer models for the simulation of social processes.

Many other disciplines have had a "computational" branch for a much longer time than the social sciences. There is computational physics, computational biology, and computational economics to name a few. Also, computational sociology has been formulated already in the time before the omnipresence of the internet and large-scale digital behavioral data, acknowledging that any modern science builds not only on a theoretical and an empirical, but also on a computational component (Hummon and Fararo, 1995).

Today, computational social science is sometimes reduced to being a new science that provides methods for retrieving digital behavioral data for the analysis of people's social behavior online. Our perspective on the field is broader, including the older simulation-based focus on fundamental mechanisms (e.g., Epstein and Axtell, 1996; Axelrod, 1997). We see computational social science as contributing to a basic scientific understanding of social processes, to the development of new methods, to societal insights informing current political debates and international relations. In the following section, we discuss how computational social science, understood in this broad sense, has already impacted on the field of conflict research.

3 Computational Approaches to Conflict Research

The use of computational approaches in conflict research is not a new endeavor. A broad range of methods, techniques, and systems have been developed in various scientific fields, including the areas of machine learning, social network analysis, geographic information systems, and computational simulation. In the following, we give a short overview of these strands of research. This review should be understood more as a starting point rather than an end point in mapping the field. Hence, we do not claim completeness and interested readers are invited to explore the works cited in the other chapters of this book, which may serve as useful additional reference points.

Machine learning methods define algorithms, or a set of step-by-step computational procedures, with the aim to find an appropriate model that describes non-trivial regularities in data. In conflict research, these methods have been initially adopted to develop predictive models of conflict outcomes (Schrodt, 1984, 1987, 1990, 1991) and conflict mediation attempts (Trappl, 1992; Fürnkranz et al., 1994; Trappl et al., 1996, 1997).[4] With the growing availability of detailed empirical data in the last decades, however, the focus has shifted from predicting outcomes in ongoing conflicts to derive early warning indicators of conflicts in the hope for preventing them (Schrodt, 1997; Beck et al., 2000; Schrodt and Gerner, 2000; Trappl et al., 2006; Subramanian and Stoll, 2006; Zammit-Mangion et al., 2012; Perry, 2013; Helbing et al., 2015). Despite the latest major efforts on developing systems of early warning (Trappl, 2006; O'Brien, 2010; Guo et al., 2018), no system has established itself as a reliable tool for policy-making yet (Cederman and Weidmann, 2017). Cederman and Weidmann (2017) identify several pitfalls and provide a number of recommendations on how existing work on data-driven conflict research can be improved.

Most of these machine learning methods cannot only be applied to numeric data, but also to symbolic data (i.e., text, images, and video). These methods are subsumed under the label of computer-aided content analysis (Weber, 1984). Conflict research benefits from these methods by identifying the relation between particular actors and indicators of violence in textual data, thus supporting the analysis of,

[4] A more detailed overview of the initial uses of these methods in conflict research can be found in Trappl and Miksch (1991).

e.g., online hate speech campaigns, cyber mobbing, and social media flame wars. Examples include analyses of collective sense-making after terrorist attacks based on Twitter comments (Fischer-Preßler et al., 2019) and verbal discrimination against African Americans in the media based on online newspaper articles (Leschke and Schwemmer, 2019). Further details and a survey on the use of these methods in conflict research are available in the chapter "Text as Data for Conflict Research" of this book.

Despite the fact that conflicts are strongly influenced by network dynamics, machine learning methods rarely integrate these dynamics to study interaction between more than two groups. Social network analysis complements these methods and sheds light on the structural and dynamic interaction aspects of the multiple groups involved in conflicts (Wolfe, 2004). Social network analysis has been recognized to be useful for mapping groups' structure, to identify the division of power within these groups, and to uncover their internal dynamics, patterns of socialization, and the nature of their decision-making processes (Kramer, 2017). Hammarstr and Heldt (2002) successfully applied network analysis methods to study the diffusion of interstate military conflict, while Takács (2002) investigated the influences of segregation on the likelihood of intergroup conflicts when individuals or groups compete for scarce resources. More specifically, the descriptive and explanatory potential of social network analysis has been demonstrated appropriate to study terrorism activities and organizations (Perliger and Pedahzur, 2011; Deutschmann, 2016), to understand the influence of social network structure on the flexibility of a rebel group in peace negotiations (Lilja, 2012), and to assess the influence of antigovernment network structures (i.e., alliances and strategic interactions) in generating conflictual behavior (Metternich et al., 2013).

Analogous to social network analysis that enhances conflict studies by integrating network dynamics, geographic information systems (GIS) offer techniques for refining these studies through the incorporation of spatial data into the analysis (Branch, 2016). Although spatial relationships have often been analyzed in a general way in qualitative conflict research, the recent advances in computing power and the increasing availability of disaggregated and high-resolution spatial data have enabled more sophisticated and quantitative studies (Stephenne et al., 2009; Gleditsch and Weidmann, 2012). Despite these advances, introducing the spatial dimension to conflict research still poses several challenges: *Practical*, because of the lack of high quality open-source GIS software tools and the lack of educational training in spatial methods and programming; *Theoretical*, related to different aspects of the definition of "space," such as choosing spatial units and the appropriate resolution for analysis, as well as the right measure of distance; and *Statistical*, because of the dependent nature of spatial units of analysis and their interaction with time (Stephenne et al., 2009; Gleditsch and Weidmann, 2012).

While the previously discussed data-driven approaches are primarily focused on uncovering correlations in empirical data, computational *simulation-based* approaches create a bridge between theory and data that can be used to demonstrate causality. Computational conflict simulation models first appeared during the Cold War (Cioffi-Revilla and Rouleau, 2010). These models used systems of ordinary differential equation or difference equations (ODE) and were implemented using the system dynamics approach (Forrester, 1968). Bremer and Mihalka (1977), following a complex systems approach, developed a discrete model composed of states arrayed geographically and with imperfect perception, provided each with a quantity of "power," endowed each with action rules based on realistic principles, and set them off to interact with one another in iterative cycles of conflict and cooperation. This model aimed to investigate the likelihood that a power equilibrium can be achieved under particular conditions (Duffy and Tucker, 1995). Cusack and Stool (1990) extended the Bremer and Mihalka model incorporating more realistic rules in which states play multiple roles and they assessed the effects that different sets of rules have on the survival and endurance of states and state systems (Duffy and Tucker, 1995). In line with the complex systems approach, Axelrod (1995) proposed a model to understand the future of global politics through extortion and cooperation among states.

Although different approaches have been used to model and investigate conflicts over the decades, system dynamics was the dominant one until the introduction of the agent-based modeling (ABM) approach (Burton et al., 2017). Cederman (2002) presented a series of agent-based models that trace complex macrohistorical transformations of actors. He argued that in addition to the advantages usually attributed to ABM (i.e., bounded rationality and heterogeneity of entities), this technique also promises to overcome the reification of actors by allowing to superimpose higher-level structures on a lower-level grid of primitive actors. The groundwork of the use of ABM in conflict research was laid by Epstein (2002), who analyzed the conditions under which individuals may mobilize and protest. He examined the complex dynamics of decentralized rebellion and interethnic civil violence and factors such as the legitimacy of a political system, risk-aversion of potential protesters, police strength, and geographic reach. Epstein's model of civil conflict has subsequently been extended (Ilachinski, 2004; Goh et al., 2006; Lemos et al., 2016; Fonoberova et al., 2018). Bhavnani et al. (2008) created an agent-based computational framework that incorporates factors such as ethnicity, polarization, dominance, and resource type, allowing the study of the relationship between natural resources, ethnicity, and civil war. Similarly, Cioffi-Revilla and Rouleau (2010) developed a model that considers how freedom of social interaction within a state may lead to rebellion and possibly regime change.

Despite the long-standing use of data-driven and simulation-based computational approaches to conflict research, the field of computational conflict research is not clearly defined yet. The efforts are spread over several scientific fields that in their majority do not have the conflict domain as their main target, but rather use it as an application domain in which their methods can be applied. Hence, our book aims at contributing to advancing the field of computational conflict research through a more complete and systematic analysis of what can be done with computational approaches in studying conflict. In the following section, we describe more concretely how the contributions of this book help achieve this goal.

4 The Contributions of This Book

This book covers computational conflict research in a range of facets, with its contributions using a variety of different approaches on several dimensions (methodology, conflict scale, geographic focus, etc.). It thereby addresses the full scope of the field, including primarily data-driven as well as primarily simulation-based approaches. The book brings together contributions from leading and emerging scholars with a diversity of disciplinary backgrounds from physics, mathematics, and biology to computer and data science to sociology and political science. The volume is also a truly international endeavor, with its authors' institutional affiliations reaching across thirteen countries on three continents.

Methodologically, the book covers a variety of computational approaches from text mining and machine learning to agent-based modeling and simulation to social network analysis. Table 1 gives a more fine-grained overview of the different methodologies and computational approaches used.

Regarding data, several chapters make use of empirical conflict data that has only recently become available in such detail, be it large corpora of text or fine-grained,

Table 1 Computational approaches used/covered in the chapters of this book

Chapter	Short title	Computational approach(es)
2	Advances in Data on Conflict	N/A
3	Text as Data for Conflict Research	Machine learning
		Automated content analysis
		Topic modeling
		Text mining
4	Relational Event Models	Social network analysis
		Relational event models
5	Migration Policy Framing	Machine learning
		Topic modeling
6	Norm Conflict in Social Networks	Social network analysis
		Agent-based modeling
7	Fate of Social Protests	Agent-based modeling
8	Non-state Armed Groups	Social network analysis
		Agent-based modeling
		Markov chain Monte Carlo
		Hawkes process
9	Violence Against Civilians	Matched wake analysis
10	Conflict Diffusion over Continuous Space	Spatial statistics
		Continuous space model
		Log-Gaussian Cox process model
11	Rebel Group Protection Rackets	Agent-based modeling

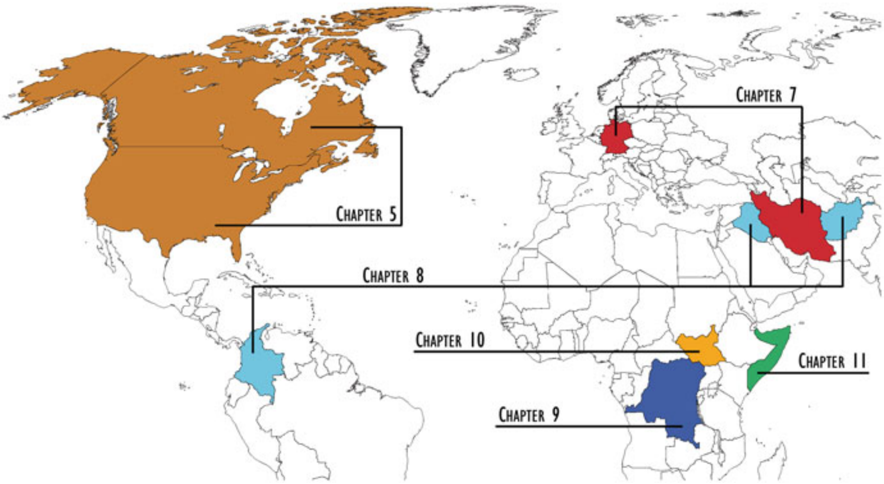

Fig. 1 Overview of the geographic location of the case studies contained in this book

geo-tagged information on conflict events coded globally from news reports.[5] Geographically, these case studies add up to a comprehensive set of analyses of recent conflicts that spans multiple continents, as the map in Fig. 1 reveals. These contentions range from conflict lines in parliamentary debates on migration policy in the USA and Canada from 1994 to 2016 (chapter "Migration Policy Framing") and the representation of street protest in Germany (2014–15) and Iran (2017–18) on social media (chapter "Fate of Social Protests") to terrorist attacks in Colombia, Afghanistan, and Iraq between 2001 and 2005 (chapter "Non-state Armed Groups") and violence against civilians in the Democratic Republic of Congo in 1998–2000 (chapter "Violence Against Civilians") to conflict diffusion in South Sudan between 2014 and 2018 (chapter "Conflict Diffusion over Continuous Space") and rebel group behavior in Somalia from 1991 to the present day (chapter "Rebel Group Protection Rackets"). Hence, a broad range of recent conflicts is covered.

The book is structured in three parts. Part I focuses on data and methods in computational conflict research and contains three contributions. Part II deals with non-violent, social conflict and comprises three chapters. Part III is about computational approaches to violent conflict and covers four chapters. In the following, we give a short overview about these individual chapters.

In the chapter "Advances in Data on Conflict," Kristian Gleditsch, building on more than two decades of experience in peace and conflict studies, takes a look at the role of data in driving innovation in the field. He argues that the growth of systematic empirical data has been a central innovative force that has brought the

[5]For an overview of recent developments in data on conflict see the contribution by Gleditsch in the chapter "Advances in Data on Conflict" of this volume.

field forward. Drawing on several examples, he demonstrates how data has served as a source of theoretical innovation in the field. This progress in data availability, he argues, has helped generate new research agendas. His contribution ends with an inventory of the most valuable data sources on conflict events to date—which, we believe, may be highly useful for readers interested in conducting their own research on conflicts globally.

In the chapter "Text as Data for Conflict Research," Seraphine F. Maerz and Cornelius Puschmann give insights into how text can be used as data for conflict research. Arguing that computer-aided text analysis offers exciting new possibilities for conflict research, they delve into computational procedures that allow to analyze large quantities of text, from supervised and unsupervised machine learning to more traditional forms of content analysis, such as dictionaries. To illustrate these approaches, they draw on a range of example studies that investigate conflict based on text material across different formats and genres. This includes both conflict verbalized in news media, political speeches, and other public documents and conflict that occurs directly within online spaces like social media platforms and internet forums. Finally, they highlight cross-validation as a crucial step in using text as data for conflict research.

In the chapter "Relational Event Models," Laurence Brandenberger introduces relational event models (REMs) as a powerful tool to examine how conflicts arise through human interaction and how they evolve over time. Building on event history analysis, these models combine network dependencies with temporal dynamics and allow for the analysis of social influencing and group formation patterns. The added information on the timing of social interactions and the broader network in which actors are embedded can uncover meaningful social mechanisms, Brandenberger argues. To illustrate the added value of REMs, the chapter showcases two empirical studies. The first one shows that countries engaging in military actions in the Gulf region do so by balancing their relations, i.e., by supporting allies of their allies and opposing enemies of their allies. The second one shows that party family homophily guides parliamentary veto decisions and provides empirical evidence of social influencing dynamics among European parliaments. Brandenberger also references her R package, which allows interested conflict researchers to apply REMs.

The chapter "Migration Policy Framing" opens Part II of the book with research on non-violent, social conflicts. Sanja Hajdinjak, Marcella H. Morris, and Tyler Amos put the text-as-data approach that was laid out in the chapter "Text as Data for Conflict Research" into empirical practice. Drawing on more than a decade of parliamentary speeches from the USA and Canada, they analyze how parties frame migration topics in political discourse. Building on work that argues that migration falls in a gap between established societal cleavages over which parties do not have robust, issue-specific ownership, Hajdinjak et al. argue that parties engage in debates on migration topics by diverting attention to areas in which they *have* established issue ownership. Using structural topic models, they test this assertion by measuring the differences in salience and framing of migration-related topics over time in the debates of the lower houses of Canada and the USA. Doing so, they do indeed find that, in both countries, liberals frame migration differently than conservatives.

In the chapter “Norm Conflict in Social Networks,” an interdisciplinary team of psychologists, sociologists, and physicists—Julian Kohne, Natalie Gallagher, Zeynep Melis Kirgil, Rocco Paolillo, Lars Padmos, and Fariba Karimi—model the spread and clash of norms in social networks. They argue that arriving at an overarching normative consensus in groups with different social norms can lead to intra- and intergroup conflict. Kohne et al. develop an agent-based model that allows to simulate the convergence of norms in social networks with two different groups in different network structures. Their model can adjust group sizes, levels of homophily as well as initial distribution of norms within the groups. Agents in the model update their norms according to the classic Granovetter threshold model, where a norm changes when the proportion of the agents’ ego-network displaying a different norm exceeds the agents’ threshold. Conflict, in line with Heider’s balance theory, is operationalized by the proportion of edges between agents that hold a different norm in converged networks. Their results suggest that norm change is most likely when norms are strongly correlated with group membership. Heterophilic network structures, with small to middling minority groups, exert the most pressure on groups to conform to one another. While the results of these simulations demonstrate that the level of homophily determines the potential conflict between groups and within groups, this contribution also showcases the impressive possibilities of ever-increasing computing power and how they can be used for conflict research: Kohne et al. ran their agent-based simulation on a high performance computing cluster; their simulation took about 315 hours to complete and generated 40 Gigabytes of output data.

Gravovetter’s threshold model and the spread of information in networks also play a role in the chapter “Fate of Social Protests,” in which Ahmadreza Asgharpourmasouleh, Masoud Fattahzadeh, Daniel Mayerhoffer, and Jan Lorenz simulate conditions for the emergence of social protests in an agent-based model. They draw on two recent historical protests from Iran and Germany to inform the modeling process. In their agent-based model, people, who are interconnected in networks, interact and exchange their concerns on a finite number of topics. They may start to protest either because their concern or the fraction of protesters in their social contacts exceeds their protest threshold, as in Granovetter’s threshold model. In contrast to many other models of social protests, their model also studies the coevolution of topics of concern in the public that is not (yet) protesting. Given that often a small number of citizens starts a protest, its fate depends not only on the dynamics of social activation but also on the buildup of concern with respect to competing topics. Asgharpourmasouleh et al. argue that today, this buildup often occurs in a decentralized way through social media. Their agent-based simulation allows to reproduce the structural features of the evolution of the two empirical cases of social protests in Iran and Germany.

In the chapter “Non-state Armed Groups,” an interdisciplinary team with backgrounds in data science, philosophy, biology, and political science—Simone Cremaschi, Baris Kirdemir, Juan Masullo, Adam R. Pah, Nicolas Payette, and Rithvik

Yarlagadda—look at the network structure of non-state armed groups (NSAGs) in Colombia, Iraq, and Afghanistan from 2001 to 2005. They use a self-exciting temporal model to ask if the behavior of one NSAG affects the behavior of other groups operating in the same country and if the actions of groups with actual ties (i.e., groups with some recognized relationship) have a larger effect than those with environmental ties (i.e., groups simply operating in the same country). The team finds mixed results for the notion that the actions of one NSAG influence the actions of others operating in the same conflict. In Iraq and Afghanistan, they find evidence that NSAG actions *do* influence the timing of attacks by other NSAGs; however, there is no discernible link between NSAG actions and the timing of attacks in Colombia. However, they do consistently find that there is no significant difference between the effects that actual or environmental ties could have in these three cases.

In the chapter "Violence Against Civilians," political scientists Andrea Salvi, Mark Williamson, and Jessica Draper examine why some conflict zones exhibit more violence against civilians than others. They assess that past research has emphasized ethnic fractionalization, territorial control, and strategic incentives, but overlooked the consequences of armed conflict itself. This oversight, Salvi et al. argue, is partly due to the methodological hurdles of finding an appropriate counterfactual for observed battle events. In their contribution, they aim to test empirically the effect of instances of armed clashes between rebels and the government in civil wars on violence against civilians. Battles between belligerents may create conditions that lead to surges in civilian killings as combatants seek to consolidate civilian control or inflict punishment against populations residing near areas of contestation. Since there is no relevant counterfactual for these battles, they utilize road networks to help build a synthetic risk-set of plausible locations for conflict. Road networks are crucial for the logistical operations of a civil war and are thus the main conduit for conflict diffusion. As such, the majority of battles should take place in the proximity of road networks; by simulating events in the same geographic area, Salvi et al. are able to better approximate locations where battles hypothetically could have occurred, but did not. They test this simulation approach using a case study of the Democratic Republic of the Congo (1998–2000) and model the causal effect of battles using a spatially disaggregated framework. Their work contributes to the literature on civil war violence by offering a framework for crafting synthetic counterfactuals with event data, and by proposing an empirical test for explaining the variation of violence against civilians as a result of battle events.

In the chapter "Conflict diffusion over Continuous Space," statistician Claire Kelling and political scientist YiJyun Lin study the diffusion of conflict events through an innovative application of methods of spatial statistics. They investigate how spatial interdependencies between conflict events vary depending on several attributes of the events and actors involved. Kelling and Lin build on the fact—similarly observed by Gleditsch in the chapter "Advances in Data on Conflict"—that due to recent technological advances, conflict events can now be analyzed using data measured at the event level, rather than relying on aggregated units. Looking at the case of South Sudan, they demonstrate how the intensity function defined by the log-Gaussian Cox process model can be used to explore the complex underlying diffusion mechanism under various characteristics of conflict events. Their findings add to the explanation of the process of conflict diffusion, e.g., by revealing that battles with territorial gains for one side tend to diffuse over larger distances than battles with no territorial change, and that conflicts with longer duration exhibit stronger spatial dependence.

In the chapter "Rebel Group Protection Rackets," Frances Duffy, Kamil C. Klosek, Luis G. Nardin, and Gerd Wagner present an agent-based model that simulates how rebel groups compete for territory and how they extort local enterprises to finance their endeavors. In this model, rebel groups engage in a series of economic transactions with the local population during a civil war. These interactions resemble those of a protection racket, in which aspiring governing groups extort the local economic actors to fund their fighting activities and control the territory. Seeking security in this unstable political environment, these economic actors may decide to flee or to pay the rebels in order to ensure their own protection, impacting the outcomes of the civil war. The model reveals mechanisms that are helpful for understanding violence outcomes in civil wars, and the conditions that may lead certain rebel groups to prevail. By simulating several different scenarios, Duffy et al. demonstrate the impact that different security factors have on civil war dynamics. Using Somalia as a case study, they also assess the importance of rebel groups' economic bases of support in a real-world setting.

The agent-based simulation models constructed in several of these chapters are all available online. They can be downloaded or applied directly in the web browser. Interested readers can thus replicate the outcomes presented in this book, adjust parameters, and build on the code to advance in their own research. An overview of this online material is available at the end of this book, together with information on further supplementary material, such as replication files and links to the data sources used.

Figure 2 shows how the chapters that are based on empirical studies (i.e., Parts II and III of the book) can be placed on a two-dimensional space that can be interpreted as representing the field of computational conflict research. In this space, the vertical axis describes the intensity of the conflict studied, running from "non-violent" to "violent." The horizontal axis describes the computational approach that is used, ranging from "simulation-based" to "data-driven." As can be seen, the book at hand covers all four quadrants that constitute the field. The chapter "Norm Conflict in Social Networks," for example, where the interaction of actors with different social norms is studied, is an example of computational conflict research that is based entirely on simulations and that deals with non-violent, social conflict. The chapter "Migration Policy Framing," in which party differences in parliamentary debates are analyzed, also deals with non-violent conflict, but is mostly data-driven. In the upper left quadrant, we see the chapter "Rebel Group Protection Rackets," which, with its agent-based model on rebel group protection rackets, deals with violent conflict and is mainly simulation-based, although some parameters are adjusted according to the real-world case of Somalia as mentioned above (accordingly, it is placed somewhat towards the center of the horizontal axis,

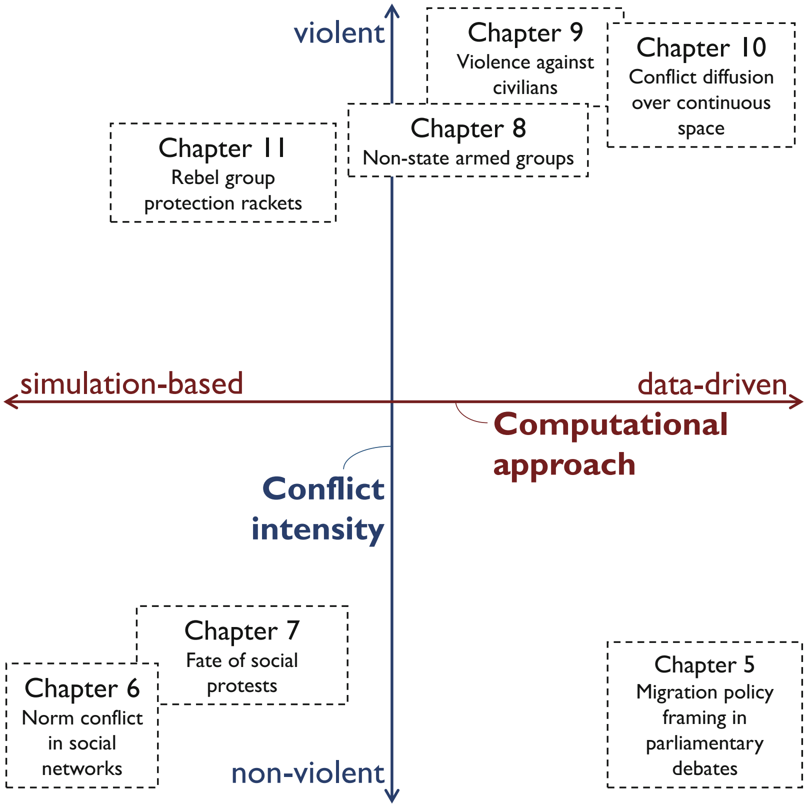

Fig. 2 Positioning the contributions of this book in a two-dimensional space that forms the field of computational conflict research

denoting a mix of both simulation-based and data-driven approaches). Finally, in the upper right corner, we see, for instance, the chapter "Conflict Diffusion over Continuous Space," which deals with the diffusion of *violent* conflict events (e.g., battles) in continuous space and is mainly data-driven. The chapter "Non-state Armed Groups" uses both a large-scale dataset and draws on simulation techniques and is thus placed toward the center of the horizontal axis.

Although this two-dimensional representation is of course quite simple—and perhaps even simplistic—it should in theory be possible to place any research conducted in the field of computational conflict research—including the studies discussed in Sect. 3—somewhere in this space. We thus hope this representation may prove to become a useful heuristic for the field.

By bringing together novel research by an international team of scholars from a range of fields, this book strives to contribute to consolidating the emerging field of computational conflict research. It aims to be a valuable resource for students, scholars, and a general audience interested in the prospects of using computational social science to advance our understanding of conflict dynamics in all their facets.

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Part I
Data and Methods in Computational Conflict Research

Advances in Data on Conflict and Dissent

Kristian Skrede Gleditsch

Abstract In this chapter, I review the role of data in driving innovation in research on conflict. I argue that progress in conflict research has been strongly related to the growth of systematic empirical data. I draw on a series of examples to show how data have served as a source of theoretical innovation. I discuss early models of conflict distributions and their enduring relevance in current discussion of conflict trends and the evidence for a decline in violence. I consider the interaction between theoretical models of conflict and empirical analysis of interstate conflict, as well as the rapid growth in disaggregated studies of civil war and developments in data innovation, which in turn help generate new research agendas. I conclude with some thoughts on key unresolved problems in current conflict research, namely the lack of attention to incompatibilities as the defining characteristics of conflict and accounting for scale and differences in event size.

Keywords Conflict · Data · Models · Distributions · Progress

1 Introduction: The Need for Data in Computational Social Science

Conflict research has a long history, where efforts to record or measure conflict have a central place, but computational approaches to date have been less common. There are some notable exceptions that clearly demonstrate how computational approaches can be very useful in order to more explicitly explore counterfactuals and variation beyond what is available to us through the historical record (Bremer and Mihalka 1977; Cederman 1997). However, computational approaches tend to be the most compelling and effective when they are closely integrated with

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subject-specific theoretical puzzles and informed by empirical data. In this chapter, I review the role of data in driving innovation in research on conflict.

The thesis I advance is that innovations in research on conflict often have followed new data developments. My argument is not that we can simply substitute theory with more data. Indeed, descriptive data rarely speak for themselves, and new and more detailed data will by themselves rarely lead to new theoretical breakthroughs. Indeed, the best data sources are usually based on solid initial theoretical foundations that guide the data collection efforts. However, it is difficult to find good examples where pure theory has had a major transformative impact on conflict research, in the absence of substantial engagement with empirical data. By contrast, data innovations have often helped restate and refine existing research agendas, and open new avenues for theoretical development.

To justify this thesis, I draw on a series of examples of how data have served as a source of theoretical innovation, starting with early models of conflict distributions and their enduring relevance in current discussion of conflict trends, and then how more recent developments in data innovation contribute to new research agendas. I conclude with some thoughts on what I see as particularly important unresolved problems in current conflict research, namely the lack of attention to incompatibilities as the defining characteristics of conflict and accounting for scale and differences in event size.

2 Conflict Research and the Impact of the Early Conflict Data

If we define data rather widely as any empirical observations, then there is of course a long history of data in terms of detailed historical accounts of individual conflicts. Many of these could be highly analytical, as Thucydides' (2000) discussion of the causes of Peloponnesian war (believed to be written around 410 BCE). However, historical accounts tend to be highly case-specific and are rarely comparative or systematic, in the sense of trying to cover a population of conflict or focus on representative cases. Moreover, outside historical accounts, much of the general early research on conflict focused heavily on theory and analyzing conflict in an abstract manner, often detached from descriptive data altogether. Hobbes (1651, p. 78), for example, argued that scholars should try to identify the general conditions that make war possible rather than individual events, just as "foul weather is not based on isolated showers, but inclination to rain." This is in many ways a quite sophisticated anticipation of security dilemmas and efforts to develop more general theory. However, the lack of attention to data and observations also moved us further away from efforts to quantify risk, such as assessing how frequent conflict actually is and how much variation in inclination we see across specific types of conditions. Kelvin (1883) famously equated the quality of science to quantification. Without measuring conflict, we are often left without realistic assessments of risk.

A statement indicating that something "is possible" tells us little more than that probability is above 0 or impossible but less than 1 and certain. Harking back to the weather analogy, the nature and shape of weather distributions certainly play a central place in meteorology. Examining descriptive data on such distributions can help us keep track of how some places have more foul weather than others, and provides a basis for evaluating the possible causes why.

Against this more stringent yardstick, comparative data on conflict are a relative recent development in the long history of conflict research. It remained until recently largely a fringe activity, perhaps in part as a result of policy orientation and aversion to statistics and quantitative methods among many traditional security studies scholars (see, e.g., Fazal 2016). One of the earliest datasets was collected by a sociologist, Sorokin (1957[1937]), who sought to use data to test his theory of conflict as a result of value divergence. With comprehensive information on the dates on key battles and troop sizes since antiquity, Sorokin's data were a major achievement. However, some features also limited their applicability. As the data were restricted to conflict between major powers, they could not speak to conflicts within states or conflicts with smaller powers. There is also no clear delineation of what makes states major powers, and a risk of circularity if influence for conflict is defined based on whether states tend to fight more.

Wright (1942/1965) developed another influential dataset, intended to test a theory of peace as a result of active interstate organization and coordination that served to constraint possible factors that may lead to conflict if left unchecked. Although these data cover a shorter period than Sorokin's, they also included a more comprehensive delineation of states involved in conflict. Wright also devoted a great deal of attention to developing clear inclusion criteria for the data collection efforts. Given his background in law, it is perhaps not surprising that the definitions were skewed towards legal conceptions of war, but his efforts and structured approach had a major influence on subsequent efforts to define war.

The most unusual data pioneer was Richardson (1960), a physicist who sought to identify a dataset of violent events to assist with more fundamental mathematical and statistical models of conflict. Richardson started to work collecting conflict data after World War I, but the data were not published until much later. Richardson's unit of analysis was deadly quarrels, based only on observable deaths. The incidents were classified by their severity in terms of fatalities, binned by "orders-of-magnitude" on a log10 scale. The data were intended to be exhaustive for events above 1.5 (about 32 fatalities). Richardson provides an important first discussion of some of the problems in counting wars from historical records—who are the combatants, when did a war start/end, how many died? In a pithy quote, Richardson (1960, p. 35) concluded that "thinginess fails" when we try to create data on wars as events, and "the concept of a war as a discrete thing does not quite fit all the facts." Moreover, he was the first to explicitly use randomization to consider the sensitivity of his conclusions to decisions about lumping together events as a single war versus splitting episodes within longer wars.

One of the first conflict distribution models analyzed by Richardson (1948) considered the severity and frequency of conflict. He noted that there was a regular

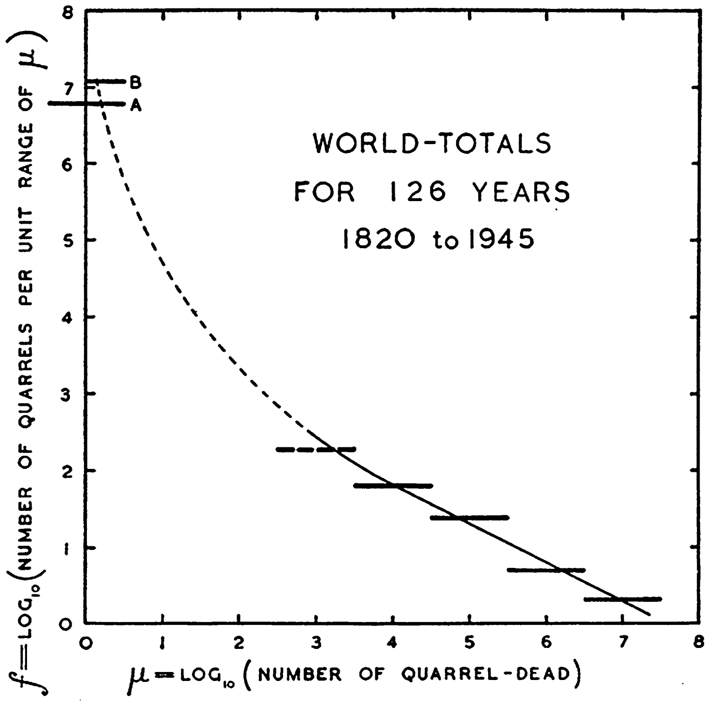

Fig. 1 Quarrel frequency and severity, from Richardson (1948). Richardson's data are binned by severity, hence the horizontal lines

relationship between conflict severity and frequency, where the severity of a conflict in terms of number of people killed x is inversely proportional to frequency. More formally, the frequency of a conflict of severity x scales as $P(x) \propto x^{-\alpha}$, where $\alpha \approx 2$. Richardson's data are displayed in Fig. 1, and provide one of the first empirical examples of a power law. One of the properties is that multiplying severity by a given factor yields a proportional division of the frequency. For example, doubling severity halves frequency. Power laws will appear as roughly linear if displayed on doubly logarithmic axes.

As shown below in Fig. 2, we find a similar relationship for other conflict data sources as well, including more recent data on interstate wars. Indeed, this relationship turns out to be a common feature of many conflict data distributions, including more fine-grained data on individual terrorist attacks (Bohorquez et al. 2009; Cederman 2003; Clauset et al. 2007). However, it is not universal, and it does not hold for all types of conflict. As can be seen in Fig. 2, the fit is much less compelling for civil wars, where we see "too few" severe conflicts in the tail for the observed data to fit well with what we would expect under a power-law distribution.

Skeptics may wonder why this should be regarded as an interesting finding. One way these results can be useful is to assess the expected frequencies of specific types

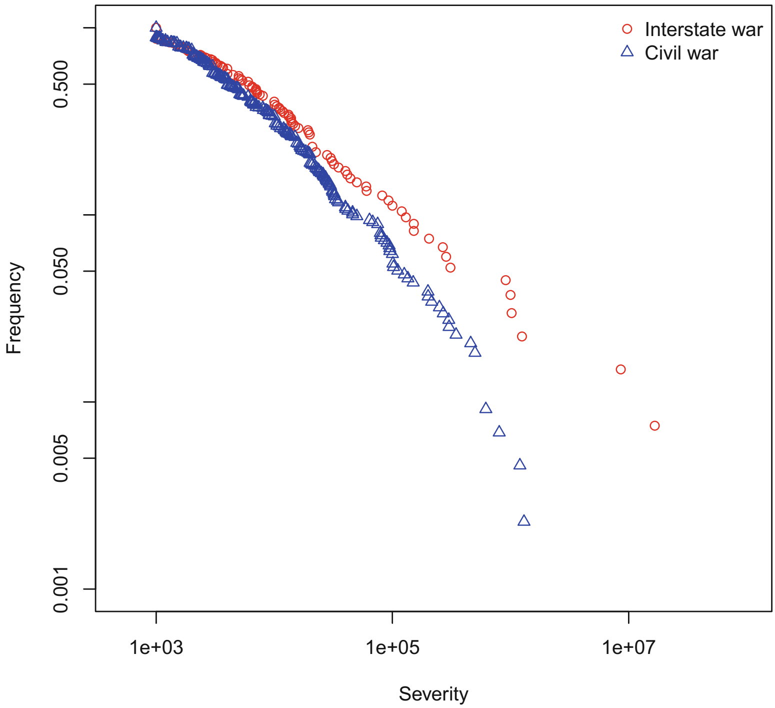

Fig. 2 Frequency-severity (i.e., casualty) distribution for wars, based on the expanded war data from Gleditsch (2004), doubly logarithmic scale

of events. For example, 9/11 is often portrayed as being an unprecedented "Black Swan" event, following the terminology of Taleb (2007). Clauset and Woodard (2013) show that the likelihood of observing an event with the same magnitude as 9/11 since 1968 based on the observed data is as high as 11–35%, depending on the specific assumptions used. The fact that tail events are more likely than many anticipate based on the apparent "typical" conflict is a stark reminder of how major conflicts such as World War I can emerge, even when observers see "no clouds on the horizon." Furthermore, finding that observed events *do not* fit a power law can also be useful to think about possible causes. For example, the poor fit for civil wars suggests that there must be some limiting factors that may prevent civil wars from escalating to more severe conflicts at the same rate as interstate wars (Miranda et al. 2016). For example, non-state actors may have limited resources to increase the war effort or hard constraints on their ability to escalate conflict beyond a certain level.

A second model considered by Richardson pertains to timing of wars. Richardson (1960) found that outbreaks by year were consistent with a Poisson process, a common model for independent random events, where "there is a constant very small probability of an outbreak of war somewhere on the globe on every day" (p. 243). More formally, the number of wars n in an interval such as a year, given a probability of a war breaking out p, will be $e^{-p}\frac{p^n}{n!}$. Given this formula, as long as p is small, we are most likely to see years without onset, followed by years with a single onset, and the likelihood of seeing a year with n (or more) wars falls quickly the higher the value of n. The idea that conflict outbreaks are random does not sit easily with traditional theories of international conflict. However, many other analyses have found that it is very difficult to reject the simple Poisson model for common conflict data sources (Gleditsch and Clauset 2018; Mansfield 1988).

Again, skeptics may wonder why this analysis is relevant. The Richardson model of timing has become important again in the recent debate over trends in conflict. There has been a great deal of research on the apparent decline in warfare and organized violence, especially after the Cold War. Prominent books by Goldstein (2011) and Pinker (2011), for example, show an observed decline in the number of wars and the number of people killed in war and discuss possible causes. Most people accept that the observed data indeed indicate a decline (see, e.g., Gleditsch and Clauset 2018). However, there is more controversy over whether the observed data provide strong evidence for a trend, or shifts in the underlying distribution of conflict. How do we know that we have not had a spell of good luck, and how confident are we that the number of conflicts would remain low? Under just a slightly different turn of events, for example, the Cuban Missile crisis could have escalated to a severe conflict (Gaddis 2005). Whether we deem trends to endure is of course to a large extent a question on theory, and here I will focus mainly on the statistical aspects of assessing trends. We are used to seeing the historical record as a population, and many find it odd to discuss alternative worlds (Tetlock 1999; Tetlock and Belkin 1996). However, if we think of conflict outbreak as a stochastic process, then it is entirely possible to see a decline of conflict over a period, even if there is no change in underlying frequency of conflict.

Whether we can reject a model of no change based on the independent outbreak and power-law distributions is explored recently in two papers by Cirillo and Taleb (2016) and Clauset (2018). Although there are a number of innovations in analysis and data compared to Richardson, they both consider variants of the timing and frequency-severity models that we have seen. In brief, Cirillo and Taleb argue that we cannot in principle say anything about trends since severe conflicts are so rare. They calculate that for a conflict with five million casualties, the expected waiting time between conflicts would be over 93 years. Based on this, one might argue that one cannot make any conclusions about notable trends just from observing a decline. Clauset also tries to test for evidence of shifts in the distribution after 1945. He finds some evidence that the most severe conflicts may be less common, but not sufficiently strong evidence to reject the no change null hypothesis. Oddly enough, changes such as nuclear weapons, the growth of the number of states, and all types of nonstationary factors we think influence war, such as democracy and trade, appear to have had no impact on the distribution of conflict.

Other scholars have started to examine a broader range of conflicts at the lower end of the distribution, and whether there is evidence of changes in the distribution more recently than 1945 (the only period considered by Clauset), using change-point detection techniques. For example, Hjort (2018) finds evidence for a break in the distribution in 1965, which coincided with the opposition to the Vietnam War and the hippie movement, so perhaps Woodstock had a longer legacy. Focusing on ethnic civil war, Cederman et al. (2017) find evidence for a change point in the series in the late 1990s, and also provide evidence that the change appears to be due to greater ethnic accommodation. Just as civil wars can be promoted by ethnic exclusion, we are less likely to see an onset of conflicts after changes towards ethnic accommodation and more likely to see conflict termination.

3 Data and Progress in Conflict Research

There have of course been many other important developments in conflict research beyond research on trends. However, one might perhaps also contend that the extent of progress has not been proportional to effort, or at least it has been more limited than the very high aspirations. There has been a great deal of path dependence, where existing data are simply duplicated, without innovation and further refinements. For a long time, there was a dominant tendency to let often ill-defined traditional theories of conflict guide empirical inquiry, and much ink has been spilled on investigating vague notions from the realist school of thought, suggesting that conflict must be some kind of function of the distribution of power across states in the system (Singer 1980). Many analyses have sampled on the dependent variable and just looked at conflict cases, without considering non-war cases or explicit baseline models (Most and Starr 1982).

However, there has undeniably also been a great deal of progress, and much of this has been driven by data developments interacting with theory development (Gleditsch et al. 2014). For example, the early efforts to come up with more explicit list of states allowed defining populations of potential actors, and to derive better explicit models of the opportunities for conflict among individual states or dyads (Bremer 1992). Data on the geography of states has similarly led to a great deal of interesting research on the role of borders, distance, and conflict (Starr and Most 1983). Data on political institutions and economic exchange helped spur the wave of research on liberal peace, or the possible restraining effects of institutions or interdependence on the use of force (Oneal and Russett 2001; Simowitz 1996). This has in turn led to new interest in using network approaches to understand how individual states are embedded in larger networks of interdependence beyond the dyad, as well as new methods for dealing with temporal and spatial interdependence in statistical analyses (Beck et al. 1998; Kinne 2009). Van Holt et al. (2016) conduct a more formal analysis of scientific influence in conflict research based on citation patterns. Their findings are visualized in terms of paths between influential articles and common topics in Fig. 3. It is clear from Fig. 3 that many of the influential articles in the graph on interstate conflict are precisely those that describe new dataset or analytical methods. Notable examples include Jaggers and Gurr (1995, introducing the Polity democracy data prominent in studies of the democratic

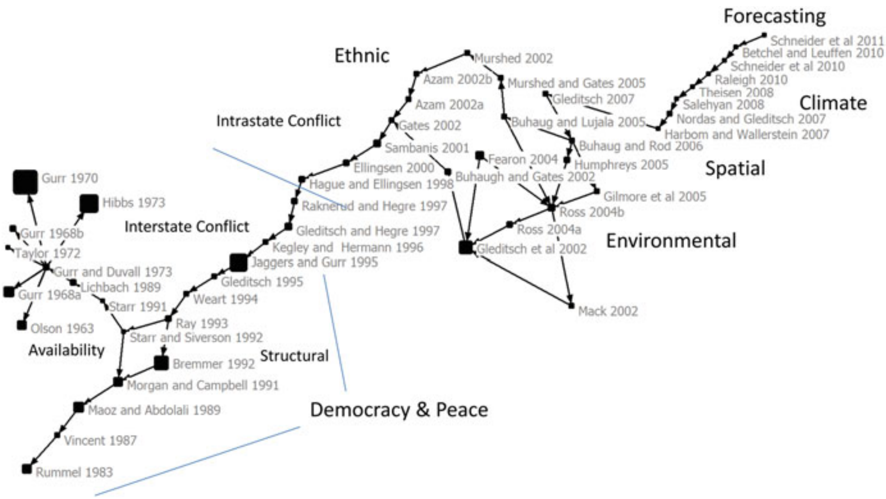

Fig. 3 Critical path and scientific influence in conflict science, reproduced from Van Holt et al. (2016)

peace) and Bremer (1992), which was one of the first articles to propose systematic approaches to dyadic analysis of the onset of Militarized Interstate Disputes (Jones et al. 1996). The article presenting the first version of the extended backdated version of the Uppsala/PRIO armed conflict data prior to 1990 stands out as central in the upper right section of the figure on interstate conflict (Gleditsch et al. 2002).

The specific topics of interest have clearly changed over time. It is notable that the entries in the section of the graph for intrastate conflict in Fig. 3 have much more recent publication dates, and the history of research on civil war differs notably from interstate conflict research. In general, quantitative research on civil war suffered much less from a legacy of traditional theories. In the mid-2000s, there was lot of interest in trying to develop more disaggregated data on civil war, in part promoted by a collaborative network of conflict research in Europe which generated a special issue of the *Journal of Conflict Resolution* (Cederman and Gleditsch 2009). We have seen the development of new data that disaggregate and identify the specific actors involved in conflict (Cunningham et al. 2009), identify more detailed information on specific attributes such as the ties of actors to ethnic groups and more detailed information on ethnic groups (Vogt et al. 2015), and data that provide more detailed information on events within conflicts and their geographical location (Raleigh et al. 2010; Sundberg and Melander 2013). There have also been a number of utilities develop to combining different data sources, such as the geo-spatial cell structure in PRIO-GRID (Tollefsen et al. 2012) and the R package MELTT to match different event data sources by location, time and type (Donnay et al. 2019). Moreover, there has been a great deal of progress in automated coding of information from text sources such as news media reports, which provides an opportunity for real-time monitoring of events (Gerner et al. 1994, Schrodt and Gerner 1994, see also Maerz and Puschmann, chapter "Text as Data for Conflict Research: A Literature Survey" in this volume). There has also been more attention to out-of-sample forecasting as a better approach to model and theory evaluation (Ward et al. 2010). Importantly, out-of-sample evaluation can help guard against the problem of in-sample overfitting, since it will often be the case that increasingly more complex models that may fit the estimation data well will perform worse out of sample than simpler models. In short, the study of civil war from the mid-2000s has been a period of rapid progress, and much of the progress has clearly been promoted by the development of new data sources and the interaction between theory and data.

4 The Essential Interaction Between Theory and Data in Conflict Research

Although more data have helped take us further, the interaction with theory remains essential. Whereas the development of data tended to follow theories or initial ideas in the early development of conflict research, it is now increasingly common to see more purely data-driven projects, exploiting the vast amount of available data on conflict. Exploratory analysis can often be very helpful and illuminating in its own right, especially if it is guided by new methods that may have advantages over the existing approaches that have commonly been used and help illuminate new aspects. Yet, there are also many cases where we arguably learn less from the analysis conducted, even if they are very competently done from a technical perspective. For example, Zammit-Mangion et al. (2012) use models from geostatistics to model high resolution data on events in Afghanistan, obtained from Wikileaks, on a database of Significant Activities (SIGACTS) compiled by the US Army. They argue that this framework can be helpful for detecting and predicting conflict dynamics such as diffusion and relocation. The model seems to have high predictive ability, but on closer inspection it becomes clear that much of the heavy lifting in the predictive ability is done by the temporal lags. There is also a discernible "ring" in the spatial forecasts of location, which appears to reflect how improvised explosive devices tend to be placed around the Highway 1/Ring Road that circles the country. Ultimately, the model has limited content on the motivation of the actors, and the framework deemphasizes conflict as interaction between antagonists. Moreover, since the SIGACTS data primarily record events by actors perceived as hostile by the US Army, these data do not contain information on the events and actions by coalition forces that we would need to actually study the interaction between the parties and how the conflict evolves as a result of this (Weidmann and Salehyan 2013). Although data can be powerful tools to evaluate and extend theories, we need to avoid putting the data cart in front of the horse, or we risk developing 'weapons of mass distraction' that provide limited insights, no matter how much they appear to be scientific.

5 Key Unresolved Problems in Data for Conflict Research

In closing I would like to flag two important problems in conflict research that I think have not received sufficient attention and remain difficult to consider in existing data sources. The first is the tendency to equate conflict exclusively with violent events, which is very widespread in applied research on conflict. This is not consistent with definitions of conflict that tend to highlight incompatibilities or conflict of interest between actors. Boulding (1963, p. 5), for example, suggests that “[c]onflict may be defined as a situation of competition in which the parties are aware of the incompatibility of potential future positions, and in which each party wishes to occupy a position that is incompatible with the wishes of the other”. From this perspective, conflict as an incompatibility could motivate the use of violence, but violence in and of itself is not a defining characteristic of conflict (see also chapters “Advancing Conflict Research Through Computational Approaches”; “Migration Policy Framing in Political Discourse: Evidence from Canada and the USA”; “The Role of Network Structure and Initial Group Norm Distributions in Norm Conflict”; “On the Fate of Protests: Dynamics of Social Activation and Topic Selection Online and in the Streets” of this volume). The requirement that conflict must be perceived by the actors help to demarcate from other very expanded definitions of conflict, such as structural violence that extend the concept of conflict to situations with “objective” interest not necessarily experienced or understood by the actors (Høivik and Galtung 1971). Most and Starr (1983) provide a comprehensive review of other definitions of conflict, most of which have a similar emphasis on conflict of interest as opposed to violent action.

The tendency to equate conflict with manifestations of organized violence has led some researchers to either explicitly or implicitly treat situations without conflict as “peace.” This is highly problematic, since we fail to distinguish cases where there are no objective conflicts of interest between actors and cases where conflicts of interest exist, yet do not result in the use of violence. Organized violence requires collective action, and all forms of efforts to initiate collective action may fail for a number of reasons (Sandler 1992). Even when actors have common interests on an issue and would benefit from a change, such as fostering regime change or replacing a government, they do not necessarily have sufficient private incentives to participate in dangerous activities. As such, there will be a temptation to free ride as the benefits of successful dissent would be public and cannot easily be restricted to active participants (Lichbach 1995; Tullock 1971). Moreover, states can deter or raise the costs of collective action by sanctions or retribution. But more fundamentally, conflict may also be waged using means other than violence, including for example demonstrations and strikes (see also chapter “On the Fate of Protests: Dynamics of Social Activation and Topic Selection Online and in the Streets” in this volume). Sharp (1973) and Chenoweth and Stephan (2011) document many instances of important campaigns waged using only non-violent means. Violent and non-violent tactics can be plausible substitutes, where we may not see organized violence used in a conflict because an actor has a comparative advantage in non-violent forms of contention. For example, over the last couple of years, Venezuela has seen massive mobilization against the Maduro government and proposed institutional changes. On 19 March 2017, a so-called Mother of all Marches of protest mobilized as many as six million participants nationwide, according to estimates by the survey company Meganálisis based on traffic flow and demonstration movement data, an extreme relative level of mobilization in a country of just over 30 million inhabitants (see Lugo-Galicia 2017). Although there have been many instances of violence against protestors as well as occasional violent responses by protestors and riots, we do not have a conventional civil war in the sense of organized armed violence by opposition. Yet, it would be absurd to characterize this as “not a conflict” since we do not see organized violence.

Many studies of civil war have tried to identify potential incompatibilities by focusing on the political and economic status of ethnic groups. From this perspective, all ethnic groups that are disadvantaged in a given state could be seen as potential conflict situations where there exist plausible grievances against the state and motives for dissent. Yet, conflict is a much more general concept than this. First, many violent conflicts are not ethnic, and the share of violent conflicts that are clearly ethnic has arguably fallen. Figure 4 displays the share of ongoing armed civil

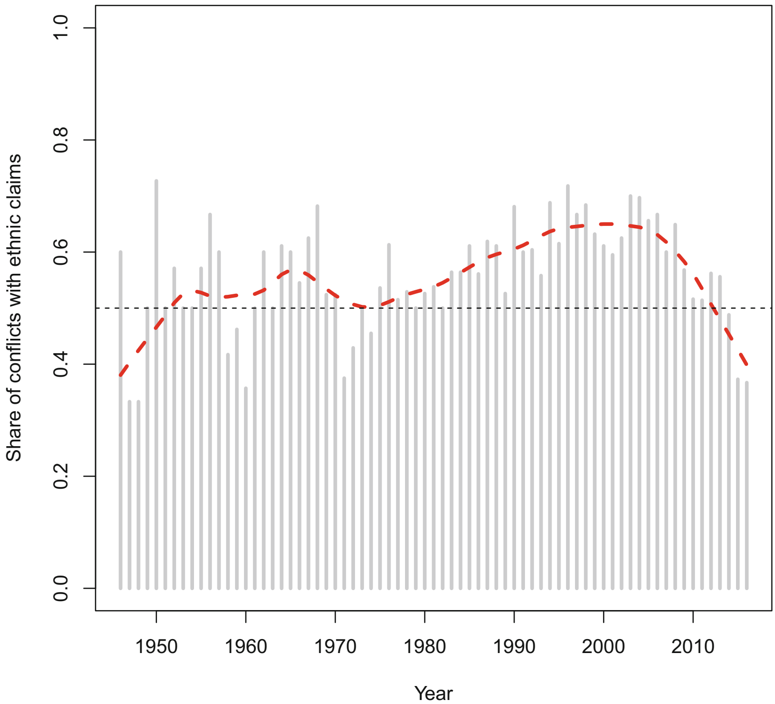

Fig. 4 Share of armed civil conflicts with ethnic claims, based on the ACD2EPR data (Vogt et al. 2015; Wucherpfennig et al. 2012)

conflicts in the Uppsala/PRIO Armed Conflict Data that are deemed to be ethnic, based on the ACD2EPR project linking actors in ongoing armed conflict to ethnic groups in the Ethnic Power Relations data, based on whether organizations make links on behalf of ethnic groups. As can be seen, historically it has been the case that the majority of armed violent conflicts that could be considered ethnic. However, the proportion has recently fallen, and is now less than 50%. One important possible explanation here is that ethnic civil wars have declined precisely since we see less of the ethnic discrimination and exclusion that promotes violence. Cederman et al. (2017) provide evidence that countries with changes toward greater accommodation and inclusion generally have lower rates of subsequent onset and higher likelihood of termination in ongoing conflict than countries that have not seen changes.

If we wish to study potential conflict outside the ethnic realm, the limitations of focusing only on violence become more apparent. The large non-violent campaigns reported in existing data sources tend to be non-sectarian campaigns against authoritarian rulers (Cunningham et al. 2017; White et al. 2015). There are few instances of large-scale direct action involving ethnic groups, although many ethnic groups have relied on various non-violent tactics that do not involve mass mobilization (Cunningham 2013). One might speculate that mass mobilization is more likely to be successful if it can overcome other divisions in a population, as seen in Syria. As such, non-violent forms of contention may be generally less likely to be successful for secessionist aims, and it may be more likely that actors resort to violence precisely when non-violent tactics are the least likely to be effective. Testing these conjectures is very difficult to do adequately with existing data, since they are limited either to violent conflicts or events or only large-scale mobilization. The need to develop better data of incompatibilities and mobilization over these defined independently of the use of violence is one of the major unresolved issues in current conflict research.

Another problem is related to the problem of scale of conflict. Dissent by non-state actors by definition must involve collective action, but the actual level of participation varies dramatically. Yet, many analyses just count events without identifying participation explicitly. For violent conflict, the scale of the conflict is often equated with the number of battle deaths. However, the number of battle deaths is not necessarily a good indicator of participation. For example, one can imagine that a conflict event could be brought to a halt when one antagonist mobilizes superior forces and successfully deters the opponent. Arguably, the number of casualties following the Warsaw Pact invasion of Czechoslovakia in 1968 was limited precisely because Czech First Secretary Dubcek ordered people not to resist the superior invading military forces (see Fraňková 2017).

More generally, participation is an essential feature of interest in its own right, and arguably key to the outcome of the contentious events. There is considerable evidence that activists and organizations seeking to mobilize in dissent see maximizing participation as one of their key objectives—in the words of Popovic (2015, p. 52) “in a nonviolent struggle, the only weapon that you’re going to have is numbers”.

A standard approach in common research is to count numbers of reported events as a measure of the magnitude of events. The idea is that a situation where we have a higher number of reported events is experiencing a more extensive and significant conflict episode. Although it may well be correct that a conflict with more extensive reporting sees more events, but there is no necessary theoretical or empirical relationship between the number of events and the extent of participation in them. For example, a group that can mobilize a very large number may focus on a single large event, while groups that can only mobilize smaller numbers may carry out many smaller-scale events by the same participants. By counting events, we may erroneously conclude that the latter is a "larger" conflict, even if it involves fewer participants. These examples are not contrived hypothetical examples, but reflect real concerns. Biggs (2018) examines the relationship between the number of strikes and actual participants in strikes, using data from the USA, and shows that the two measures are not highly correlated. Many discussions of event data have been very concerned about the possible selection biases or the problem that smaller events may be omitted due to for example media biases (Weidmann 2016). However, if we scale events by size then it should be easier to get differences in orders of magnitude right, even if there is uncertainty, and we are generally less concerned about the influence of possible noise at the very low end.

In addition to the theoretical problems in using event counts as measure of scale, there are also a number of practical issues arising in delineating what constitutes one "event" as opposed to two or more "separate" events. Many event data projects use different types of "deduplication" efforts to determine whether different reports are to the same or different events, typically considering events to be "the same" if they fall on the same date. However, there is no guarantee that this will work, and it is often the case that report dates may be ambiguous with respect to the day of reporting and the day the events described occurred. Even worse, there is plausibly an inverse relationship between size and granularity in some data sources. The Social Conflict Analysis Data (SCAD) provides a much used event dataset, which extends data on exclusively violent conflict and data limited to large-scale organized non-violent campaigns by providing more detailed event data on social conflict as well as geographical location information (Salehyan et al. 2012). However, many events in the SCAD data are coded as nationwide, where the number of simultaneous events across a country is deemed to be so large that coders can no longer identify exhaustively all the individual events. The nationwide events are likely to have more participants than smaller events that are easy to identify as discrete events, yet analysts counting events may count the former as "less significant" since it is reflected in fewer event counts.

I think these are genuine problems, but in keeping with the theme of theory-data interaction here, I am also relatively optimistic about our ability to find useful approaches to overcome them. With regards to identifying incompatibilities, there is much that can be done to identify conflict constellations using methods such as expert surveys or automated content analyses. For example, recent work on conflict prediction using topic modelling suggests that it may be possible to identify anti-government claims in news media sources (Mueller and Rauh 2018). Similar types of content analysis techniques could be useful for identifying cleavages or contention more generally, separately from violence or large-scale mobilization. With regards to counting participation, we also have active developments of alternative coding approaches, using photos where we can assess the density or social media data such as twitter via geolocation (Barberá et al. 2015; González-Bailón and Wang 2016; Won et al. 2017). It turns out again that since many things scale, we can use proportionality measure to infer participation. Steinert-Threlkeld (2018) notes that this tracks participation well in so-called women's marches in the USA.

6 Conclusion

In this chapter I have reviewed some examples of the interaction between data development and theoretical progress in the field of conflict research. I hope that I have successfully shown that data in some cases may have preceded theory, but in most cases data have been collected and developed in direct response to initial theoretical beliefs and hunches. However, the availability of data has often led to theoretical re-evaluations and progress; initial hunches may not be fully supported, while other findings lead to new puzzles or research questions. I hope this overview can give some sense of the excitement that I am left with over the progressive nature of interaction between theory and data in conflict research and the maturity of the field. Future central data resources are likely to come from new technologies or sources that have been difficult to use in the past. For example, satellite images are now readily available, and also relatively easy to analyze on a standard computer. Such data can be used to extract information on features for which no meaningful official data exist, such as variation in local income and wealth in countries with poor infrastructure and governance (see Jerven 2013; Weidmann and Schutte 2017). Many sources—including information that was previously classified– can now be extracted from digital sources, rapidly disseminated on the internet, and advances in text analysis and extraction makes it much easier to conduct systematic analysis of such data sources (see, e.g., Biggs and Knauss 2011, Deutschmann 2016). Simulation can provide an important complement to limited observed data, and counterfactual computational analysis can be particularly compelling if it is linked to clear theoretical arguments and grounded in known empirical information (Cederman 1997; Tetlock and Belkin 1996). It is difficult to predict—especially about the future. I make no claim to be able to predict specific new scientific innovations or salient new topics with much confidence, but I am very confident that new data sources and methodologies for data development will figure prominently in a future updated version of a graph of scientific influence in conflict research akin to Van Holt et al. (2016).

A.1 Appendix: Key Contemporary Data Sources, Listed Alphabetically

Armed Conflict Location & Event Data Project (https://www.acleddata.com/). A disaggregated conflict data collection, with dates, actors, types of violence, locations, and fatalities of reported political violence and protest events. The ACLED data are not global, but cover a number of countries in Africa, Asia, and the Middle East.

Correlates of War Project (http://www.correlatesofwar.org/). Provides access to episodic data on interstate wars and militarized interstate disputes. The COW project also collects data on various state-based characteristics such as military capabilities and diplomatic ties between states.

Global Database of Events, Language, and Tone (https://www.gdeltproject.org/). Provides access to machine coded event data from electronic sources from 1979 to the present, using the Conflict and Mediation Event Observations (CAMEO) coding scheme.

Global Terrorism Database (https://www.start.umd.edu/gtd/). Provides access to data on terrorist attacks since 1970, as well as some supplementary data sources on terrorist group profiles.

Integrated Crisis Early Warning System (https://dataverse.harvard.edu/dataverse/icews). Daily event data coded from electronic news sources, with actor, event, and location identifiers. Note that the most recent public version of the data has a 1 year embargo.

Phoenix [Cline Center Historical Phoenix Event Data] (https://clinecenter.illinois.edu/project/machine-generated-event-data-projects/phoenix-data). Event data for the period 1945–2015, machine coded from 14 million news stories from the New York Times (1945–2005), the BBC Monitoring's Summary of World Broadcasts (1979–2015) and the CIA's Foreign Broadcast Information Service (1995–2004).

Phoenix [Real time Phoenix data] (http://eventdata.utdallas.edu/data.html). A real time machine coded event dataset complementing the historical data, available from October 2017.

Non-violent and Violent Campaigns and Outcomes (https://www.du.edu/korbel/sie/research/chenow_navco_data.html). Provides access to an influential dataset that also documents non-violent mobilization over maximalist claims on a government.

Social Conflict Analysis Database (https://www.strausscenter.org/scad.html). Provides access to event data on protests, riots, strikes, inter-communal conflict, government violence against civilians, and other forms of social conflict not systematically tracked in other conflict datasets. SCAD currently includes information on social conflicts from 1990–2017, covering all of Africa and now also Mexico, Central America, and the Caribbean.

Uppsala Conflict Data Program (https://ucdp.uu.se/downloads/). Provides access to data on various types of violent conflicts, including state-based interstate and intrastate conflict, violence against civilians, and non-state/inter-communal conflict, as well as geo-referenced event data.

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Text as Data for Conflict Research: A Literature Survey

Seraphine F. Maerz and Cornelius Puschmann

Abstract Computer-aided text analysis (CATA) offers exciting new possibilities for conflict research that this contribution describes using a range of exemplary studies from a variety of disciplines including sociology, political science, communication studies, and computer science. The chapter synthesizes empirical research that investigates conflict in relation to text across different formats and genres. This includes both conflict as it is verbalized in the news media, in political speeches, and other public documents and conflict as it occurs in online spaces (social media platforms, forums) and that is largely confined to such spaces (e.g., flaming and trolling). Particular emphasis is placed on research that aims to find commonalities between online and offline conflict, and that systematically investigates the dynamics of group behavior. Both work using inductive computational procedures, such as topic modeling, and supervised machine learning approaches are assessed, as are more traditional forms of content analysis, such as dictionaries. Finally, cross-validation is highlighted as a crucial step in CATA, in order to make the method as useful as possible to scholars interested in enlisting text mining for conflict research.

Keywords Computer-aided text analysis · Text as data · Dictionary · Supervised and unsupervised machine learning · Topic models · Cross-validation

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1 Introduction

It is by now an old adage that the internet has transformed many areas of social life, from industry and politics to research and education. Computational techniques have benefited from this development through the rapid growth in open source software and cloud computing, both of which simplify research that utilizes computational approaches immensely, making them both simpler and less costly for social scientists to implement. However, there has also been a rapid growth in the availability of content to study—that is of text, images, and video—which is of relevance to social scientific inquiry. Focusing on text, such data range from administrative documents and digitized books to social media posts and online user comments. They also include traditional research data, such as open survey responses and interview transcripts, which may be scrutinized with computational techniques.

The field of computer-aided text analysis (CATA) subsumes methods used to study such data. The goal of this chapter is to provide an overview of computational methods and techniques related to the area of (semi)automated content analysis and text mining, with emphasis on the application of such approaches to conflict research. We describe three central areas of CATA in order of their respective age: techniques relying on dictionaries and simple word counting, supervised machine learning (SML), and unsupervised machine learning (UML). While doing this, we provide a survey of published studies from a variety of fields that implement CATA techniques to study conflict. We then proceed to address issues of validation, a particularly important area of CATA.

Throughout the chapter, we offer a host of examples of how the application of CATA may advance conflict research. Our working definition of conflict in this chapter is twofold: we cite studies using CATA to study violent conflict on a regional or national level, usually by means of relating textual data that applies to a particular actor (for example, a country) to some indicator of violence. Such studies aim to uncover hidden relationships between issues, frames, and rhetoric on the one side and violent conflict on the other. The second branch of studies that we cite are those where conflict is non-violent but there is a considerable aggressive potential, for example, in online hate speech campaigns, cyber mobbing, and social media flame wars. Such studies are as diverse as their respective objects, but a commonality is that because there is usually ample data to document the conflict, CATA may be used to draw a precise picture of the actors, issues, and temporal dynamics. By presenting both branches of physical and virtual conflict research side by side, we do not imply that one follows from the other, but rather that the same approaches may be useful in studying both.

The techniques that we describe can be seen as existing on a continuum, from approaches that are more deductive in nature and presuppose very detailed domain knowledge and precise research questions/hypotheses, such as dictionary analysis, to (more) inductive methods such as unsupervised learning that are more suitable for exploration (cf. Table 1). The latter methods also tend to be more

Table 1 CATA methods for conflict research, adjusted from (Boumans and Trilling, 2016, p. 10)

	Dictionary	Supervised (SML)	Unsupervised (UML)
Typical research contexts/material in conflict studies	Sentiment analysis of documents from opposing parties or extremist groups, or time series of sentiment fluctuation	Relatively homogeneous, numerous texts, e.g. from newspapers; sentiment classification of sentences or paragraphs	Large amounts of unexplored material, e.g. from field research, official documents, social media
Common statistical procedures	Counting of word frequencies, string comparisons	Support vector machines, Naive Bayes, Neural Networks	(Structural) topic modeling, latent Dirichlet allocation
Reasoning	Deductive →		Inductive

computationally resource-intensive than the former, though this will only really be felt when truly large volumes of data are analyzed on a regular desktop or laptop computer, and they tend to be more opaque and subject to interpretation than simple dictionary techniques which have been in use for decades. However, this is not truly a dichotomy as in typical CATA workflows multiple methods are often combined in different stages of the research. This can both serve the purpose of developing one resource based on the output of another (for example, developing a topical dictionary based on the results of unsupervised machine learning) or on the validation of a particular technique with another.[1]

Similar overviews of CATA for other fields have been provided before, for example, in political science, communication studies, and sociology (Boumans and Trilling, 2016; Grimmer and Stewart, 2013; DiMaggio, 2015). We aim to extend this body of work with an overview of research in conflict research that will be useful to computational social scientists aiming to use CATA in their work.

2 Dictionary Approaches for Conflict Research

Dictionary methods are among the oldest techniques employed in text mining and automated content analysis in the social sciences (Stone et al., 1966) and are popular in part due to their simplicity and transparency when compared with more recent methods (Grimmer and Stewart, 2013). In fact, dictionary approaches are both comparatively easy to interpret and computationally cheap, making them popular across a wide range of fields and research subjects. Dictionary approaches rely on

[1] For a comprehensive, hands-on introduction to CATA with Python for social scientists see Trilling (2018), for a similar introduction with R (in German) see Puschmann (2018).

the frequency of specific words (those contained in the dictionary) to assign each document in a corpus to a category. For example, a list of words describing violent conflict may be used to operationalize the topic, allowing the researcher to gauge the level of debate of this issue over time or by actor, or such a list may be used to identify potentially relevant material in a larger corpus.[2] Specialized topical or psychological dictionaries as they are used within the social sciences should not be confused with linguistic techniques such as part of speech-tagging, syntactic parsing, or named entity recognition (NER), which also allow the reduction of words to aggregate categories (nouns, sentence subjects, place names, etc.), but are usually intended to describe linguistic form rather than social or communicative function.

In some implementations, membership in a dictionary category is proportional to the number of words occurring in the text that belong to that category, while in others a winner-takes-all approach is used in which the document is assigned to the single category with the largest number of matching terms. The difference between the two styles is the weighting applied to the document feature matrix which contains the dictionary terms and the texts in which they occur, which is usually conducted after the words are counted (Grimmer and Stewart, 2013, p. 274).

The increasingly popular method of sentiment analysis—also called opinion mining in computer science and computational linguistics—is in many cases a simple variant of dictionary analysis in which the dictionary terms belong to one of two categories, positive or negative sentiment (although sentiment dictionaries with three or more types of sentiment also exist). Sentiment dictionaries exist in many variants across languages,[3] text types, and applications and are often quite comprehensive when compared with specialized topical lexicons. In the case of binary classification (which applies to many forms of sentiment analysis), the logarithm of the ratio of positive to negative words is often used to calculate a weighted composite score (Proksch et al., 2019).

Other dictionaries also exist in a wide variety of shapes and formats, and for a large number of different applications (Albaugh et al., 2013; Burden and Sanberg, 2003; Kellstedt, 2000; Laver and Garry, 2000; Young and Soroka, 2012). These include policy areas, moral foundations and justifications, illiberal rhetoric as well as place and person names, and other strongly standardized language use. Such off-the-shelf dictionaries provide a level of validity by being widely used and (in some cases) even being able to assign material in different languages to similar categories by having corresponding word lists for each category (Bradley and Lang, 1999; Hart, 2000; Pennebaker et al., 2001). Dictionaries can also be created through a variety of techniques, including using manually labeled data from which the most distinctive terms can be extracted.

A key strength of dictionary approaches (and of both supervised and unsupervised learning) is their ability to reduce complexity by turning words into category

[2] See Payson Conflict Study Group (2001) for such a list.

[3] See, for example, Proksch et al. (2019) for a multilingual sentiment analysis based on automatically translated dictionaries.

distributions. The basis of this approach is what is known as the bag-of-words philosophy of text analysis which turns a sequence of words and sentences into an undifferentiated "bag" which records only the frequency of each word within each text, but no information on where in a text a particular word occurs (Lucas et al., 2015, p. 257). Oftentimes this is not a hindrance, as in most quantitative research designs scholars will be interested primarily in distilling some aggregate meaning from their data, rather than retaining its full complexity. This decision entails a number of trade-offs, however, from a loss of structure and meaning that occurs when a text is pre-processed and cleaned to the alignment of the dictionary categories with the specific meaning of the material under study. The loss of syntactic information and argument structure is also an important limitation in bag-of-word approaches, which are often used in dictionary analysis (though dictionaries of n-grams are both technically possible and in widespread use).

Dictionaries have long played an important role in conflict research. Baden and Tenenboim-Weinblatt (2018) rely on a custom-built cross-linguistic dictionary of more than 3700 unique concepts, including actors, places, events, and activities which they use to study the media coverage of six current violent conflicts in domestic and international media over time. While compiling such a dictionary is burdensome, machine translation can be used to turn a mono-linguistic dictionary into one covering corresponding concepts across languages. Person and place names, specific events, and actions can all be captured by such a dictionary with relative accuracy, underlining why such a simple approach can be extremely effective (Baden and Tenenboim-Weinblatt, 2018), though translation always needs careful validation from experts. A broadly similar approach is used by Brintzenhoff (2011) who relies on a proprietary software to identify instances of violent conflict. There are also examples of studies that rely on data mining to generate dictionaries or resources similar to them. Montiel et al. (2014) present an analysis of the national news coverage on the Scarborough Shoal conflict between the Philippines and China relying on RapidMiner, a commercial machine learning software suite. A principal component analysis differentiates specific issues that are specific to Filipino and Chinese news sources from each other.

Dictionaries are also used to study conflict in virtual environments. Ben-David and Matamoros-Fernández (2016) rely on simple word frequencies in their study of hate speech on the Facebook pages of extreme-right political parties in Spain. After cleaning the data and removing stopwords, they group posts according to broad thematic categories and then extract those terms most frequently within each group, yielding category descriptions of different groups of immigrants and other "enemies." This approach is then combined with an analysis of hyperlinks and visual data. Broadly similar, Cohen et al. (2014) suggest identifying specific categories of radicalization as they manifest in "lone wolf" terror subjects through a combination of ontologies such as WordNet (Miller, 1995) and dictionaries such as LIWC (Tausczik and Pennebaker, 2010). While their overview is rather general, it points to the potential of composite solutions for linking behavior and language use.

As Grimmer and Stewart (2013) note, problems occur when dictionaries from one area are applied in another domain, leading to potentially serious errors when the problem is not caught. The authors cite the example given by Loughran and McDonald (2010) in which corporate earnings reports that mention terms such as "cancer" or "crude" (oil) are assigned negative sentiment scores, even when health care or energy firms mention these terms in an entirely positive context. This problem may seem entirely unsurprising, but particular assumptions about the nature of language (and in many cases writing) lead to the belief that a specialized dictionary that is appropriate in one domain will also produce valid results in another. As the example shows, even something as presumably universal as sentiment is a case in point: a dictionary that is suitable for capturing the opinion of a consumer about a product in a review on a shopping site will not produce equally valid results when applied to political speeches or newspaper articles, because (1) in them the same words may express different meanings, (2) such texts are presumably much more neutral in tone to begin with, (3) such texts do not necessarily express the opinion of their author, but institutional viewpoints, and (4) such texts report on or respond to the opinions of others.

Dictionaries should always be validated using the data to which the dictionary is to be applied, in other words it should not be presumed that the dictionary will produce accurate results if it is applied to a domain that is in any way different from the one for which it was developed. This applies equally to off-the-shelf and self-made dictionaries. Systematically validating dictionary results, for example, by means of traditional content analysis, is one common pathway to overcoming these problems.

3 Supervised Methods

Supervised machine learning (SML) represents a significant step away from the useful but also quite limited methods described in the previous section, towards more advanced techniques that draw on innovations made in the fields of computer science and computational linguistics over the past 30 years. This does not mean that such techniques are generally superior to dictionary approaches or other methods that rely on word counting, but that they utilize the extremely patterned nature of word distributions. In particular, supervised machine learning is able to connect feature distribution patterns with human judgment by letting human coders categorize textual material (sentences, paragraphs, or short texts) according to specific inferential criteria and then asking an algorithm to make a prediction of the category of a given piece of text based on its features. Once a classifier has been trained to a satisfactory level of accuracy, it can be used to classify unknown material. The algorithm thus learns from human decisions, allowing for the identification of patterns that humans are able to discern, but that are otherwise not obvious with methods relying purely on words and word distribution patterns.

The perhaps most typical research design consists of a set of labeled texts (alternatively paragraphs, sentences, social media messages, rarely more complex syntactic structures) from which it is possible to derive feature distributions, typically words (alternatively n-grams, part of speech information, syntactic structures, emojis). First, the data is split into a training and a test data set. An algorithm then learns the relation of the label to the distribution of the features from the training data set and then applies what has been learned to the test data set. This produces a set of metrics which allow to evaluate the classifier's performance. If the quality of the automated coding is deemed as satisfactory (i.e., similar to or better than human annotation) in terms of its precision and recall, the classifier can be applied to new, previously uncoded material. There are three major uses to this basic technique, including the validation of a traditional content analysis, the automated annotation of unknown material, and the discovery of structural relationships between external variables that prove to be reliable predictors for language use (Puschmann, 2018).

The applications of SML to conflict research and to social science more broadly are manifold. In a traditional content analysis, achieving a high inter-coder reliability is usually a key aim, because it signals that a high degree of inter-subjectivity is feasible when multiple humans judge the same text by a previously agreed set of criteria. In this approach, the machine leaning algorithm in effect becomes an additional "algorithmic coder" (Zamith and Lewis, 2015) that can be evaluated along similar lines as a human would be. Crucially, in such an approach the algorithm aims to predict the—presumably perfect—consensus judgment of human coders that is treated as "ground truth." Social scientists who rely on content analysis know that content categories are virtually never entirely uncontroversial. Since obviously humans disagree with one another, there is a risk of "garbage in, garbage out" when training the classifier on badly annotated material. Thus, the quality of the annotation and the linguistic closeness of the relation between content and code is the key, and the notion of "ground truth" should be treated with care.

This is usually not an issue when what is being predicted is the topic or theme of a text. For example, Scharkow (2013) relies on SML to gauge the reliability of machine classification in direct comparison to human coders, comparing the topics assigned to 933 articles from a range of German news sources. He finds automated classification to yield very good results for certain categories (e.g., *sports*) and poor results for others (e.g., *controversy* and *crime*), with implications for conflict research. As the author points out, even for categories where the classification results are less reliable, the application of SML yields important findings on the quality of manual content analyses. Similarly, van Atteveldt et al. (2008) are able to predict different attributes and concepts in a manually annotated corpus of Dutch newspaper texts using a range of lexical and syntactic features for their prediction. In both bases, the SML approach yields good results because the annotation is of high quality and the categories that are being predicted are strongly content-bound, rather than interpretative.

While frequently the categories coded for are determined through content analysis and relatively closely bound to the text itself (themes, issues, frames, arguments), or can be related to social or legal norms (e.g., hate speech), it is worth noting that any relevant metadata may be used as the label that the classifier aims to make a prediction on. For example, Kananovich (2018) trains a classifier on a manually labeled data set of frames in international news reports that mention taxes, and tests two hypotheses related to the prevalence of certain frames in countries with particular political systems.

Burscher and colleagues have shown that supervised machine learning can be used to code frames in Dutch news articles and reliably discern policy issues (Burscher et al., 2014, 2015). Sentiment analysis using SML has also been applied, with results considerably better than those of approaches that are purely based on the application of lexicons (González-Bailón and Paltoglou, 2015).

Burnap and Williams (2015) train a sophisticated supervised machine learning text classifier that distinguishes between hateful and/or antagonistic responses with a focus on race, ethnicity, or religion; and more general responses. Classification features were derived from the content of each tweet, including grammatical dependencies between words to recognize "othering" phrases, incitement to respond with antagonistic action, and claims of well-founded or justified discrimination against social groups. The results of the classifier draw on a combination of probabilistic, rule-based, and spatial classifiers with a voted ensemble meta-classifier.

Social media data can also be productively combined with demographic and geospatial data to make predictions on issues such as political leanings. For example, Bastos and Mercea (2018) fit a model that is able to predict support for the Brexit referendum in the UK based on the combination of geo-localized tweets and sociodemographic data.

Though manual classification is the norm, in some cases, a combination of unsupervised and supervised machine learning may yield good results. Boecking et al. (2015) study domestic events in Egypt over a 4-year period, effectively using the metadata and background knowledge of events from 1.3 million tweets to train a classifier.

Other approaches that connect manual content analysis with supervised machine learning that are presently still underutilized in the social sciences include argumentation mining. For example, Bosc et al. (2016) provide an overview of argument identification and classification using a number of different classifiers applied to a range of manually annotated Twitter data sets. Using a broader range of features in particular appears to increase the performance of SML techniques markedly.

4 Topic Modeling as Unsupervised Method in Conflict Research

The main difference between supervised and unsupervised text as data methods is that unsupervised techniques do not require a conceptual structure that has been defined beforehand. As explained above, dictionary applications and supervised techniques are *deductive* approaches which rely either on a theoretically informed collection of key terms or a manually coded sample of documents to specify what is conceptually interesting about the material before applying a statistical model to extend the insights to a larger population of texts. In contrast to this, unsupervised methods work *inductively*: without predefined classification schemes and by using relatively few modeling assumptions, such algorithm-based techniques shift human efforts to the end of the analysis and help researchers to discover latent features of the texts (Lucas et al., 2015, p. 260, Grimmer and Stewart, 2013).

Unsupervised text as data techniques are useful for conflict research—especially for understudied areas and previously unknown primary sources or the many rapidly growing digitized resources—because they have the potential to disclose underlying clusters and structures in large amounts of texts. Such new insights can either complement and refine existing theories or contribute to new theory-building processes about the causes and consequences of conflict.

While there are several variations of unsupervised methods,[4] our literature survey shows that topic modeling is the most frequently used technique in conflict research. Common to topic modeling is that *topics* are defined as probability distributions over words and that each document in a corpus is seen as a mixture of these topics (Chang et al., 2009; Grimmer and Stewart, 2013; Roberts et al., 2014). The first and still widely applied topic model is the so-called LDA—latent Dirichlet allocation (Blei et al., 2003; Grimmer and Stewart, 2013). Recently, the Structural Topic Model (STM) has been proposed as an innovative and increasingly used alternative to the LDA (Roberts et al., 2014; Lucas et al., 2015; Roberts et al., 2016). Whereas the LDA algorithm assumes that topical prevalence (the frequency with which a topic is discussed) and topical content (the words used to discuss a topic) are constant across all documents, the STM allows to incorporate covariates into the algorithm which can illustrate potential variation in this regard (Roberts et al., 2014, p. 4).

Typically, the workflow[5] of topic modeling starts with a thorough cleaning of the text corpus, as commonly done for quantitative bag-of-words analyses which transform texts into data. Depending on the research focus, such automated preprocessing includes lowercasing of all letters, erasing of uninformative non-letter characters and numbers, stopword removal, stemming, and possibly also the removal of infrequently used terms. Text cleaning procedures can have significant and unexpected effects on the results of unsupervised analyses which is why Denny and Spirling (2018) recommend "reasonable" preprocessing decisions and suggest a new technique to test their potential effects.[6] Subsequently, researchers must make some model specifications such as determining the number of topics (K) to

[4]Grimmer and Stewart (2013) provide a useful overview in this regard.

[5]While some researchers perform topic modeling in *Python* (2018), the detailed vignettes as well as online support and tutorials of packages in *R* (2018) such as *quanteda* (Benoit et al., 2018) or *stm* (Roberts et al., 2018) make these tools easily accessible.

[6]For detailed explanations of how to apply these tests see Denny and Spirling (2018).

be inferred from the corpus and—in case of the STM—the choice of covariates. Through Bayesian learning, the model then discriminates between the different topics in each document. Concretely this means, for example, that based on updated word probabilities, the algorithm would group terms such as "god," "faith," "holy," "spiritual," and "church" to one topic in a document, while the same document could also contain words such as "bloody," "violent," "death," "crime," and "victim" constituting a second topic. Lastly, it is the researchers' task to adequately label and interpret such topics and make more general inferences.

Topic modeling is a new methodological trend in conflict research—the recent growth in studies which apply such methods point to the great potential these innovative approaches have in this area. Examples cover a broad range of issues: Stewart and Zhukov (2009), for instance, analyze nearly 8000 public statements by political and military elites in Russia between 1998 and 2008 to assess the country's public debate over the use of force as an instrument of foreign and defense policy. The LDA analysis of Bonilla and Grimmer (2013) focuses rather on how external threats of using force and committing a terrorist attack influence the themes of major US media and the public's policy preferences at large. Other studies applying the LDA algorithm scrutinize patterns of speaking about Muslims and Islam in a large Swedish Internet forum (Törnberg and Törnberg, 2016) or generally look into how controversial topics such as nuclear technology are discussed in journalistic texts (Jacobi et al., 2016). While Fawcett et al. (2018) analyze the dynamics in the heated public debate on "fracking" in Australia as another example of non-violent conflict, Miller (2013) shows that topic modeling can be also valuable to study historical primary sources on violent crimes and unrest in Qing China (1722–1911).

One central and rather broad contribution to conflict research is the study of Mueller and Rauh (2018). Based on LDA topic modeling, they propose a new methodology to predict the timing of armed conflict by systematically analyzing changing themes in large amounts of English-speaking newspaper texts (articles from 1975 to 2015, reporting on 185 countries). The added value of using unsupervised text-mining techniques here is that the explored within-country variation of topics over time help to understand *when* a country is at risk to experience violent outbreaks, independent of whether the country had experienced conflicts in the past. This is truly innovative because earlier studies could merely predict a general, not time-specific risk in only those countries where conflict had appeared before. Mueller and Rauh (2018, p. 359) combine their unsupervised model with panel regressions to illustrate that (not) reporting on particular topics increases the likelihood of an upcoming conflict. They show, for example, that the reference to judicial procedures significantly decreases before conflicts arise.

Other recent conflict analyses apply the newly proposed STM model of Roberts et al. (2014, 2016, 2018). As explained above, the difference between the LDA and STM algorithm is that the latter allows to include document-level metadata. Lucas et al. (2015), for example, specify in their model on Islamic *fatwas* whether clerics are Jihadists or not. Based on this, they illustrate crucial topical differences between both groups—thus, Jihadists mostly talk about "Fighting" and "Excommunication" while non-Jihadists rather use topics such as “Prayer” and “Ramadan” (Lucas et al., 2015, p. 265). Terman (2017) uses STM to scrutinize Islamophobia and portrayals of Muslim women in US news media. Her findings of analyzing a 35-year coverage of journalistic texts in the *New York Times* and *Washington Post* (1980–2014) on women in non-US countries show that stories about Muslim women mostly address the violation of women’s rights and gender inequality while stories about non-Muslim women emphasize other topics. Further research on conflicts which also make use of STM include Bagozzi and Berliner’s (2018) analysis of crucial variations over time concerning topic preferences in human rights monitoring or Mishler et al. (2015) test of detecting events based on systematically analyzing Ukrainian and Russian social media.

Validating model specifications and particularly the labeling and interpretation of topics as model output is an absolutely crucial part of any unsupervised text analysis. As Grimmer and Stewart (2013) point out, such post-fit validation can be extensive. However, systematic validation procedures and standardized robustness tests for unsupervised methods are still pending. Frequently, applications of topic models in conflict research and other fields of study exhibit two shortcomings in this regard: First, the model specification of determining the number of topics (K) is not sufficiently justified. Second, the labeling and interpretation of topics seem arbitrary due to lack of information about this process.

The selection of an appropriate number of topics (K) is an important moment in topic modeling: too few topics result in overly broad and unspecific categories, too many topics tend to over-cluster the corpus in marginal and highly similar topics (Greene et al., 2014, p. 81). The general aim in this regard is to find the number of K that yields the most interpretable topics. While there are methods and algorithms to automatically select the number of topics (Lee and Mimno, 2014; Roberts et al., 2018), Chang et al. (2009) show that the statistically best-fitting model is usually not the model which provides substantively relevant and interpretable topics. To reach this goal, we recommend to conduct systematic comparisons of model outcomes with different Ks, similar to Bagozzi and Berliner (2018), Jacobi et al. (2016), Mueller and Rauh (2018), Lucas et al. (2015). Visualizations of such robustness tests such as in Maerz and Schneider (2019) further increase the transparency concerning the decision-making process of determining K.

A valid process of labeling and interpreting topics as model outcome includes a thorough analysis of the word profiles for each topic. While computational tools can efficiently support such examinations, one should keep in mind that this is a genuinely interpretative and rather time-consuming act which needs to be documented in a comprehensible manner. The *R* package *stm* offers several functions to visualize and better understand the discursive contexts of topics (Roberts et al., 2018). This includes the compilation of detailed word lists with most frequent and/or exclusive terms per topic (*lableTopics*), the qualitative check of most typical texts for each topic (*findThoughts*), or estimating the relationship between metadata and topics to better understand the context and interrelation of the topics at large (*estimateEffect*). In addition, Schwemmer’s (2018) application *stminsights* provides interactive visualization tools for STM outcomes to facilitate a straightforward validation. In the following section, we make several suggestions of how to further strengthening the validity of automated content analysis in conflict research by combining topic modeling with other text-mining techniques and quantitative or qualitative methods.

5 Techniques of Cross-Validation

In their groundbreaking article on automated content analysis of political texts, Grimmer and Stewart (2013, p. 269) suggest four principles of this method: *(1) While all quantitative models of language are wrong, some are indeed useful. (2) Automated text analysis can augment, but not replace thorough reading of texts. (3) There is no universally best method for quantitative text analysis. (4) Validate, validate, validate.* It is particularly the latter point which we would like to emphasize in this section. Automated text analysis has the potential to significantly reduce the costs and time needed for analyzing a large amount of texts in conflict research—yet, such methods should never be used blindly and without meticulous validation procedures that illustrate the credibility of the output.

As we have argued above, the validation of dictionary approaches and supervised techniques needs to show that such methods can replicate human coding in a reliable manner (Grimmer and Stewart, 2013, p. 270). For unsupervised methods, it is important to justify and explain model specifications and demonstrate that the model output is conceptually meaningful. Beside these necessary steps for each method individually, we recommend to combine dictionary approaches and supervised as well as unsupervised techniques as efficient tools for cross-validation. In agreement with Grimmer and Stewart (2013, p. 281) we hold that these different techniques are highly complementary and suggest two strategies of designing such multi-method validations. The first procedure of cross-validation is rather inductive and particularly suitable for exploring new theoretical relations and conceptual structures in large amounts of hitherto broadly unknown texts. This technique is similar to what Nelson (2017) describes as "computational grounded theory." Figure 1 provides a simplified illustration of this process, which we refer to as the inductive cycle of cross-validation. The starting point of this framework is topic modeling because it allows for an inductive computational exploration of the texts. Nelson (2017) calls this the pattern detection step, which subsequently facilitates the formulation of new theories. Based on this theory-building process, a targeted dictionary or coding scheme is conceptualized. The outcome of applying this newly developed dictionary or coding scheme can illustrate that the results of the preceding topic modeling are indeed conceptually valid and—to a certain degree—comparable to measures from supervised models (Grimmer and Stewart, 2013, p. 271). Furthermore, such supplementary supervised analyses are more focused

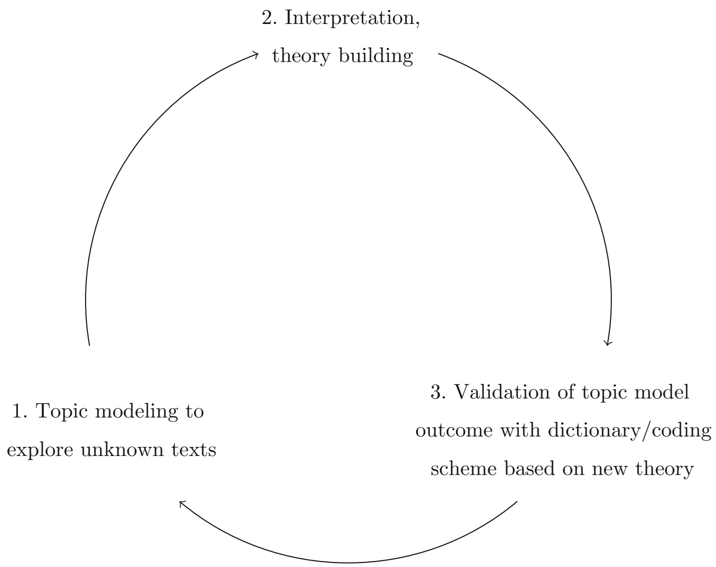

Fig. 1 The inductive cycle of cross-validation

and helped to illuminate specific aspects of the texts which are theoretically more interesting than the broad outcome of the explorative topic modeling.

The rich and original material gained during ethnographic field research is one example from conflict studies for which the inductive cycle would be a suitable approach. After having conducted open-ended surveys in a country torn by ethnic conflicts, for instance, one is confronted with huge amounts of unique texts which ask to be analyzed. Topic modeling is a fruitful start in this regard (Roberts et al., 2014), followed by a more fine-graded and theory-guided dictionary analysis or supervised learning. Overall, the suggested framework allows for a thorough cross-validation of the different analytic steps and is a comprehensive way of computationally accessing new information—in this example about the nature of ethnic conflicts.

The second procedure of cross-validation is a deductive approach that implies that the researcher has an existing theoretical framework in mind when developing a dictionary or coding scheme for supervised learning. Alternatively, one could also apply an already established dictionary to a corpus of texts for which this application is theoretically and substantially justified (yet, see Sect. 2 regarding the risks of blindly adopting dictionaries for diverging fields of inquiry). As illustrated in Fig. 2, this first step is followed by a topic model applied to the same corpus of texts to additionally explore hidden features in the material that might be of theoretical interest but are not yet captured by the dictionary or coding scheme. The outcome of the topic modeling—typically a report of top terms appearing in K topics—has then the potential to validate but also significantly complement and refine the existing dictionary or coding scheme, leading to more solid results.

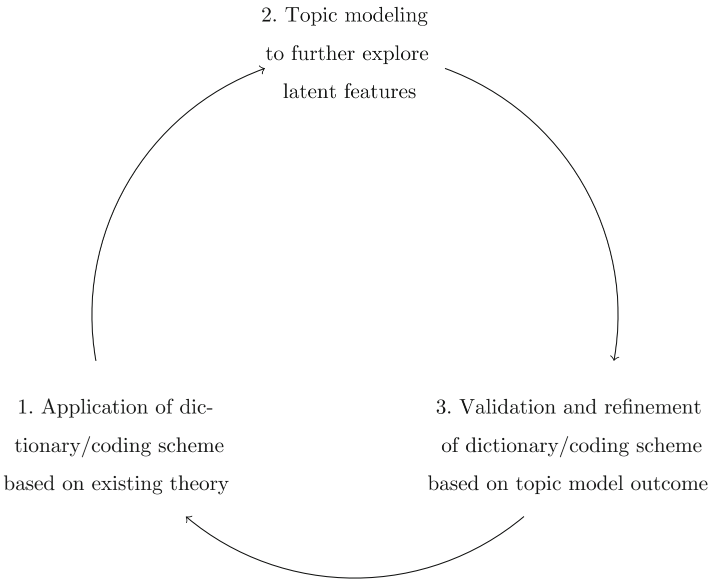

Fig. 2 The deductive cycle of cross-validation

The analysis of propaganda magazines or online material published by a newly emerging Islamist terrorist group is one example from conflict research that could be adequately analyzed with the described deductive framework. Making use of existing theories about Islamist communication strategies or applying an already established dictionary that was developed to analyze Islamist rhetoric seems adequate to scrutinize the content of such texts in a first step. However, since the assumed terrorist group would be a new formation in the field of Islamist fundamentalism, the additional application of topic modeling could disclose so far unknown aspects about this group or the language of terrorists in general. This, in turn, contributes to further improving the existing dictionary or coding scheme and, overall, enables a more valid analysis.

Existing empirical analyses from related fields of research that apply a similar validation cycle include the study of the language of autocrats by Maerz (2019) or the analysis of illiberalness in the speeches of political leaders by Maerz and Schneider (2019). The latter further expand the validity tests to qualitative checks and network analysis to handle their particularly heterogeneous material. While we have focused here solely on a fruitful combination of various text as data techniques, the inclusion of other qualitative and quantitative methods and visualization techniques is another option to further test and illustrate the validity of the results.

6 Conclusion

In this chapter, we discussed several CATA methods used in conflict research as new techniques to handle growing amounts of written on- and offline resources. Table 2 compares the performance of the different approaches which we have described in the preceding sections. The first technique—dictionary applications—is rather straightforward and comparatively easy to apply once a theory-guided selection of keywords has been defined. For conflict researchers interested in text mining methods, this first approach might be particularly suitable if material was collected from a research field that is already widely covered by established theories. The dictionary analysis could help, for example, to further refine those theories. Yet, as Table 2 specifies, one disadvantage of dictionary applications is that it can be very challenging to justify why a certain selection of terms is more suitable than alternative word lists. Such procedures typically imply extensive qualitative procedures to illustrate the validity of the dictionary.

The second approach we discussed is supervised machine learning. Supervised text mining is a more sophisticated approach than dictionary applications because it is not limited to a fixed list of keywords. Instead, these semi-automated methods make use of algorithms which *learn* how to apply the categories of a manually coded training set to larger amounts of texts. One downside of supervised learning is that the manual coding of the training set can be highly work-intensive. This is why we recommend this method for conflict researchers who are either experienced in the manual coding of texts or have sufficient capacities to handle this first and laborious step of the analysis.

Lastly, we reviewed topic modeling as the most current unsupervised method applied in conflict research. Topic modeling is particularly suitable for sizable amounts of new texts that cannot be manually screened since these methods help to explore the underlying structure and topics of the hitherto unknown texts. While this inductive detection of topics is fully automated, the definition of model specifications and interpretation of the model outcome require high human efforts and transparency to ensure valid and non-arbitrary inferences (cf. Table 2).

Table 2 Comparing the performance of different CATA methods

	Dictionary	Supervised (SML)	Unsupervised (UML)
Advantages	Relatively easy to apply, no comprehensive cleaning of corpus needed	Not limited to fixed keywords, extends manually coded training set to large amounts of texts	Reveals latent features in (hitherto unknown) texts, analysis is fully automated
Disadvantages	Validation of dictionary challenging, re-usage of dictionary in different contexts problematic	Laborious manual coding of training set required	Model specifications and interpretation of model outcome requires high human efforts

As one recommendation for future text mining projects in conflict research, we highlighted validation as a crucial element of all text as data methods. Ideally, tests for validity evaluate model performance and compare the output of the model to the results of hand coding, illustrating that the automated analysis closely replicates the human-coded outcome. However, applying such procedures can be costly and difficult to implement in many settings. This is why we additionally suggested two cycles of combining dictionary approaches, supervised methods and unsupervised techniques to effectively cross-validate the outcome of these applications.

Apart from extensive validation procedures, we believe that transparency in terms of methodological decisions and steps, accessibility to data and replication files as well as open access publications are critical to advance computational methods in conflict research and beyond. While researchers have started to follow these practices in providing online appendices on methodological details and robustness tests and making their replication files publicly available on dataverses,[7] there is still a large number of studies that are rather nebulous about these things, further enforcing the much-discussed replication crisis in the social sciences. Text as data approaches are currently experiencing a hype—yet, while plenty of innovative tools and techniques are being developed, there is the need for platforms and digital hubs that bundle the newly gained knowledge and make it accessible to a broader community of researchers.[8] Such new policies of data sharing and digital cooperation pave the way for a more networked and progressive computational methodology in the social sciences.

Appendix

See Table 3.

[7]For example, https://dataverse.harvard.edu/.

[8]First steps into this direction are initiated by research institutes such as the Social Media and Political Participation Lab (https://smappnyu.org/), the MediaCloud (https://mediacloud.org/), the Berkman Klein Center for Internet and Society at Harvard (https://cyber.harvard.edu/), the Oxford Internet Institute (https://www.oii.ox.ac.uk/) or the newly founded Digital Democracy Lab (https://digdemlab.github.io/).

Table 3 This overview is not an exhaustive list but rather a selection of text mining examples in the field of conflict research

Author(s)	Conflict	Data	Text mining technique	Software[a]	Validation[a]
Baden and Tenenboim-Weinblatt (2018)	Six selected armed conflicts	896,480 news texts from 66 news outlets	Dictionary based on cross-linguistic semantic concepts	*R*	–
Bagozzi and Berliner (2018)	Human Rights monitoring	6,298 State Department Country Reports on Human Rights practices (1977–2012)	STM topic modeling	*R*	Alternative Ks[b]
Bastos and Mercea (2018)	Brexit	8,821,116 tweets, 10,000 of which were hand-coded	Supervised learning	*R*	Combined with hand-coding
Burnap and Williams (2015)	Woolwich murder	450,000 tweets, 2,000 of which were hand-coded	Supervised learning	*Java* (Weka)	Combined with crowdsourced hand-coding
Fawcett et al. (2018)	Frame conflicts over the future of 'fracking' in Australia	Relevant newspaper articles	LDA topic modeling	–	Combined with hand-coding
Greene et al. (2018)	Human rights violations	US State Department Human Rights Reports (1978–2010)	Supervised learning algorithms	*R*	Cross-validation with different models
Macnair and Frank (2018a)	Islamic State	IS propaganda magazines *Dabiq* and *Rumiyah* (25 issues)	Sentiment analysis (over time)	*SentiStrength*	–
Macnair and Frank (2018b)	Islamic State	IS online media, transcripts of IS-produced videos	Sentiment analysis	*SentiStrength*	–
Mueller and Rauh (2018)	Prediction of armed conflict	Relevant newspaper articles	LDA topic modeling	*Python*	Alternative Ks[b]
Arendt and Karadas (2017)	Mediated associations with Islam	German news coverage of Islam	Contrast Analysis of Semantic Similarity (CASS)	CASS software	Reference to Holtzman et al. (2011, 2015)
Medzihorsky et al. (2017)	Syrian Civil War	347 speeches from UN Security Council members of 37 states	Dictionary scaling with dynamic model	*R*	Qualitative checks

(continued)

Table 3 (continued)

Author(s)	Conflict	Data	Text mining technique	Software[a]	Validation[a]
Scharkow (2013)	Various news issues, including *crime* and *controversy*	933 hand-coded newspaper articles	Supervised learning	*Python*	Combined with hand-coding
Terman (2017)	Islamophobia	Media portrayals of Muslim women in US news media	STM topic modeling	*R*	–
Tingley (2017)	International conflicts	Survey data on bargaining between declining and rising power	STM topic modeling	*R*	Combined with experiment
Jacobi et al. (2016)	Nuclear technology	New York Times coverage of nuclear technology (1945–2013)	LDA topic modeling	*R*	Assessment of alternative Ks[b], comparison with earlier deductive works
Törnberg and Törnberg (2016)	Islamophobia	Muslims in Swedish social media discourse (2000–2013)	LDA topic modeling	–	Combined with discourse analysis
O'Halloran et al. (2019)	Violent extremist discourse	IS propaganda magazine *Dabiq*	Dictionary analysis based on Wikipedia classifications, visualisation based on image processing algorithms	–	Qualitative analysis of text-image relations
Dowell et al. (2015)	Autocracies in crises	Texts of Fidel Castro, Zedong Mao, Hosni Mubarak	Coh-Metrix, LIWC dictionary	–	Reference to Tausczik et al. 2010
Lucas et al. (2015)	Islamic/Jihadi rhetoric	27 248 texts from Jihadists and non-Jihadists Muslim clerics	STM topic modeling	*R*	Network analysis and other visual tools
Mishler et al. (2015)	Ukrainian crisis	Ukrainian and Russian social media to study public opinion and detect events	STM topic modeling	*R*	Crosscheck with hand-coded sample

Burscher et al. (2014)	Conflicts described in news articles (among other frames)	Dutch front-page news articles (1995–2011)	Supervised learning	*Python*	Comparison of two models
Cohen et al. (2014)	Lone wulf terrorism	No empirical analysis	Discussion of different text analysis techniques to detect potential lone wulf terrorists in the Internet	–	–
Bonilla and Grimmer (2013)	Democracy and terrorism	51 766 US newspaper stories, major nightly news broadcasts (ABS, CBS, NBC)	LDA topic modeling	–	Survey data
Miller (2013)	Crime, unrest in Qing China (1722–1911)	Official records on violent crime and unrest ('the veritable records')	LDA topic modeling	–	–
Pennebaker (2011)	Language and terrorism	296 speeches, interviews, articles from four extremist groups	LIWC dictionary	–	Reference to Tausczik et al. 2010
Hart and Lind (2011)	Islamic activist rhetoric	327 Islamic texts compared with rhetoric of US politicians, protesters and preachers	Dictionary	DICTION software	–
Pennebaker (2011)	Islamist language styles	296 texts from four Arabic-speaking extremist groups with violent past	LIWC dictionary, function words	–	–
Stewart and Zhukov (2009)	Public debates in Russia over the use of force	7,920 public statements (1998–2008)	Expressed Agenda Model	–	Combined with supervised techniques

The primary aim of the table is to offer conflict researchers interested in text mining a first impression about topics under investigation, applied techniques, software used and validation tests

[a]NOTE: Table elements with—signify that no specific information about used software or validation procedures was found in the respective article

[b]K = Number of topics

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Interdependencies in Conflict Dynamics: Analyzing Endogenous Patterns in Conflict Event Data Using Relational Event Models

Laurence Brandenberger

Abstract Relational event models are a powerful tool to examine how conflicts arise or manifest through human interactions and how they evolve over time. Building on event history analysis, these models combine network dependencies with temporal dynamics and allow for the analysis of group formation patterns—such as alliance or coalition formation processes—influencing dynamics or social learning. The added information on both the timing (and order) of social interactions as well as the context in which social interactions take place (i.e., the broader network in which people or actors are embedded in) can give powerful new evidence to theorized social mechanisms. This chapter provides an overview of REMs and showcases two empirical studies to illustrate the approach. The first study examines political alliance-formation patterns among countries engaging in military actions in the Gulf region. The REM shows that countries engage in military actions with other countries by balancing their relations, i.e., by supporting allies of their allies and opposing enemies of their allies. The second study shows that party family homophily guides parliamentary veto decisions and provides empirical evidence of social influencing dynamics among European parliaments.

Keywords Dynamic networks · Inferential network analysis · Conflict event data · Social mechanisms · Temporal dependence

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1 Introduction

Conflict has an inherently social aspect. Conflicts often arise between two parties and are often perpetrated in a broader context with the involvement of third-party actors[1] (see for instance Nelson, 1989; Crescenzi, 2003; Knoke, 1994; Wasserman and Galaskiewicz, 1994). One potential source of conflict relates to the social mechanism of social influencing and the social dynamics that build from it. Social influencing can be described as a relational process where actors modify their behavior or values to become more alike with the actors they interact with (for an overview, see Flache et al., 2017). Influencing has been described as an active force, where some actors try to persuade others to change their beliefs, attitudes, or even behavior—or as a passive force, where actors mimic values or behavior of others with whom they interact (Lindstädt et al., 2017; Shalizi and Thomas, 2011).

Social influencing can lead to conflicts within groups, as it brings some actors to do things they may not necessarily want to do (Myers, 1982; Welch and Wilkinson, 2005). Furthermore, social influencing can lead to coalition formation, where groups of actors develop their own dynamics and engage more strongly with their own group members than with other actors outside their group (Jehn et al., 2013; Berardo and Scholz, 2010). This can lead to situations where if one member of a group stands in conflict with another actor outside the group, the entire group may develop a negative relation with this outside actor. By doing so, the group reinforces their own group cohesion. Heider (1946) summarizes these coalition formation dynamics in his balance theory, where he stipulates that the enemy of my friend eventually becomes my enemy as well (see also Newcomb (1961) and Kohne et al. in the chapter "Norm Conflict in Social Networks" of this book). This indicates that conflict dynamics can go beyond dyadic relationships and a conflict between two actors can escalate into a conflict between larger groups or coalitions (Hadjikhani and Håkansson, 1996; Crano and Cooper, 1973; Labianca et al., 1998).

A question that naturally arises is: How can we detect and examine these social dynamics that can lead to conflicts in social interactions? Relational event models (REM) can be used to study multiple social mechanisms and their explanatory power of the temporal dynamics behind social interactions. REMs are inferential models that make use of temporally fine-grained records of social interactions to model complex interaction patterns and endogenous processes. REMs can be used to detect social influencing (Malang et al., 2018), understand social exchanges (Butts, 2008; Zenk and Stadtfeld, 2010; Quintane et al., 2014; Kitts et al., 2016; Stadtfeld and Geyer-Schulz, 2011), and determine causes for group or conflict formation processes (Lerner et al., 2013a; Leifeld and Brandenberger, 2019; De Nooy and Kleinnijenhuis, 2013). Building on event history analysis, REMs try to explain the occurrence of relational events. The use of the network approach allows REMs to detect complex patterns in these relational events that go beyond dyadic

[1]For sake of linguistic simplicity, this chapter refers to *actors* as a general term for different social entities, such as individuals, organizations, governments, groups, teams or other collective actors.

dependencies (i.e., go beyond direct person-to-person interactions to include, for instance, the effect of third parties in these patterns) (Butts, 2008).

This chapter provides an overview over relational event models for the analysis of conflict event data. First, relational events as records of social interactions are discussed. Afterwards, REMs are presented, including how they build on event history analysis to statistically model event occurrence. The heart of REMs are endogenous network statistics that operationalize social mechanisms or patterns. The most commonly used statistics are presented in Sect. 4, together with a discussion of the temporal aspects of REMs. Section 5 gives two empirical examples and discusses their operationalizations of alliance formation and social influencing. The chapter closes with a discussion of the limitations of REMs and their link to agent-based modeling through the shared use of operationalizations of social mechanisms of human interactions.

2 Relational Events

Conflict events often entail both a relational and directional aspect. Relational in the sense that these events report interactions among individuals, groups, or actors. These interactions are often directed from one party to another and signed. They can be negative or openly conflictive in nature and reflect opposition between two engaging parties, for instance through an act of aggression from one party directed at another party. However, they can also be positive in nature and reflect support, for instance through the exchange of information or resources. In the latter case, the absence of positive interactions may be an indication of potential conflicts among actors not sharing resources.

Alternatively, conflicts can also arise through surrounding issues and be recorded in indirect social interactions, where an active actor engages in passive issues or events. By looking at the surrounding involvement of other actors in these issues or events, a complex entanglement of actors becomes evident, where conflicts manifest themselves for instance in coalition structures and close-knit clusters of actors engaging in the same issues or events. A political debate can serve as an example here, where political actors take stances on different political issues, thus revealing their underlying coalition structure and support system (see for instance Leifeld (2017) and Hadjdinjak et al. in the chapter “Migration Policy Framing” of this book). Relational event models aim at uncovering patterns that guide these interactions and help explain how conflicts arise or manifest themselves in social interactions and how they evolve over time.

At the minimum, relational events consist of a sender node a, a target node b, and either a time stamp t that records the interaction in continuous time or the place of the event in the time-ordered sequence. Once sorted in time, these events form a so-called event sequence—or event stream. Relational events can be expanded to reflect more diverse interactions. Events can be signed, for instance, to classify allegiance and opposition in international relations, friendship, and animosities in interpersonal interactions or agreement and disagreement in communication networks. Additionally, relational events can be weighted to reflect the intensity of the interaction. For instance, in international relations, weighted events can signify the degree of military aggression that an event encodes. In an event sequence consisting of email exchanges between colleagues in a firm, the weight of each event could correspond to the number of characters in the email or the degree of friendliness in the tone of the email. Sometimes, social interactions cannot be weighted but allow categorization. A relational event sequence can consist of different types of social interactions among sender and target nodes. For instance, in legislative politics, an event sequence can consist of members of parliament referencing (or attacking) each other in speeches, supporting each others' legislative proposal by cosponsoring them, or organizing joint press events to discuss relevant topics with the public. The assumption guiding these different types of interactions is that they co-evolve and affect each other over time.

In sum, relational event sequences are relatively flexible and are generally constrained by the data-gathering process and the degree to which social interactions can be quantified in a meaningful way.

3 Relational Event Models

The goal of REMs is to explain the temporal order of social interactions. Why do two people suddenly start exchanging emails? Why do two governments start engaging in military conflicts? Why do two members of parliament start collaborating with each other on a new legislative proposal? The answer to these questions is sometimes found in the broader context of these events. If two countries take up arms against each other, the alliances that form beforehand play a key role. If two people start exchanging emails it is possible that a mutual friend introduced them to each other beforehand. And if two members of parliament start working on a mutual proposal it is possible that they both learned about their mutual interest by both opposing a proposal by another member.

The events that occurred in the past often guide subsequent events and the relational event point of view can help uncover not simply how previous interactions of the two involved people or actors a and b shape their future interactions but also how changes in their surrounding network (i.e., with events that do not even involve a or b) affect how a and b interact in the future. It is a powerful framework for time-stamped or time-ordered analysis of social interactions that takes the surrounding context or a person's or actor's embeddedness into account. And so REMs build on event history analysis to ask the question: why does one event occur at time t and has not occurred before? And in a broader sense: which patterns of past interactions can help explain a specific sequence of events?

Figure 1 depicts a simple event sequence involving four actors (=nodes). The first three recorded interactions represent support among nodes a, b, and c. After a longer break, a new node d initiates a negative interaction with b, prompting b to affirm their positive relationship with node a which then brings a to oppose d. This example already hints at the complex surroundings actors are embedded in because

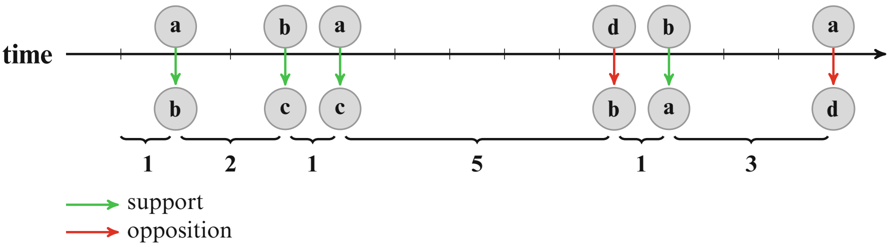

Fig. 1 Illustration of a relational event sequence depicting positive and negative interactions among four nodes a, b, c, and d

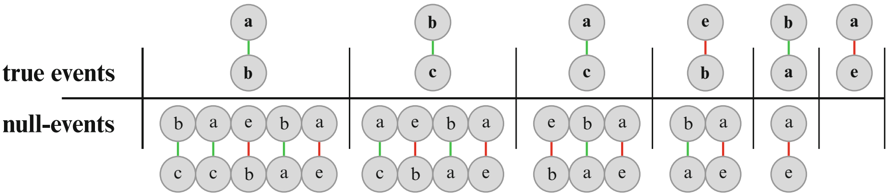

Fig. 2 Counting process data setup to estimate relational event models for the event sequence presented in Fig. 1. Each event in the event sequence forms a true event and is compared against events that could have occurred at time t but did not (so-called null events). The simplest definition of the risk set for each stratum (as shown here) contains events which eventually will take place but so far have not

even though actor d does not directly attack actor a, a may react to an indirect threat that occurs when d attacks b. The figure also shows the additional information that can be gained by recording events in time, as the time between events holds valuable information on how strongly future events depend on past events. The assumption that a reacts to an indirect threat by d is dampened a little bit by the long time it takes a to oppose d (4 time units in Fig. 1). The additional information on the timing of events can be used when encoding patterns, further discussed in Sect. 4.

In order to analyze the event sequence in Fig. 1, the sequence has to be transformed into so-called counting process data, first introduced by Andersen and Gill (1982). Figure 2 shows the setup of the counting process data for the event sequence presented in Fig. 1. For each unique time point in the event sequence, a stratum—or risk set—is build, containing both the true event (i.e., the event or events that occurred at time t) and null events. Null events are events that could potentially have occurred at time t but did not. The simplest definition of a risk set D at time t contains the true events that occurred at time t as well as all events that occur after time t. As the null events can add considerable observations to the data set, this definition of the risk set (restricted to events that occurred at one point in the event sequence) is the most sparse definition. Alternatively, if the event sequence allows for repeated events (i.e., interactions between two nodes can occur multiple times), a broader definition of the risk set may be desirable. For instance, the risk set could simply contain all possible combinations of sender and target nodes. In case the event sequence is signed and thus records both positive (e.g., supporting) and negative (e.g., hostile) interactions among nodes, the risk set can contain all combinations of sender and target nodes with both positive and negative edges. In the case of the event sequence presented in Fig. 1, the maximally large risk set could contain 24 events ($4 \cdot 3 \cdot 2 = 24$; 4 sender nodes times 3 remaining sender nodes (omitting self-loops) times 2 because each edge can be supporting or opposing) (see Brandenberger (2018) for additional information of risk set compositions).

Once the null events are added to the data, the hazard of event occurrence can be estimated. Standard inferential models from event history analysis can be employed because REMs assume that events are conditionally independent of one another if both exogenous and endogenous covariates are controlled for (Butts, 2008; Lerner et al., 2013b). The simplest form of the REM models event occurrence as a piecewise constant hazard model. This model assumes that the hazard (or chance) of an event occurring is constant within a time interval.

The likelihood that a specific number of events $n_{ij}(t)$ take place on a dyad (i, j) within the time interval t is given by the hazard rate $\lambda_{ij}(t)$, and then multiplied by the survival function $exp(-\lambda_{ij}(t))$, which captures all events that could have occurred at time t yet did not (see Lerner et al. 2013a, pp. 18–19 and Butts 2008, pp. 161–163):

$$Pr(n_{ij}(t)) = \frac{\lambda_{ij}(t)^{n_{ij}(t)} \cdot exp(-\lambda_{ij}(t))}{n_{ij}(t)!}. \tag{1}$$

The probability density of the event sequence E can be gained by multiplying all dyads and all unique times t_1 to t_N:

$$f_\lambda(E; \theta^\lambda) = \prod_{t=t_1}^{t_N} \left(\prod_{ij \in D_{\text{act}}(t)} \frac{\lambda_{ij}(t)^{n_{ij}(t)}}{n_{ij}(t)!} \right) \cdot exp \left(- \sum_{ij \in D} \lambda_{ij}(t) \right), \tag{2}$$

where $D_{\text{act}}(t)$ refers to all dyads in which at least one event occurred over E and D refers to all possible events that could have occurred (Lerner et al., 2013a, pp. 18–19).

For continuous-time sequences, REMs use duration models or a stratified Cox model to model the time-to-next-event (for an example, see Brandenberger, 2018). In Fig. 1 these inter-event times are summarized below the curly brackets. If the exact timing of events is irrelevant or only discrete-time information is available, a stratified Cox model with constant event times can be used (Butts, 2008). The stratified Cox model estimates which factors affect event occurrence, i.e., cause an event to occur during one particular strata at time t, and assumes that the baseline hazard of each event is constant within a stratum but varies between strata (Cox and Oakes, 1984; Allison, 1982; Box-Steffensmeier and Jones, 2004; Allison, 2014). The stratified Cox model with constant event times can be estimated with a conditional logistic regression (Gail et al., 1980; Allison, 1982) and has become the most widely used model for REMs (Kitts et al., 2016; Quintane et al., 2014; Vu et al., 2015). In the conditional logistic regression each stratum (or risk set) compares true events, set to 1, to null events, set to 0. Independent and control variables are used to explain why true events occurred and null events did not.

The standard output of a REM is comparable to outputs from logistic regressions, where for each covariate a beta-coefficient is estimated, which reflects this covariate's weight on the hazard of event occurrence. Coefficients are usually reported as log-odds and follow standard interpretations of logistic regressions.

4 Controlling for Endogenous Network Effects

The heart of REMs are the endogenous statistics that encode patterns in past interactions to help explain event occurrence. REMs can incorporate time-varying exogenous and endogenous variables or statistics. They are used to explain why some events take place at time t and why they have not occurred before. By encoding endogenous patterns in these statistics, complex social mechanisms that guide social interactions can be uncovered. Moreover, by calculating different patterns, their effect on event occurrence can be quantified and compared to each other, illuminating which are the driving factors of social interactions.

The patterns that are encoded in these endogenous network statistics are limited only by the researchers' creativity, theoretical ideas on social mechanisms, and computational limitations (as further discussed in Sect. 5).

There are six commonly used statistics that can be expanded into more complex patterns of social interactions (see Fig. 3). *Inertia* measures whether events have a tendency to repeat themselves in the event sequence. *Reciprocity* measures whether a previous target node (node a in Fig. 3) directs an event at the previous sender node (b). *Activity* measures how active a sender node is over the course of the event sequence and *popularity* measures how popular a target node is. *Closing triads* measures whether two nodes engage with each other due to their previous engagements with a shared partner (node b in Fig. 3) and *four-cycles* measure whether indirect engagements (nodes a and d in Fig. 3) drive network closure. In directed event sequences *closing triads* and *four-cycles* can be used to operationalize different closure effects (e.g., cycles or transitive triads). *Inertia*, *activity*, *popularity*,

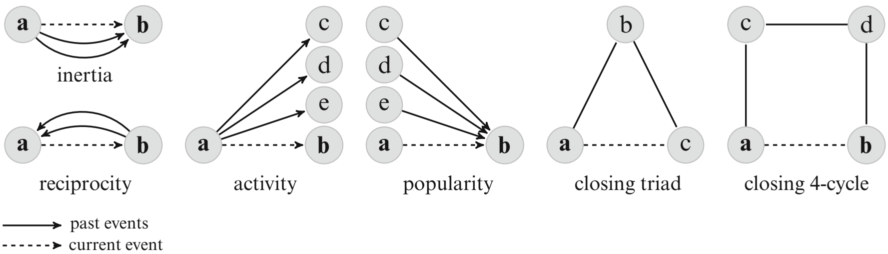

Fig. 3 Classic endogenous network effects can be used to test different interaction patterns in temporal event sequences

and *four-cycles* can also be used in two-mode event sequences (where sender nodes and target nodes stem from different node sets).

In the case of country-to-country military aggression, *inertia* reflects repeated attacks from one country to another and *reciprocity* reflects whether countries have a tendency to retaliate. *Activity* measures whether some countries are more active in pursuing alliances or conflicts and *popularity* measures whether some countries are attacked (or called to an alliance) at higher rates than others. *Closing triads* measure whether events involving shared partners spur countries into action (for instance to defend their allies) and *four-cycles* measure whether there is a tendency for certain countries to remain neutral versus one another (countries a and d in Fig. 3).

These six statistics can be made more complex by allowing for attributes of the nodes (i.e., checking reciprocity levels among countries with the same national language) or by incorporating edge attributes (such as filtering triadic closure for positive and negative ties). The two empirical examples introduced in the next section both incorporate some of these commonly used statistics in their REM and by including edge and nodal attributes find evidence for more complex social patterns of interaction that lead to social cohesion and balance.

Another important component of endogenous network statistics is how they incorporate time. Temporal dynamics of social interactions are crucial in understanding how interactions evolve and build up over time. For relational events, each true and null event belonging to the same stratum at time t (i.e., belonging to one unique point in time on the event sequence) builds a so-called *network of past events* G_t to look back over the event sequence prior to time t to determine whether previous events can explain which events in the stratum are true events and which are null events.

The network of past events is defined as

$$G_t = G_t(E) = (A; B; w_t), \tag{3}$$

where $E = (e_1, e_2, \ldots, e_n)$ represents the set of events, A is the set of sender nodes, B the set of target nodes (where $A = B$ for one-mode networks), and w_t represents a weight function that can be applied to each event before time t.

The weight function in its simplest form gives a constant weight of 1 to each past event in G_t. However, the weight function can also be used to give events further in the past less weight than more recent events (Lerner et al., 2013a). For instance, an exponential decay function can be used to account for memory loss or forgetting:

$$w_t(i, j) = \sum_{\substack{e:a_e=i,b_e=j,\\ t_e<=t}} |w_e| \cdot e^{-(t-t_e)\cdot\left(\frac{ln(2)}{T_{1/2}}\right)} \cdot \frac{ln(2)}{T_{1/2}} \tag{4}$$

where $i = a_e \in A$ and $j = b_e \in B$, w_e is the weight of event e, t is the current time, t_e is the time of event e. $T_{1/2}$ represents the value of the half-life parameter.

The half-life parameter specifies how fast the weight of past events diminishes, with a smaller half-life giving more weight to more recent events (Lerner et al., 2013a).

The weight function is applied to each past event that completes a social pattern or mechanism. For instance, the reciprocity statistic for the dyad (a, b) counts how often an event (b, a) occurred in the past:

$$\texttt{reciprocity}(G_t, a, b) = w_t(b, a) \tag{5}$$

For each past event (b, a) the time difference $(t_e - t)$ to the current event dictates how much weight should be ascribed to this past event. The triadic closure statistic can be operationalized as:

$$\texttt{closingTriad}(G_t, a, b) = \sqrt[2]{\sum_{i \in A} w_t(a, i) \cdot w_t(i, b)} \tag{6}$$

This approach allows for the testing of complex social mechanisms that involve multiple people or actors and follow distinct paths.

A number of statistical tools are available to estimate REMs. They include commands to prepare the data structure of REMs, calculate the endogenous network statistics, and estimate REMs. In the statistical computing environment `R` (R Core Team, 2016), the packages `relevent` (Butts, 2015) and `rem` (Brandenberger, 2019) are available to run REMs, where the latter supports exponential time weighting of past events. Alternatively, a java-based tool called `eventnet` (Lerner, 2019) is available for the analysis of event networks.

5 Empirical Examples of Alliance Formation and Social Influencing

In this section, two empirical examples are presented where alliance-building patterns and social mechanisms behind social cohesion are discussed and analyzed using relational event data.

5.1 Military Alliance-Formation Dynamics

Lerner et al. (2013a) model military engagements among nations involved in the Gulf region. They build on balance theory (Heider, 1946; Newcomb, 1961) to examine whether alliance-formation patterns follow the proposed patterns of interactions. Balance theory postulates that relationships among individuals or actors always have to be balanced in order to endure the passage of time. For instance in a triad (i.e., a triangular relationship pattern involving three actors), the number of positive relationships among the three actors has to be odd.

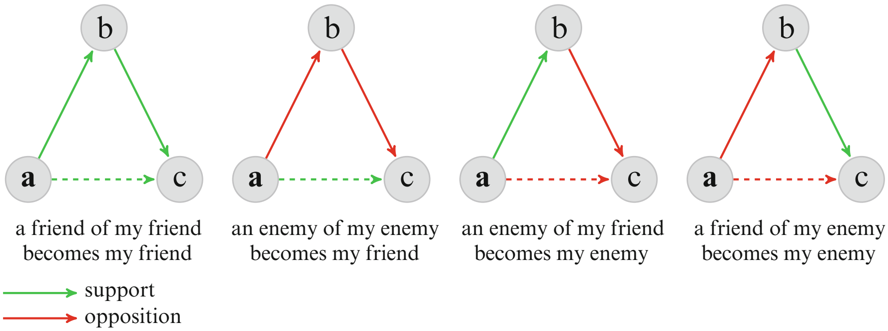

Fig. 4 Hypotheses of balance theory: Triads are only stable if their number of positive ties is odd. The focal actor a becomes active in closing the open triad (dashed relation from node a to c). Lerner et al. (2013a) find strong evidence of signed triadic closure in military engagements of different nations, indicating that alliances are formed and maintained based on the mechanisms postulated by balance theory

Figure 4 shows all four possible combinations of closed triads with signed edges. All three triangles are balanced if the dyad (a, c) is closed with an edge in the respected sign. Lerner et al. (2013a) use REMs to test whether nations have a tendency to close triads and if so, whether these triads are closed in the way balance theory suggests (and depicted in dashed edges between nodes a and c in Fig. 4).

They use data from the Kansas Event Data System (KEDS) on military actions in the Gulf region between 1979 to 1999. The event sequence involves over 200,000 events among 168 nations (Lerner et al., 2013a, p. 7). Events are coded as one-mode network events, with $nations \times nations$ interactions encoded in time. Additionally, for each event, a weight ranging from $[-10, 10]$ encodes the strength of the interaction with positive values indicating friendly interactions and support among the two nations, and negative interactions denoting military aggression. They use the `eventnet` application to estimate the effects of (balanced) triadic closure on event occurrence. Their results give strong support to balance theory. Moreover, they find that controlling for external alliances no longer yields any additional insights if reciprocity and triadic closure is adequately controlled for in the model (Lerner et al., 2013a, p. 28). This indicates that this form of balanced triadic closure can properly represent alliance-formation processes in international relations.

5.2 Influencing Dynamics Among EU Parliamentary Chambers

Malang et al. (2018) examine social influencing dynamics among national parliaments in Europe. They examine the case of the Early Warning System of the EU, where national parliaments in Europe are allowed to veto legislative proposals brought forth by the European Commission. If over one third of the parliaments (or more precisely parliamentary chambers) veto the same proposal, the European Commission is forced to re-evaluate and defend the proposal. Malang et al. (2018) argue that this vetoing threshold poses an incentive for chambers to influence each other and try to get them to veto the same proposal.

They use data from 353 vetoes issued between January 2010 and September 2016 by 39 parliamentary chambers in the EU. Here, not $person \times person$ events are examined but $chambers \times proposals$, i.e., a two-mode (or bipartite) event sequence, where sender nodes are different from target nodes and events record interactions or engagements between the two. The vetoes can be thought of as conflictual interactions of chambers with legislative proposals.

Previous studies on these vetoing actions link a chamber's decision to veto a proposal on their general attitudes towards the EU, how long they have been part of the EU, or their capacity to evaluate each proposal. However, these studies neglect the relational aspect that such collective vetoing dynamics brings with them. In order to reach the threshold, one third of all chambers have to issue a veto, but evaluating each proposal and drafting a veto takes time and resources and it is possible that chambers simplify their decision to veto by reacting to previously issued vetoes and take them as a signal to veto the proposal as well. Alternatively, it is possible that chambers try and influence each other by directly approaching members of parliament and convincing them to veto a proposal. Both explanations imply a strong social mechanism that drives vetoing behavior. One important question that arises is whether chambers influence each other based on distinct attributes they share. Do chambers with a specific attribute only react to vetoes issued by other chambers who share that attribute? And which attributes have this signaling power?

Malang et al. (2018) examine four different attributes of chambers through which this social influencing can run. They test whether two chambers are currently ruled by a party from the same party family (i.e., measuring left-right leaning similarities of chambers), whether two chambers are governed similarly and embedded in the same political system, whether two chambers joined the EU at the same time or whether the chambers are from neighboring countries. They use a popularity statistic and enhance it with chamber (or country) attribute homophily in order to test which similarities guide vetoing dynamics:

$$\texttt{chamberHomophily}(G_t, a, b) = w_t(i, b)[a_x = i_x], \tag{7}$$

where a refers to the focal chamber, deciding to veto a proposal b and i refers to other chambers that have vetoed proposal b in the past and share the same attribute x as the focal chamber (indicator function $[a_x = i_x]$) (Malang et al., 2018, p. 13).

For each of the four proposed channels of influence, they calculated the `chamberHomophily`-statistic. Parameter estimates for the four different operationalizations of homophily (as well as a broad range of control variables) were obtained from a conditional logistic regression on an ordinal-timed sequence of vetoes. They use the `rem`-package in `R` to calculate the homophily statistics and estimate the REM. Results of the REM revealed that only two of the four homophily statistics had positive and significant effects on vetoing dynamics. Chambers governed by parties from the same party family and embedded in similar political systems tend to veto the same proposals (Malang et al., 2018, p. 16). Using a permutation approach on the vetoing sequence they further show that only party family similarities drive influencing dynamics because they produce event sequences with strong temporal correlation among the order of events (Malang et al., 2018, pp. 14–15).

6 Discussion

With increasing prowess of automated data collections, gaining access to data with higher temporal resolution of social interactions (both on- and offline) has become easier. The added temporal information in the data in turn sharpens empirical evidence and opens up new avenues of research on social interaction patterns. Social mechanisms that guide social interactions can be analyzed in much more detail and opposing hypotheses can be tested against each other.

These new avenues also pose a challenge: Many theories on social interactions do not offer clear insights into how social mechanisms can be operationalized and tested. However, the long-standing tradition of modeling dynamic behavior in agent-based models (ABM) can offer important insights. REMs can borrow interaction rules and patterns from ABMs to help operationalize different patterns in event networks. Furthermore, REMs can be used to examine the interplay of different patterns (e.g., through interaction effects of different mechanisms). Often social interactions evolve and develop over time and REMs can track these changes in behavior (for instance through temporal interaction effects) to understand how some social mechanisms evolve into others or under which circumstances (i.e., a distinct period of time, for instance an election cycle) some mechanisms dominate others. REMs can also be used to examine if social mechanisms differ between groups, as for instance shown by Brandenberger (2018) that reciprocity guides collaboration strategies of Republican members of Congress, but not Democratic members.

One limitation of REMs are computational constraints. Particularly complex (or higher-order) endogenous network statistics are challenging to compute as the calculations have to cycle through the event sequence several times to determine which past events contribute to a certain interaction pattern. This is especially difficult if event sequences are large as the network of past events G_t becomes too extensive to filter. Sampling strategies can help alleviate this issue and reduce the computational burden.[2] However it remains to be tested, which sampling strategies prove efficient for REMs in that they do not prevent the detection of complex social patterns in large and sometimes noisy social interaction data.

[2]Sampling strategies are often used in rare event logistic regressions (see for example King and Zeng, 2001) and could be adapted to REMs.

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Part II
Computational Research on Non-violent Conflict

Migration Policy Framing in Political Discourse: Evidence from Canada and the USA

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Abstract How do parties discuss migration policy in legislative speeches? Legislative bodies are an arena for verbal conflicts where the parties vie for their ideological interests but also sharpen new rhetorical figures. Political parties develop policy stances strategically different from those of competing parties and elucidate those stances through legislative debates and public statements. A large body of literature argues that some issues, like migration, fall in a gap between established societal cleavages over which parties do not have robust, issue-specific ownership. More recent research suggests migration may be a part of a new transnational cleavage that pits cosmopolitan sensibilities against nationalist sentiments in a conflict over issue ownership and policy framing. Building off this debate, we hypothesize that parties discuss migration topics by diverting attention to subcomponents of migration policy over which they have established issue ownership. Using machine learning techniques, we test this assertion by measuring the differences in salience and framing of migration-related topics over time in the debates of the lower houses of Canada and the United States—the Canadian House of Commons and the United States' House of Representatives from 1994 to 2016. We find that there are substantive differences in the emphasis on and framing of the migration policy between the two ideological blocks. Democrats in the USA and liberals in Canada emphasize subcomponents of the migration debate which they traditionally own, such as welfare and humanitarian aspects. Both conservative blocks do the same by framing their discussion of migration through a focus on security and legalistic aspect of migration. However, due to strong polarization in the USA, the differences in the emphasis on the issues traditionally owned by the two ideological camps are stronger in the USA than in Canada.

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1 Introduction

Conflict is part and parcel of politics on the international, national, and local levels. Morgenthau's influential work defined politics as a struggle for power (Morgenthau 1960). Originating in legislative bodies of modern democracies, parliamentary debates offer an optimal source of information for an in-depth analysis of political conflict (Grimmer and Stewart 2013). Migration policy, the substantive focus of this chapter, is not only a prominent, much debated political and research issue, but its framing in legislative bodies also poses a theoretical puzzle.

Most political issues, as discussed in the issue ownership literature, fall in either the liberal or conservative political domain. This proposal is based on the nature of liberal and conservative[1] political issue ownership where parties develop stances on issues that resonate with voters so a common citizen would be able to place a particular issue or issue frame with the "correct" political party (Petrocik 1996). For instance, voters might reasonably associate social welfare policy domains with liberal parties or military and defense policies with conservative parties. In this case, on these two issues, the two political camps have issue ownership. However, migration policy has been argued to represent an exception as it creates conflicts within both ideological camps—market liberalism versus value conservatism (for the conservatives) and international solidarity versus welfare state/labor market protectionism (for the liberals) (Odmalm 2011a). This leads us to the question: how do liberal and conservative parties discuss migration issues in parliamentary speeches?

The literature suggests parties compete against each other by framing policies so they resonate with voters and their own platforms (Chong and Druckman 2007a, b; Nelson and Kinder 1996). We suggest that parties debate migration policy by emphasizing the subcomponents of the migration policy which they own. In addition, we suggest parties will emphasize their strengths more in polarized party systems as this allows their rhetoric to capture the median voter more regularly. We expect in a less polarized system, there will be less difference in emphasis parties place on issues they own.

While much of the literature on issue ownership and policy framing—upon which our work builds—focuses on campaigning and media statements, this chapter analyzes migration policy in legislative speeches. Lefevere et al. (2017) argue policy framing is aimed at either winning the rhetorical struggle or at gaining

[1] We refer to liberal and conservative ideology in the North American context, which follows the lines of the left-right political spectrum. Liberal ideology is identified as left-leaning, egalitarian, multicultural, and in support of social policies that appeal to the working class. Conservative ideology stands for right-leaning, orientation to tradition, and protection of private property and individualism.

public support. Thus, we argue floor speeches allow for members and their staff to sandbox ideas for talking points or policy frames in a low stakes environment prior to developing or revising a party manifesto, campaign platform, or press release. Moreover, being the center stage of the formal conflict between the parties, legislative speeches are a weapon parties use to demonstrate their strengths in the rhetorical arena.

To test our hypotheses regarding migration policy framing and polarization, we use a most similar comparative case study framework (Anckar 2008; Gerring 2009) and select the cases of the United States and Canada. Both economies were founded largely by immigrants and the discussion on migration policy is a constant question for decades in both the USA and Canada. While the two share a clear ideological divide between liberal and conservative camps, they differ regarding the degree of political polarization—the effect of which we are interested in exploring through our comparative case study design.

Our analysis includes debates in the lower houses of the national legislature in Canada and the United States—the Canadian House of Commons and the United States' House of Representatives from 1994 to 2016. As the migration debate is one that has existed in the political sphere of Canada and the United States since their founding as nations of immigrants, we test our hypotheses on a wide, contemporary timeframe that captures both liberal and conservative legislatures and executives as well as different waves of migration patterns from a variety of conflicts spanning much of the world.

Methodologically, we rely on unsupervised machine learning for our analysis of text data. The availability of the legislative speeches in easily accessible digital form and the computational power necessary for the analysis of large datasets at hand have jointly led to a surge of interest in analysis using automated text analysis techniques (see also Maerz and Puschmann in the chapter "Text as Data for Conflict Research: A Literature Survey" of this volume). Automated text analysis can be used to discover new patterns and structures in the political texts, as well as to verify how known covariates affect these patterns. We use structural topic modeling to identify specific migration-related topics in the dataset and to understand the differences in issue salience and policy framing between the parties.

The chapter is structured as follows. Section 1 outlines the relevant theoretical literature and introduces hypotheses. Section 2 summarizes research design, data, and methods. Section 3 presents our results and discusses the implications. Section 4 summarizes findings and real-world implications of this work and discusses future avenues we see as viable and helpful in this research realm.

2 Theory

2.1 Party-Based Issue Ownership

Issue ownership is an established theoretical framework within which most work focuses on party manifestos and campaigns. Issue ownership represents "the perceived competence in handling issues and problems" (Stubager and Slothuus 2013). Generally, the issue ownership framework includes the following: campaigns setting the criteria for voter choice, candidates emphasizing issues that present themselves as advantaged and their opponent as disadvantaged during a campaign to influence voter choice in the election. In the context of our study, issue ownership campaigning has been shown to take place in presidential elections in the United States and in national elections in Canada (Bélanger 2003; Petrocik 1996). Walgrave and De Swert (2007) find that both the party, from the time of inception and their driving manifesto, and the media, from the discussion surrounding the party and their actions, contribute to the establishment of issue ownership although the direction of the causal arrow remains unclear between the two. Issue ownership comprises more than just partisanship or attitudes; rather it includes constituency-based ownership and perceived development as it relates to the real world (Stubager and Slothuus 2013).

While issue ownership is a well-defined concept that clearly matters for voters choosing between parties and candidates in the ballot box, it is established through party platforms, manifestos, and, via media coverage, in everyday politicking (Lefevere et al. 2015). Scholars suggest that issue ownership can also be identified in legislative speeches (Green-Pedersen and Mortensen 2010; Sulkin 2005; Vliegenthart and Walgrave 2011). We use transcripts from the floors of national legislatures to see how issue ownership relates to the migration policy in political debates. In the next section, we discuss policy framing as a method that political actors use in political debates and communication.

2.2 Policy Framing

According to Sniderman and Theriault (2004), a framing effect is a "central organizing idea or story line" that relates the policy domain in contention to the public such that it resonates. Critically, multiple frames can be applied to the same issue and can be placed in competition with each other. Further, frames can be linked through issue ownership to distinct parties (ibid). Within this realm of competition over policy domains and attention from the public, politicians deploy policy frames to compete over the dominant train of thought or association over relevant policy domains (Nelson and Kinder 1996). The issue ownership literature suggests that parties strategically emphasize issues they own to boost electoral prospects. However, when external events or crises force them to address issues their opponents hold an advantage over, parties frame the issues by choosing to focus on a subcomponent of an issue (De Vreese 2005). To provide an example within the context of migration policy, liberals can leverage framing by discussing humanitarian subcomponent of proposed migration policy.

Inherent in the context over policy framing and issue dominance, policymakers compete over multiple audiences. Parties can seek to frame issues for individuals or journalists differently and the dominant framing strategies depend on the design and implementation within the particular audience environment (Chong and Druckman 2007b).

Research suggests that there are two factors—quality of frames and competition over policy frames—that play into policy framing's impact on public perceptions that reduce to a question of quality versus quantity of framing (Chong and Druckman 2007a, b). Using experimental design, Chong and Druckman (2007a) find that the strength or quality of the frame matters most to citizens. Moreover, the general debate rallies where competition over policy frames arises. Further, for a policy frame that does not resonate with the population, the resulting preferences rely on the underlying value distribution of the population. However, with a strong frame, public opinion was successfully changed for both competitive and non-competitive issues (ibid). Thus, inherent in the contest over policy framing is a contest over the lens through which voters view the policy at hand and a successful frame can be hugely beneficial to a party's ability to win the policy debate and achieve policy goals in line with their platform.

Additionally, policy framing can be followed by policy reframing, where parties deliberately shift the policy frame from one issue to another, separate issue. Reframing typically occurs when the debate is topically relevant and matters to the party. Parties push the newly reframed issue to bring the debate back in line with the domain the party owns (Lefevere et al. 2017). The literature argues that parties not only frame and reframe based on issue ownership, but also that issue ownership can be bolstered by proper policy framing, especially in areas of contested ownership like the immigration debate sphere (Hänggli and Kriesi 2010). Empirically, the literature has only started to disentangle the occurrence and effect of framing and reframing in political debates (ibid). Continuing with our previous example of migration policy, liberals could decide not to focus on migration-related humanitarian subcomponent, but rather to impose the debate on humanitarianism proper as a completely distinct policy domain. Next, we consider the role of issue ownership within the migration policy domain specifically as it presents complex dynamics within the debates.

2.3 Inter-Party Contest over Migration Policy

Most issue ownership debates scaffold up from Downsian ideas of democracy, in which, parties work to win votes by adopting uniquely dominant policy stances that cross a number of issues (Downs 1957). The tactic of building issue-based ownership is further complicated when one issue, like migration, encompasses multiple, opposed issues. Odmalm (2011b) argues that the questions included in the immigration policy split both traditionally liberal and traditionally conservative parties down the middle, since immigration touches on both moral liberalism and value conservatism while also including international solidarity and welfare system protectionism, thus causing internal strife within both major ideological camps.

Specifically, he argues migration and other policy areas that have "old" or economic value-laden issues and "new" or socio-cultural issues present these types of internal conflicts for parties (ibid). Odmalm (2012) argues that in cases like these, parties divert to subtopics within the broader topic on which they have a strategic advantage and can hold dominant stances but ultimately are not well equipped to handle a complex idea like migration with its cross-issue composition. This argument is exemplified in research pointing to party restructuring within Europe. On topics of European and national identity, Lahav (1997) finds that traditional right-left party construction "has been reinvented which is mirrored in the debates on immigration within the EU." Further, Helbling (2014) finds policy framing on migration topic occurs across Western Europe based on the political events surrounding the debate and the actors engaged in the debate, thus linking the political debate around migration topics to both issue ownership and policy framing literatures.

This logic of migration and other policy domains that fall between party-based issue ownership potentially restructuring party-issue orientation flows from cleavage theory. Within cleavage theory, first, party systems are "determined in episodic breaks from the past," second, parties are generally inflexible in their approaches to their core issues and beliefs, and third, new parties result in changes to the current systems (Hooghe and Marks 2018). A signal of this could be parties shifting away from issues that reinforce their cores and instead stretch them across multiple, competing issues thus weakening them, and possibly allowing space for new parties to form. An indication of this could be the inability to formulate a cohesive party message on the floors of the legislature on key policy issues like migration (Hooghe and Marks 2018; Odmalm 2011b, 2012). Yet the study of issue ownership and policy framing on migration topics is dominated by studies of European contexts (Helbling 2014; Lahav 1997; Odmalm 2011a). This study works to bring this important question to the shores of North America where a different, but no less salient conversation is ongoing.

2.4 Hypotheses

Building on the theoretical frameworks of issue ownership and policy framing and on the literature that uses computational tools to examine the content of political texts, we focus on identifying issue ownership, changes in issue salience, and patterns of policy framing in USA and Canadian lower legislative chamber speeches. According to Odmalm's theory, parties will avoid topics which raise inconsistencies along "old" (economic issues, e.g., taxation and welfare) and "new" (multicultural, environmental) cleavages (Odmalm 2011b). Even when parties change their rhetoric due to popular dissatisfaction with immigration policies, their framing or tone of the issue will reflect the (in)stability of the societal fault lines, and the relative fit between these cleavages and parties' choice of issue framing (economic or socio-cultural) (Odmalm and Super 2014).

We suggest parties will discuss migration in a way that allows them to focus on subcomponents of the migration topic over which they have issue ownership. More precisely, we expect that migration-related issues over which liberal issue ownership is well established, such as poverty, education, weapon control, environment, and health will be more often debated by Democrats in the USA and liberals in Canada. By contrast, we expect Republicans in the USA and conservatives in Canada to discuss more often migration-related topics such as external threats and security. Due to differences in polarization between the two countries, we hypothesize that differences in emphasis on the migration-related topics will be stronger in the USA than in Canada. More specifically, we expect that differences in the emphasis parties place on migration-related subtopics and in policy framing will be smaller between liberals and conservatives in Canada than between Republicans and Democrats in the USA.

3 Data and Methods

3.1 Comparative Case Study Approach

In order to test our hypotheses, we adopt Mill's most similar systems design (Gerring 2009). The two selected cases are the United States and Canada. The two countries hold the lion's share of power on the North American continent and are geographically isolated from other states. Apart from their common border, the USA has a significant southern land border with Mexico, while Canada has a large but mostly uninhabited northern border. Both face challenges with legal, illegal, and humanitarian-based migration, although to differing degrees in those categories. Both have dominant conservative and liberal ideological camps that historically and competitively vie for power, thus allowing our study to examine the differences in language used in legislative debates.

However, they differ with regards to party polarization. As a two-party system, the United States serves as an example of high polarization. Canada, as a multi-party system, despite recent changes since 2007 (Brady 2014), is recognized in the literature as the epitome of a non-polarized system (Johnston 2015). These differences allow for the exploration of migration topics across two similar political systems that differ with regards to the levels of polarization. Importantly, both are nations founded (largely) by immigrants and are often seen as bastions of hope for those trying to start a new life. Therefore, the two case studies are very different from the European nation-states on which the recent migration literature has focused (Lahav 1997; Odmalm 2011a, 2012). From a practical perspective, two points motivated this case selection because they facilitate comparison. First, English-speaking Canada and the USA face many of the same policy issues. Second, both legislatures publish detailed transcripts of debates in English.

For the United States analysis, we use Gentzkow et al. (2018) *Congressional Record for the 43rd–114th Congresses: Parsed Speeches and Phrase Counts* data, which captures all floor debates from the United States House of Representatives. We subset the data to include only the House of Representatives' speeches from Winter 1994 to Fall 2016. For the Canadian analysis, we collected debates from the House of Commons from Beelen et al. (2017). We use the OpenParliament.ca PostgreSQL dump provided by Beelen et al. (ibid), which covers speeches from 1994 and trim the US data accordingly. Similarly, we remove speeches in the Canadian data that come after 2016, as this would have no counterpart in the US data. We focus only on the lower houses of the national legislature to maintain comparability across cases. This is necessary as the United States' Senate is an elected body and the Canadian Senate is not. From there, we processed the data into text corpora for analysis.[2]

To better characterize differences in rhetoric on the topics of migration and build a comparison between the United States and Canadian political sectors, we divided parties into "liberal" and "conservative" groups. For the USA, this was straightforward with Democrats as the liberal camp and Republicans the conservative.[3,4] However, in Canada, the divide is more complicated. In this paper, when we discuss "conservative" parties in Canada, we are referring to the Conservative (C), Canadian Alliance, Progressive Conservative (PC) and Reform parties. Liberal (L), New Democratic Party (NDP) and any successors of the Bloc Quebecois parties all become "liberal."[5] In the USA, this time span includes the Presidencies of Bill Clinton (D), George W. Bush (R), and Barack Obama (D) and the 103rd–114th Congresses within which the majority party changed several times. In Canada, this spans the Campbell (PC), Chretien (L), Martin (L), and Harper (C) Governments, who also represent liberal and conservative blocks in power. Further, this timespan includes migration during the fall of Yugoslavia and ensuing violent conflicts, the genocide in Rwanda, both Desert Storm and Desert Shield/Operation Iraqi Freedom, the September 11, 2001 attacks, the war in Afghanistan, the Arab Spring protests, and the beginning of the Syrian Civil war, the rise of violence in Central America as well as a number of other conflicts.

[2]In addition to the high-level overview in the following sections, detailed steps to replicate this data collection process for the United States and Canada is provided in supplemental documentation.

[3]Historically there have been realignments between the parties, which are of interest to the topic of migration generally. However, realignments are not an issue in the time period analyzed in this paper.

[4]For the US data, we kept the independent members of Congress in the dataset but dropped strictly logistical and parliamentary speeches from the data. In the analysis, we are not focusing on the Independent member's speeches as the number of speeches is not representative. For the Canadian data, we dropped all strictly logistical parliamentary speeches from the data as well.

[5]It should be noted that other, smaller parties are also collapsed into the liberal category. All parties that are not Independents (dropped), or included in the conservative grouping, are collapsed into the liberal group.

3.2 Dataset Subsetting: Dictionary Approach

To identify migration-related speeches and reduce the size of the corpus in initial analyses, we use a dictionary approach to subset the data. The original US dataset has 377,817 Democratic speeches, 374,397 Republican speeches, and 1840 Independent Speeches. The original Canadian dataset has 231,681 Liberal Party speeches and 172,089 Conservative Party speeches, with a combined 71,068 speeches by other conservative parties.[6] For the purposes of investigating the outlined research question and particularly for application in the USA and Canadian context, we take a simple approach to subset the corpora of speeches to include only those that are relevant to migration topics. We use a dictionary approach but limit it to three words: *asylum*, *refugee*, and *immigration*.[7] These words are stemmed along with our corpora and we analyze the speeches that include at least one of these three words relevant to the migration debate in the United States and Canada.[8] The resulting datasets include 15,547 (5% of all) and 15,072 (2% of all) speeches for Canada and the United States, respectively.

3.3 Structural Topic Modeling

Existing computational social science literature suggests that political disagreement and issue ownership can be understood by quantitatively analyzing relative emphasis on different terms, ideas, and arguments in political texts (Baum 2012; Lowe 2008; Sakamoto and Takikawa 2018). Based on US legislative data, Gerrish and Blei (2012) outlined legislators' policy positions on specific issues and, using supervised machine learning, explored how the language of laws is correlated with political support. Combining political psychology and machine learning, topic modeling has been applied to the House of Representatives floor speeches to measure member personality traits (Ramey et al. 2016). Hierarchical topic modeling was applied to look at how the Tea Party Republicans relate with regards to their ideal points to the

[6] Other parties have: 116,867 (NDP), 64,845 (Bloc Quebecois and related parties), 38,132 (Reform Party), 21,003 (Canadian Alliance), 11,928 (Progressive Conservative), 3573 (Green), 1865 (Independent).

[7] As a robustness check, we conducted the analysis with a much broader dictionary, which delivered similar results. However, a minimalistic version of the dictionary ensures that the speeches we include and topics resulting from the analysis truly belong to a migration-related policy area.

[8] As an interesting feature of stemming data like ours that focuses on the word refugee, we retain the stem *refuge* which results in a number of wildlife preservation speeches, especially in the case of the United States where the Arctic National Wildlife Refuge (ANWR) and oil exploration there was of great contest during our time frame of analysis. However, as wildlife refuge issues are not of relevance for the analysis of human migration, we classify wildlife refuge related issues as "irrelevant." In the following section, we explain more on how we coded this and other topics to ensure focus on migration policy-related issues.

remaining of the Republican representatives in Congress (Nguyen et al. 2015). A similar hierarchical modeling approach was used to analyze the political priorities emphasized in US Senate press statements (Grimmer 2010). However, the existing studies have not expanded the computational science approaches to study how issue ownership and policy framing affect legislative debates. To test the above-outlined hypotheses, we use unsupervised machine learning techniques, specifically structural topic modeling.

Topic modeling is a non-supervised machine learning technique that allows for the detection of topics in a text corpus that has not been previously manually analyzed and coded. The idea behind topic modeling, in general, is that each word from the text has a certain probability of belonging to a topic and each document represents a mixture of topics (for our purposes a document is a legislative speech). Structural topic modeling allows for the assessment of the role of selected covariates on the latent topics detected through topic modeling. To analyze how political camps frame the migration policy in the legislative speeches, we employ structural topic modeling implemented in R (2018) in the stm package (Roberts et al. 2017). As we are interested in understanding how topic prevalence (frequency of topic discussed across speeches) and topic content (how a topic is discussed) are affected by the ideological camp to which the politician belongs, stm is the optimal choice of software for this analysis.

The stm package builds on Latent Dirichlet Allocation (Blei et al. 2003) and it also offers the spectral initialization—a non-negative matrix factorization of the word co-occurrence matrix. Following the literature on spectral decomposition with particularly large datasets (more than 10,000 units in the vocabulary), we opt for this approach (Roberts et al. 2017). Using the migration-related subset of the parliamentary speeches, we process the data by removing custom and built-in stop words as well as the words that only appear in one document. We also took the standard steps of case lowering, stemming, and removing punctuation to clean our corpus.

Moreover, using the advantages of the structural topic modeling approach, we specify the interaction effect of the ideological position of the speaker and the date of the speech as the prevalence covariate and ideological position of the speaker as a content covariate. The prevalence covariate allows us to analyze how the selected attributes from the linked metadata effects the contribution of each topic in the documents. The content variable provides the ability to consider how the metadata attributes effect which words are prominent in each topic.

To shed light on the empirical plausibility of the outlined hypotheses, we proceed to develop two models: one for the speeches in the US House of Representative and the other for the speeches in the Canadian Parliament. Both models were defined to include 20 topics. In selecting the number of topics, we tested several other options—providing either a more nuanced or crude understanding of migration policy and relevant subcomponents outlined in the speeches. While stm package offers a technical solution to determining the most informative number of topics, we instead chose the number based on theoretical underpinning. We opt for 20 topics for two reasons. First, it allows a fairly nuanced overview of topic subcomponents as the literature suggests are being debated along with the core migration issues (e.g., culture, economy, and security). Second, it also enables us to distinguish a humanitarian subcomponent. The previous work on migration issue ownership largely focuses on the European continent and on economic, cultural, and security aspects of it (Odmalm 2014). The humanitarian aspect, while certainly present in the media and public space, is packaged as the legalistic discussion on the asylum rights and has to an extent been left out in the existing studies focusing on migration policy in the European context. Our model allows us to explore the framing of this part as well.

3.4 Labeling and Categorizing Topics

In order to conceptualize the differences between the United States' and Canadian speeches descriptively over the approximately 20 years in our study, we categorize the 20 topics from each of the two country models into six broader-areas or categories that crisscross lenses of issue ownership: the Economy, Culture, Security, Human Rights, Migration Core, and Irrelevant category. This step is necessary as unsupervised machine learning does not guarantee interpretable results that are comparable across corpora. More concretely, one raw topic from the Canadian corpus is not directly comparable to another raw topic in the USA without human interpretation and validation to ensure the topics are reasonably alike. The grouping stage by human coders accomplishes this goal. We categorize the model outputs for both countries based on the most frequent policy areas that the models found. While descriptive in nature, these summary statistics allow us to draw comparisons between our two cases and better understand the nature of the topics within our data.

To ensure objectivity and coherence between the two countries, while taking into account case study expertise of the team working on this paper, each topic was coded by two of the three authors. If the coding differed, the third author (and case study expert) adjudicated and assigned the final label.[9]

4 Results

We divide the results section into four parts. We first outline the 20 topics our model has produced to give readers a better understanding of the data we analyzed. Second, we analyze which migration-related topics can be associated with either of the two ideological camps. Here, we disregard time and focus on the entire dataset. Third, we focus on the changes in topic salience across time for a number of theoretically relevant topics. Fourth, we focus on understanding how parties frame

[9]Marcella Morris for the USA and Tyler Amos for Canada.

migration policy through the selection of representative keywords from individual speeches. Each of these steps allows for the testing of our hypotheses from a different perspective. For each of the steps, we start with the United States, which we then compare with Canada.

4.1 Topics in the USA and Canada

Figure 1 shows the number or count of topics that we coded under broader categories of the Economy, Culture, Security, Human Rights, Migration Core, and Irrelevant topics. Within the Migration Core category, across both cases, we see topics related to acts of immigration by humans crossing borders and the law enforcement efforts involved in border protection but also the legal parameters lawmakers wrestle

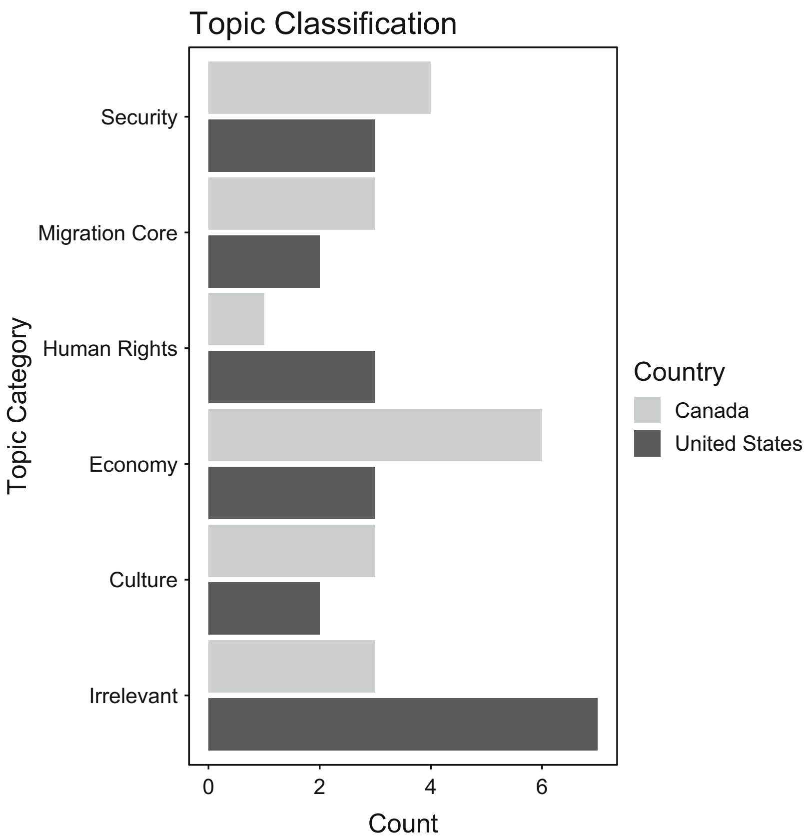

Fig. 1 Topic categorization: migration subsample for the US House of Representatives and the Canadian House of Commons (1994–2016)

with, such as regulation of visas and requirements for citizenship. Within the economic topics, we categorize budget, welfare programs,[10] international trade, job programs, and infrastructure type topics which arise as a feature of the discussions about the impact of immigration. Under Culture, we find topics related to welfare, religion, aspirational descriptions of citizenship, multiculturalism, and the legacy of immigration for the national identity. The Security and Human Rights categories are clearer than some of the others. For Security, we include the topics that focus on terrorism, international conflicts, or wars, while Human Rights includes topics that include humanitarian aid, violence against women, and refugee rights.

It should be noted that we categorized a number of topics as "Irrelevant." This category mostly includes topics comprised of parliamentary speech and procedural language required by the chambers from which the speeches originate.[11]

Table 1 presents the 20 topic outputs for the United States and Canada along with the coding into broader categories. Asterisks are used to denote truncated words. We stemmed our corpora in order to better match words, here illeg* indicates the dictionary would include all words that include the root of illeg, regardless of its ending thus including both illegal, illegally, and illegals in our data with only one dictionary entry. We list the topics in the same order as the model produced them, making it easier for the readers interested in replicating our steps to also follow our coding of the topics. In the following pages, we unpack these differences more through the lens of ideological camps, but the differences in the raw data provide helpful context to the broad questions we tackle, as there are clear differences between the two countries, their politics, and debates.

In addition to the coding scheme used to group topics produced by the model in six broader categories, Fig. 2a, b list topics according to their proportion across speeches. In the next section, we present differences in topic salience between ideological camps in the USA and Canada.

4.2 Topic Association by Ideological Block

We first focus on topic prevalence in the US House of Representatives. It answers the question which migration-related topics are associated with the Democrats or Republicans. Out of the 20 topics from the model, we coded a number of them as irrelevant for the analysis—having mostly been dealing with the procedural aspects of the parliamentary debates.[12] Keeping the time component of the structural topic model fixed, we first analyze which migration-related topics the two US parties

[10]The economic welfare programs comprise spending and job training programs from a budgetary perspective while cultural welfare topics include social safety-net-type programs.

[11]We include the wildlife refuge topics which were present in the United States' and Canadian topics in the "Irrelevant" category.

[12]A list of topics and words available in Table 1a, b.

Table 1 STM topic output and classification

No.	Label	Topic output (marginal highest probability output)	Category
(a) United States			
1	Immigration types	immigr*, illeg*, countri*, legal, american, will, state, come, unit, law, citizen, famili*, reform, visa, system, million, nation, citizenship, children, status	Migration Core
2	Law enforcement	law, enforc*, feder*, state, alien, crimin*, local, crime, immigr*, offic*, illeg*, depart, justic*, polic*, communiti*, will, citi*, case, deport, attorney	Migration Core
3	Procedural 1	gentleman, yield, thank, texa*, california, madam, consum*, act, rank, subcommitte, gentlewoman, judiciari*, minut*, bipartisan, may, balanc*, reform, chair, distinguish, section	Irrelevant
4	Wildlife refuge	refug*, nation, land, wildlif*, park, area, protect, water, will, servic*, forest, state, fish, feder*, conserv*, acr*, manag*, resourc*, public, legisl*	Irrelevant
5	Voting	presid*, vote, constitut*, congress, law, court, elect, execut*, state, power, action, act, will, voter, suprem*, senat*, right, obama, district, branch	Culture
6	Multicultural America	american, nation, state, communiti*, world, unit, histori*, honor, asian, america, great, countri*, first, freedom, serv*, day, contribut*, pacif*, live, island	Irrelevant
7	Human trafficking	women, violenc*, victim, protect, act, state, right, will, abus*, administr*, domest*, american, report, traffick*, terrorist, crime, countri*, human, one, kill	Human rights
8	Foreign aid	million, fund, assist, provid*, program, include*, aid, state, intern, will, increas*, billion, effort, request, help, develop, countri*, foreign, guam, appropri*	Human rights
9	Procedural 2	one, say, will, countri*, great, thing, state, serv*, life, talk, nation, come, live, district, famili*, now, citi*, school, first, honor	Irrelevant
10	Security	secur*, border, homeland, depart, nation, terrorist, will, protect, need, fund, agent, state, agenc*, patrol, guard, intellig*, terror, commiss*, enforc*, attack	Security

(continued)

Table 1 (continued)

No.	Label	Topic output (marginal highest probability output)	Category
11	Procedural 3	say, dont, now, come, thing, one, talk, will, job, back, countri*, got, american, that, look, america, let, happen, money, tri*	Irrelevant
12	Budget	republican, tax, budget, will, american, cut, care, health, billion, pass, spend, democrat, congress, reform, pay, major, vote, money, job, cost	Economy
13	Oil production	energi*, oil, gas, drill, will, price, percent, nation, state, need, product, use, develop, water, environment, increas*, million, compani*, american, arctic*	Economy
14	Procedural 4	amend, chairman, rule, provis, will, act, requir*, appropri*, fund, languag*, state, legisl*, provid*, offer, debat*, author, process, report, confer*, member	Irrelevant
15	Education	educ*, school, will, america, children, state, one, american, need, unit, student, law, come, nation, number, million, now, countri*, problem, place	Culture
16	International conflicts	state, unit, peac*, war, will, world, nation, israel, presid*, forc*, militari*, must, refuge*, countri*, resolut*, genocid*, now, intern, one, continu*	Security
17	Threats	border, iraq, state, mexico, drug, unit, war, militari*, will, come, troop, patrol, afghanistan, one, mexican, illeg*, forc,* nation, iraqi, soldier	Security
18	Welfare	program, children, state, health, educ*, care, will, provid*, need, famili*, percent, worker, child, school, benefit, food, servic*, employ, help, english	Economy
19	Humanitarianism	refuge*, human, right, state, unit, china, haiti, vietnam, religi*, freedom, will, polici*, countri*, cuba, persecut*, cuban, polit*, democraci*, haitian, asylum	Human rights
20	Procedural 5	will, legisl*, american, opportun*, believ*, need, america, hope, colleagu*, trade, abl*, deal, good, issu*, countri*, state, forward, agreement, problem, congress	Irrelevant

(continued)

Table 1 (continued)

No.	Label	Topic output (marginal highest probability output)	Category
(b) Canada			
1	Budget	conserv*, liber*, will, prime, budget, elect*, parti*, money, cut, public, now, chang*, job, one, say, vote, tax, promis*, polit*, noth*	Economy
2	Humanitarianism	refuge*, humanitarian, syrian, help, assist, million, will, countri*, syria, need, provid*, aid, intern, crisi*, communiti*, situat*, effort, region, resettl*, organ*	Migration Core
3	First nations	nation, will, aborigin*, land, first, agreement, treati*, protect, water, environ*, environment, throne, act, speech, area, park, territori*, develop, chang*, climat*	Irrelevant
4	Procedural 1	will, member, parti*, opposite*, parliament, debat, vote, legisl*, reform, report, liber*, stand, consult, ask, made, amend, act, day, elect, say	Irrelevant
5	Immigration types	immigr*, citizenship, applic*, famili*, canadian, resid*, process, foreign, worker, countri*, system, program, will, come, temporari*, perman*, visa, citizen, number, offic*	Migration Core
6	Citizenship	act, court, citizenship, law, right, legisl,* canadian, amend*, will, citizen, case, charter, person, process, chang*, one, decis*, rule, claus*, may	Culture
7	Welfare	women, health, care, poverti,* need, senior, program, will, social, live, hous*, medic*, equal, system, incom*, feder*, provinc*, servic*, access*, countri*	Economy
8	Law enforcement	crimin*, crime, victim, will, justic*, law, sentenc*, offenc*, serious, marriag, women, person, commit, forc*, deport, act, polic*, protect, legisl*, violenc*	Security
9	Provincial concerns	quebec, feder*, provinc*, languag*, bloc, will, french, nation, offici*, one, cultur*, popul*, constitut*, québécoi*, must, provinci*, jurisdict*, francophon*, canadian, recogn*	Culture
10	Asylum process	refuge*, countri*, system, immigr*, claim, appeal, will, claimant*, protect, process, status, decis*, asylum, board, case, determin*, arriv*, need, divis*, safe	Migration Core

(continued)

Table 1 (continued)

No.	Label	Topic output (marginal highest probability output)	Category
11	History of immigration	canadian, countri*, communiti*, world, nation, histori*, one, great, cultur*, immigr*, day, proud, first, divers*, societi*, contribut*, valu*, recogn*, will, live	Culture
12	Family support	famili, children, tax, child, parent, live, communiti*, young, ride, will, home, school, help, one, care, incom*, pay, need, centr*, member	Economy
13	Investment in Jobs	will, program, budget, tax, need, job, invest, econom*, economi*, fund, plan, help, busi*, billion, provid*, increas*, million, feder*, employ, benefit	Economy
14	Privacy or security	inform, will, act, canadian, privaci*, public, servic*, person, census, data, state, use, provid*, air, passeng*, access, may, legisl*, concern, one	Security
15	Human trafficking	human, right, intern, traffick*, protect, countri*, smuggl*, will, immigr*, exploit*, organ*, freedom, include*, trade, abus*, convent*, victim, smuggler, crimin*, law	Human rights
16	Economic sectors	industri*, will, trade, agricultur*, product, region, communiti*, farmer, ride, compani*, provinc*, job, agreement, atlant*, busi*, area, coast, sector, island, nova	Economy
17	Security	secur*, border, state, will, terrorist, unit, terror, agenc*, nation, offic*, safeti*, american, organ*, custom, canadian, septemb*, need, protect, rcmp, polic*	Security
18	International conflicts	will, forc*, war, militari*, peac*, must, intern, mission, world, nation, canadian, conflict, state, secur*, unit, iraq, afghanistan, action, countri*, nato*	Security
19	Procedural 2	countri*, one, say, come, talk, thing, will, look, problem, need, deal, happen, back, tri*, someth*, good, realli*, colleagu*, ask, kind	Irrelevant
20	International trade	trade, countri*, intern*, polici*, canadian, develop, will, world, foreign, econom*, depart, per, agreement, cent*, state, unit, must, interest, canada, global	Economy

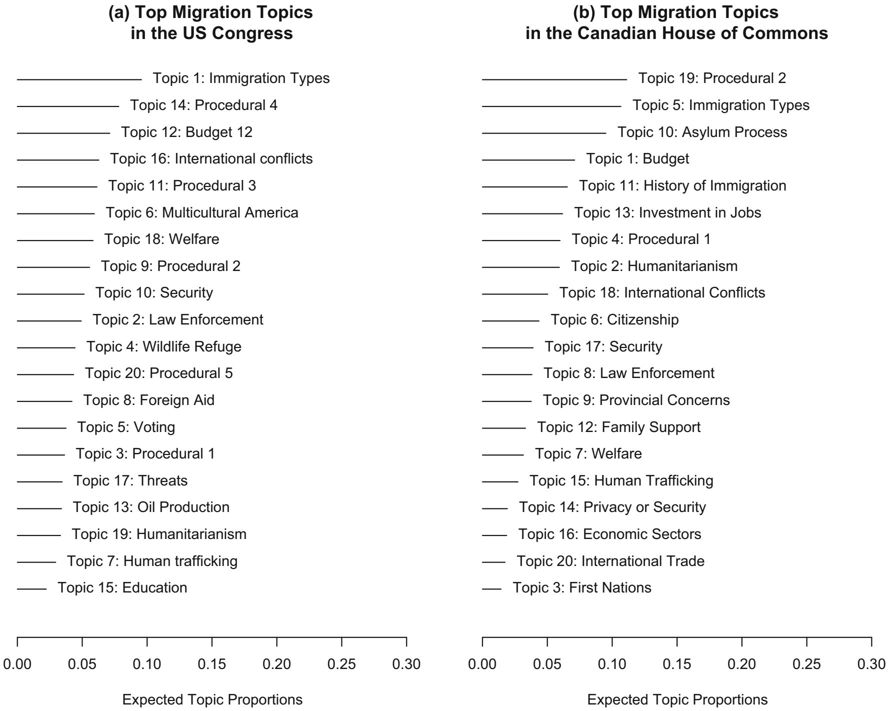

Fig. 2 Expected migration-related topics proportion legislative speeches in the US Congress and Canadian House of Commons. (**a**) Top migration topics in the US Congress. (**b**) Top migration topics in the Canadian House of Commons

emphasize. Figure 3a provides a visualization of the expected topic prevalence contrasted for Republicans and Democrats—excluding topics coded as irrelevant. The sequence of the topics follows the categorization introduced in the previous subsection and allows comparison across two cases—from Migration Core, Security, Economy, Culture to Human Rights. Republicans dominate the discussions on the types of immigration, law enforcement, security, and threats when compared to Democrats. Budgetary aspects, use of resources, and international conflicts fall more on the side of the Democrats. Both parties emphasize equally multiculturalism in the USA, welfare, and education aspects of migration.

In Canada, we see a similar picture with differences in the topic association being smaller between the two blocks (see Fig. 3b). Topics such as immigration type and legal aspects of migration policy, which we classified in the Migration Core area, fall between the two ideological blocks. Moreover, humanitarianism, human trafficking, security, and international conflicts are equally associated with liberals and conservatives. A number of topics, traditionally owned by liberals, such as budget, welfare, and family support topics are indeed more strongly associated with liberals. Historical migration with an emphasis on Canadian multicultural nation

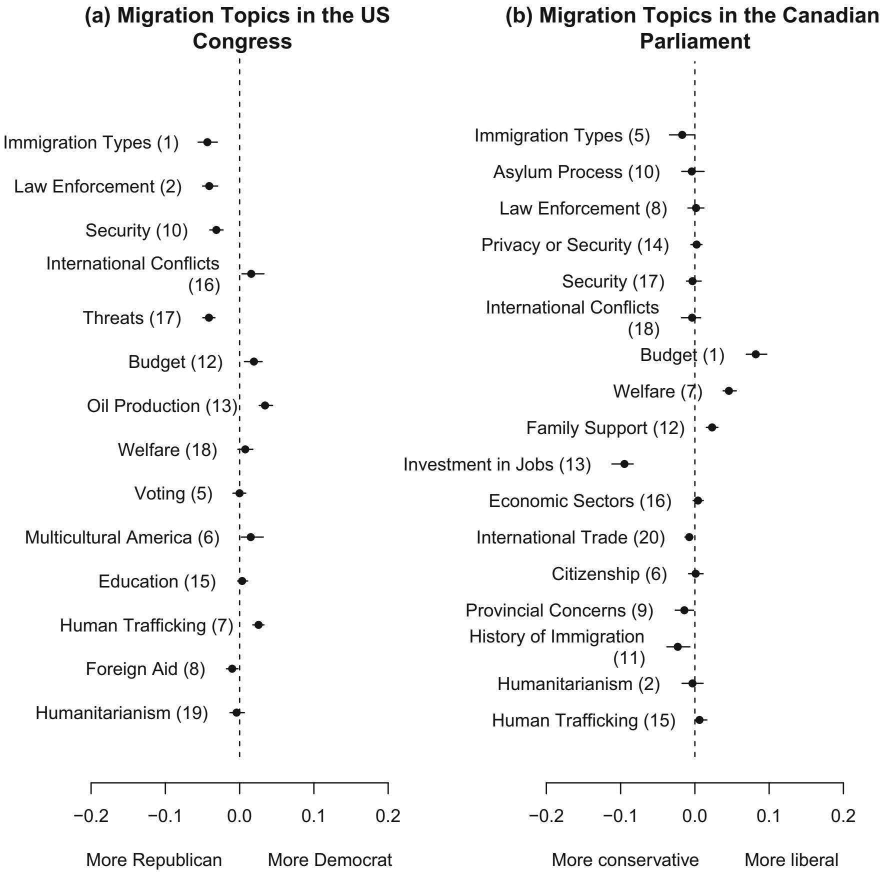

Fig. 3 Expected Migration-related Topics Proportion between Parties in the US House of Representative and the Canadian House of Commons. The coefficients refer to the expected topic proportion of the text corpus determined as a function of the selected variables. In this case, the topic prevalence for each of the migration-related topics is contrasted for two parties, Republicans and Democrats. (**a**) Top migration topics in the US Congress. (**b**) Top migration topics in the Canadian Parliament

and debates on jobs fall to the side of the conservatives. We see a contrast in the budget and jobs topics association—while the budget aspect of the migration is more salient for liberals, the jobs aspect is more associated with conservatives. Topic association in both the USA and in Canada is aligned with our hypotheses. Ideological camps tend to emphasize more subcomponents of migration policy over which they traditionally have ownership over. We also show that, as expected, the differences in the topic association are, due to weaker polarization, smaller in Canada than in the USA.

4.3 Topic Prevalence Across Time

Figure 4 illustrates how House members in the United States discussed migration topics from 1994 to 2016. To understand how the emphasis of the migration-related topic changes across time, we select four topics—two topics from the core migration area, one topic representing issues traditionally owned by Democrats, and one by Republicans. The four selected topics are the following: an immigration type topic, an immigration enforcement topic, a security-related topic, and a human trafficking topic.[13] For each of these topics, we analyze how topic prevalence has changed across time and party.

First, we focus on the types of immigration topic. The topic deals with different types of immigration from the perspective of legality, legal status, and procedures immigrants go through. Change in topic prevalence over time is visualized in Fig. 4 Three peaks are visible in the period between 1994 and 2016. The first peak occurred in the late 1990s, in parallel to the aftermath of the Yugoslav and Rwandan conflicts and during the NATO bombardment of Serbia and Montenegro during the 1999 Kosovo crisis. By the beginning of the 2000s, the topic of immigration types become somewhat less salient, only to return to the House in the 2000s, likely as a result of the rise of the threat of terrorism related to the 9/11 terrorist attack. Both in the late 1990s and in the early 2000s, Republicans emphasized the topic more than Democrats. The last peak in topic salience occurs in 2014, which coincides with the Syrian conflict and moreover with the offensives after the break of Kofi Anan's ceasefire attempt in 2013. While Republicans emphasized discussion of the types of immigration more during the first two peaks, Democrats saw it as more salient in the last period.

The second topic we focus on is migration law enforcement. This topic deals with the violation of the legal framework related to migration and its consequences. After 2001, it becomes a more salient topic in the House of Representative and Republicans emphasize it more. From the law enforcement perspective, 2005 and 2014 represent important points in the timeline.

While both of these topics represent core migration area issues, our US model outlined another subcomponent of the migration topic, which has, to our knowledge, not been discussed extensively in existing studies—human rights or more specifically human trafficking. This topic refers to issues related to crime and abuse, particularly emphasizing women and trafficking crimes. Following our expectations, Democrats appear to own this issue from the mid-1990s through 2015, as they place greater emphasis on this topic.[14]

[13]For an overview of the words constituting each topic, consult Table 1a, b.

[14]The change in prevalence on the human trafficking topic from Democrats to Republicans around 2015 may be a feature of the campaigns for the 2016 Presidential election, the increased migration (or focus on migration) as a result of the Central American crises or another set of issues. Future work could explore such changes over time in more detail.

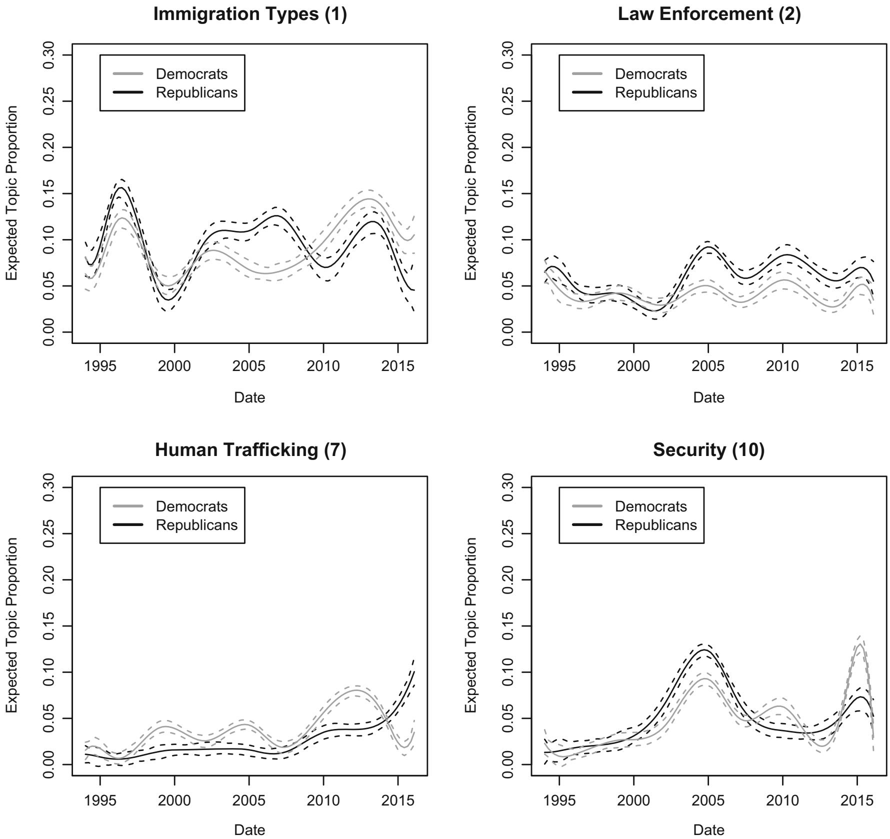

Fig. 4 Migration-related Topics Association between Parties in the US House of Representatives (1994–2016). We report the expected topic proportion not simply topic proportion, because it is an approximation based on the default STM settings—incorporation of uncertainty in proportion estimates via the method of composition (Roberts et al. 2017)

We now turn our attention to the security graph in Fig. 4 as a subcomponent along which migration policy is often discussed. This topic refers to border protection as well as security issues like terrorism. Security is an issue traditionally associated with Republicans, which can also be seen in Fig. 4's Security panel that illustrates the security topic from our US model. Republicans emphasize the security topic more until the second part of the 2000s when it becomes more salient for Democrats.

Using the same theoretical approach for Canada as for the US model, we again select four topics to include two core migration area topics, one issue traditionally owned by liberals and one owned by conservatives. Moreover, the selected topics are also similar content-wise to the topics selected for the US case, thus facilitating a comparative case study approach. The selected topics are the following ones:

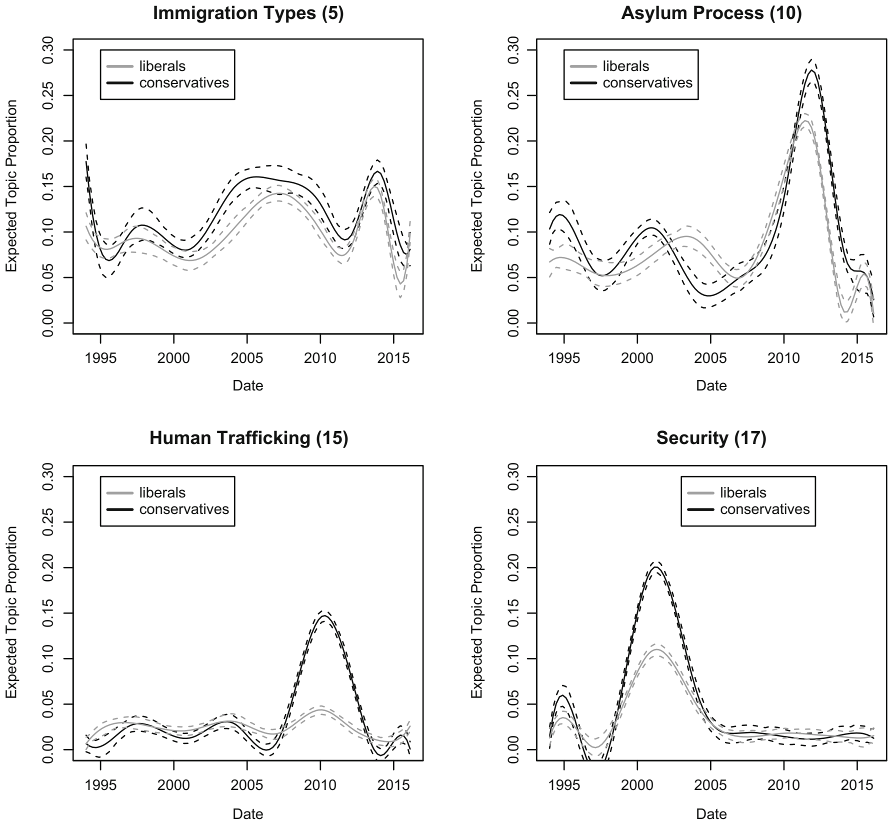

Fig. 5 Migration and Migration-related Topics across Time in the Canadian House of Commons

an immigration type topic, an asylum-process-related topic, a human trafficking topic,[15] and a security-related topic (see Fig. 5).

As expected by our hypotheses, the contrast in migration-related topic prevalence between the two Canadian political camps appears smaller than between the USA political camps across time. There are some periods where trends for the two groups of parties diverge, notably with respect to asylum and security, but overall both parties display quite similar trends. This contrasts with the American case where with the human trafficking topic, for example, the Democrats' topic prevalence trend is completely different from the Republicans'. When there are differences in emphasis, the two ideological camps emphasize an issue that they are traditionally considered to own (e.g., conservatives with security), just as our hypotheses suggest.

[15] An explanation for the spike in conservative discourse on the Human Trafficking topic around 2010 is not readily apparent based on our current reading of the relevant literature. Future work could explore such anomalies in more detail.

Analysis of both US and Canadian topics across time also shows that differences in prevalence fluctuate over time. While the interpretation of the reversals surpasses the scope of this chapter, the literature suggests that framing strongly depends on the external events and the salience of the topic in the public discourse (Lefevere et al. 2017). We suggest the fluctuations could be a result of pertinent legislative acts, important political events, and majorities in the lower houses of the legislative bodies in the USA and Canada.

4.4 Migration Policy Framing: Word Use

In the earlier two subsections, we discussed how the two ideological blocks quantitatively contribute to the migration topics, first by taking the whole dataset into account and then by emphasizing the changes across time. In this subsection, we focus on the results from the perspective of how the two ideological blocks discuss migration policy. We will analyze the choice of the words liberal as opposed to conservative camps uses—providing an in-depth understanding of the framing strategies. Figure 6a, b are visualizations of the word choice comparisons we present in this section. They represent the types of words from the Human Trafficking topic from the United States' and Canadian Speeches, respectively. We provide visualizations for the other topics in the appendix. We first analyze how Republicans and

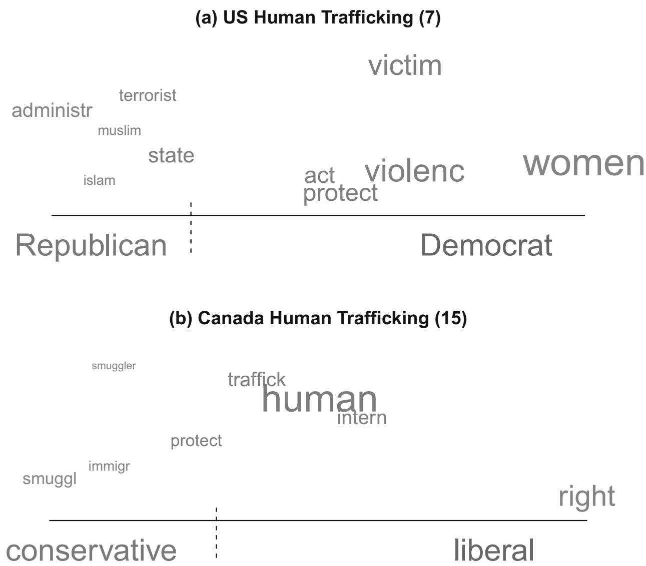

Fig. 6 Word choice comparison plot for Human Trafficking topic. (a) US. (b) Canada

Democrats in the US House of Representatives discuss migration-related topics.[16] With regard to types of immigration, Republicans emphasize "illeg," "american," and "state" while Democrats emphasize "immigr*" and "family." Similarly, when discussing enforcement of immigration policy, Republicans emphasize "illeg," "alien," "crime," "criminal," and "immigr" whereas Democrats emphasize "local" and "offic*". We interpret this as the parties framing policies by leaning into migration umbrella issues they own. In this case, Republicans own law enforcement and crime. This supports Odmalm's (2011a) theoretical approach, which suggests parties' debate migration policy in ways which allows them to avoid competences of their opponents and focus on their strengths.

The topic of human rights issues, with a specific focus on women's rights and rights of refugees, is another interesting case. When discussing gender-based violence, Democrats use words such as "victim," "women," "violence," "traffick*", "domes*", "abuse," as well as "protect," "right," and "act." Republicans emphasize "islam," "terrorist," "muslim," as well as "american" and "kill." In this context, Republicans appear to emphasize perceived threats, while Democrats appear to be adopting a women's rights lens—areas which play to their perceived issue ownership. When discussing geography with respect to Human Rights, Democrats emphasize more cases in which refugees are entitled to protection—using words such as "haiti" or "haitian." Republicans use a vocabulary of Human Rights to discuss the countries with authoritarian systems of government, such as Cuba and China. Both parties equally emphasize freedom.

Considering the topic of security, Republicans frame the policy to outline their ownership over it—they emphasize "secur*", "terrorist," and "nation," while Democrats speak about the procedural issues related to the border, such as "fund*" and "agent*". The topic of threats is discussed within the frame of "border*", "patrol," "illeg*", and "Mexico," while Democrats talk about "troops" and "militari*", in connection to Iraq and Afghanistan. The most striking is the topic of international conflicts, where Democrats focus on "peac*", while Republicans discuss "war," "militari*", and "Iraq."

Culture as one of the topics often emphasized as part of the broader migration theme is also represented in parliamentary speeches. Both Republicans and Democrats emphasize "nation" in this context, but Republicans talk about "great*", "freedom*", and "serv*", while Democrats emphasize "communiti*", "histori*", as well as "asian" and "pacif*". Our interpretation is that Democrats emphasize the multicultural aspect of the USA as a country founded by immigrants, while Republicans emphasize the role of freedom and its role in the American culture. On economic topics, Republicans discuss the budget in relation to taxation and spending on healthcare, while the Democrats refer more explicitly to "cuts," "budget," and "republican," perhaps referring to tax or spending cuts Republicans are introducing.

[16] See the online Appendix for a graphical illustration of this point.

Now turning to the Canadian context, we analyze how conservatives and liberals frame migration-related topics. In Canada, with regard to legal aspects of immigration, conservatives emphasized: "citizenship" and "canadian*", while liberals focused on "immigr*", "applic*", and "process." When discussing the security subcomponent of migration policy, liberals focused on "secur*" and "border*", while the conservatives emphasize "terrorist*". We analyze this framing with our theoretical approach in mind—conservatives tend to emphasize issues which they own, such as security and protection from terrorism, but compared to the USA, there is a weaker distinction between liberals and conservatives with respect to their framing of migration discussions.

As in the USA, the issue of human rights, with a specific focus on human trafficking is also outlined in our Canadian model. When discussing this topic, conservatives emphasize the connection between "immigr*" and "smuggl*", while liberals emphasize "human*", "traffick*" and "right" (see Fig. 6b). We suggest that also here we can identify patterns of framing based on issue ownership. For liberals, the focus is on trafficking, victims, and their rights, while conservatives dedicate more attention to the crime of smuggling in connection with immigration. However, the differences are not as striking as in the USA between Republicans and Democrats. When discussing humanitarian aspects of migration, conservatives emphasize "syria*", "syrian*", "help," "humanitarian," and "assist," while for liberals it is more about "refuge*".

Similar again to the USA, the culture topic that emerges from our Canadian model seems to revolve around the multicultural origins of Canada and diversity of the origins of its inhabitants. However, there are no clear differences in the framing of this subcomponent between the two blocks. Conservatives emphasize "canadian" and "histori*", while for liberals the focus is on "community," "nation," and "great*", all of which also occur in the US debates.

Finally, migration-related economic topics are of great importance in the Canadian model. When discussing the labor market, conservatives use words such as "job", "plan," and "econom*". For liberals, the emphasis is more on "budget," "invest*", "tax," "program," and "need." Differences in policy framing are perhaps clearer when considering the aspect of welfare, where the conservatives focus on "tax," "incom*", and "pay," while liberals emphasize "famili*", "children," "child," "parent," and "communiti*".

Analysis of the differences between the two ideological blocks in word use within topics confirmed our expectations. In the USA, there are clear differences in the framing of the migration-related issues. When forced to discuss migration policy—over which neither block has clear issue ownership—political elites' choice of words implies policy framing in a way that allows them to emphasize the subcomponent they have established ownership over. We find this pattern both in the USA and in Canada but the issue ownership differences in word choice are more pronounced in the USA than in Canada. In the next section, we briefly summarize our findings and conclusions.

5 Conclusion

The chapter explored how ideological camps in the USA and Canada discuss migration policy in legislative speeches. We argued that political camps tend to avoid discussing migration directly as it represents a political cleavage encompassing multiple, opposing issues over which lines of ideological ownership are not yet clearly drawn. Modeling parliamentary discourse as an area where politicians sandbox their ideas, we explored how political camps frame migration policy in their speeches.

Our analysis showed that politicians in the USA and Canadian legislatures debate migration policy in a way that allows them to emphasize migration aspects over which their parties traditionally hold issue ownership. Specifically, our results confirmed that Democrats in the USA and the liberals in Canada, in their migration-related legislative speeches, stress issues they own—such as poverty, welfare, weapons control, and health. In contrast, US Republicans and Canadian conservatives instead focus on the external threats, security, and sovereignty aspects of migration policy as issues they traditionally own.

Our results suggested that parties not only emphasize the issues they own more, they also frame migration in a way that emphasizes their competences over subcomponents of the broader policy area. Republicans and conservatives frame subcomponents of migration such as humanitarianism in a way that emphasizes issues traditionally owned by their political camp. Democrats and liberals do the same—they frame migration policy by focusing the debate on their strengths, even when discussing security threats for which their competition can be considered as more competent.

Through our focus on differences in polarization between the case studies, we also found evidence that the differences in migration policy framing between the two political camps are more pronounced in the USA than in Canada. The chapter contributes to the existing migration policy literature by expanding the research on legislative speeches in the USA and Canada, two cases which have not yet been explored in this context. By showing that political actors tend to emphasize issues they own more in a polarized context, we expanded the research on the effects of polarization on policy framing in legislative speeches.

Our exploratory study of migration framing in legislative debates in the USA and Canada has also enabled a better understanding of humanitarian subcomponent of migration issues. While the humanitarian migration subcomponent is present in the public discourse, the existing studies, have neglected it, at least thus far. We suggest that future studies should emphasize this aspect of the policy. Particularly, future research could examine how it relates to other, already established components of the migration debate—such as the economy, security, and culture.

The chapter represents a methodological contribution by providing a guide on how automated text analysis and in particular structural topic modeling can be used to study intricate and complex research questions from social sciences—such as rhetorical conflicts in framing migration policy in legislative speeches. Further extensions of this work should incorporate validation of the findings either through human coding of a part of the selected dataset or through comparison with existing qualitative studies. Expanding the time frame, and therefore incorporating more international conflicts, may clarify the relationship between conflict abroad and policy framing by domestic political elites. We hope this chapter encourages more researchers to use quantitative text analysis to explore social science research puzzles.

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A.1 Appendix

Supplementary materials, replication code, and links to the relevant datasets are available online.

Repository: www.github.com/tamos/ValuesInText

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The Role of Network Structure and Initial Group Norm Distributions in Norm Conflict

Julian Kohne, Natalie Gallagher, Zeynep Melis Kirgil, Rocco Paolillo, Lars Padmos, and Fariba Karimi

Abstract Social norms can facilitate societal coexistence in groups by providing an implicitly shared set of expectations and behavioral guidelines. However, different social groups can hold different norms, and lacking an overarching normative consensus can lead to conflict within and between groups. In this chapter, we present an agent-based model that simulates the adoption of norms in two interacting groups. We explore this phenomenon while varying relative group sizes and homophily/heterophily (two features of network structure), and initial group norm distributions. Agents update their norm according to an adapted version of Granovetter's threshold model, using a uniform distribution of thresholds. We study the impact of network structure and initial norm distributions on the process of achieving normative consensus and the resulting potential for intragroup and intergroup conflict. Our results show that norm change is most likely when norms are strongly tied to group membership. Groups end up with the most similar norm distributions when networks are heterophilic, with small to middling minority groups. High homophilic networks show high potential intergroup conflict and low potential intragroup conflict, while the opposite pattern emerges for high heterophilic networks.

Keywords Social norms · Conflict · Homophily · Network structure

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1 Introduction

In this chapter, we study the impact of network structure and initial group norm distributions on the process of arriving at a normative consensus between groups and the potential for intragroup and intergroup conflict that might emerge under different conditions. To this end, we first provide a brief theoretical overview on social norms, normative group conflict, and the process of finding consensus through social influence. Second, we give an overview on the role that network structure as well as the initial distributions of norms can play in this process. Specifically, we argue that homophily/heterophily (preference for forming connections to similar/dissimilar others) between members of different groups, relative group sizes, and the initial distribution of norms within groups are all important factors for reaching normative consensus, and consequently relevant determinants of conflict potential. Based on this reasoning, we develop an agent-based model that simulates social networks of agents from two different social groups where each agent holds one of the two social norms. In an adapted version of Granovetter's threshold model (Granovetter, 1978), each agent updates its social norm by comparing the proportion of norms held by its immediate neighbors to an internal threshold drawn from a uniform distribution. Agents are thus "observing" the "openly displayed behavior" of their neighbors and adapt their own behavior accordingly if enough of their neighbors display a different norm. We apply this model to different network structures, defined by relative group sizes and homophily/heterophily between agents from different groups. This allows us to assess the impact of these structural network properties on the process of reaching normative consensus and associated conflict potential. In addition, we run our model for different levels of initial group norm distributions, so that we can also assess the influence of alignment (or independence) of norms and social group membership. We define and examine three relevant outcomes: the degree to which norm distributions change, the degree to which the difference in norm distributions between the two groups changes, and the potential for conflict within and between the groups. Lastly, we discuss our results with respect to their applicability, the limitations of our model, and possible directions for future research.

2 Social Norms

Social norms can be defined as unwritten behavioral rules (Bicchieri and Mercier, 2014) or "social standards that are accepted by a substantial proportion of the group" (Forsyth, 2018, 145). They are a shared set of situation-specific behaviors that facilitate social interaction by providing an implicitly shared set of expectations and behavioral guidelines (Bicchieri, 2006). Such behaviors can range from an implicit dress code at work, to the expression of religious and political symbols, or (not) interacting with other social groups. Norms are implicitly negotiated between members of a group and enforced through informal sanctions, such as gossip, censoring, or ostracism (Bicchieri, 2006). They are passed through generations via socialization processes in childhood (House, 2018) and are, in contrast to laws, not necessarily enforced by an institution. Norms come in multiple types, for example, *prescriptive norms* define behaviors that one should enact (e.g., “offering elderly people a seat on the subway”), while *proscriptive norms* define undesirable behaviors that one should avoid (e.g., “interrupting people while they speak”). The most important distinction for our purposes is between *injunctive* and *descriptive* norms. Injunctive norms focus on beliefs about how people should act, while descriptive norms are defined by the observation of how people actually do act (Melnyk et al., 2010; Cialdini et al., 1990). For instance, “everybody should recycle” is an injunctive norm, while the observation that many people do not recycle represents a descriptive norm (Cialdini et al., 1990). Both types of norms are important determinants of behavior, but previous research suggests that injunctive norms primarily elicit behavioral change by changing attitudes (Melnyk et al., 2010; Megens and Weerman, 2010), while descriptive norms directly impact behavior (Cialdini, 2007). In this chapter, we are interested in descriptive norms, because they are directly inferred from the observed behavior of others. Injunctive norms can differ from directly observed behavior, and can involve more complex cognitive processes (House, 2018), which are beyond the scope of our model. Therefore, when we are referring to social norms with respect to our model, we are specifically addressing descriptive social norms.

2.1 Normative Conflict

A large body of previous research has focused on the potential for positive impact of social norms on behavior. Predominantly, these studies were interested in changing individual beliefs or behavior by presenting normative information at odds with the individual’s current beliefs or behavior. Examples include the reinforcement of non-delinquent behavior through the influence of peers (Megens and Weerman, 2010), positive effects of punishment on cooperative behavior (Fehr and Gächter, 2000), effects of social norms on compliance to vaccination programs (Oraby et al., 2014), reduction of binge-drinking in college students (Haines and Spear, 1996), and littering (Cialdini et al., 1990). However, inconsistent norms do not only elicit behavioral change; they can lead to interpersonal and intergroup conflict (Hogg and Reid, 2006). The potential risk of such normative conflicts is especially high in multicultural contexts where different cultural groups must coexist (Wimmer, 2013). A recent example of normative conflict in Europe is women wearing a veil to cover their face in public. This practice is a prescriptive social norm in some predominantly Muslim countries and it has elicited mixed reactions when immigrants engaged in the practice in their new countries (Kılıç et al., 2008). Some Western countries such as France, Belgium, and Switzerland have banned this practice. In France, lawmakers claimed that a ban was necessary to ensure *“peaceful cohabitation”* (Zeit Online, 2019). Likewise, in Germany, face veils have been controversially discussed in the past years: For instance, the German Minister of the Interior stated *"[. . .] we reject this. Not just the headscarf, any full-face veils that only shows eyes of a person [. . .] It does not fit into our society for us, for our communication, for our cohesion in the society . . . This is why we demand you show your face"* (McKenzie, 2019). This backlash reflects an underlying normative conflict, with a large majority (81%) of Germans supporting a ban in public institutions and a substantial group (51%) even supporting a general ban. Only a minority of the national population (15%) indicate that they are not in favor of any kind of regulation (Infratest Dimap, 2018).

However, such normative societal conflicts exist not only along established cultural and religious divides, but can cover a wide array of topics and elicit intergroup and intragroup conflicts (Hogg and Reid, 2006). For instance, gun ownership is a controversial normative debate within US society (Kleck, 1996), involving subgroups with different cultural orientations (Celinska, 2007). Abortion is another topic debated worldwide, with disagreements concerning women's rights, health care systems, and moral constraints (Marecek et al., 2017). Empirical research shows how the controversy around abortion leads to a polarization of opinions within Protestants and Catholic groups in US society (Evans, 2002). Other inconsistent norms can concern controversial national traditions such as *Zwarte Piet* ("Black Pete"), a folklorist character and helper of *Sinterklaas* (Santa Claus) in the Dutch culture. The character is typically displayed with blackface makeup, bright red lips, and colorful clothing. The display has been increasingly criticized as a racist stereotype, predominantly by minority and immigrant groups, while many native Dutch citizens argue that "Black Pete" is a positive character and part of their national tradition (Rodenberg and Wagenaar, 2016). In essence, inconsistent social norms within a larger collective have the potential to lead to intergroup, as well as intragroup conflict. With respect to trends of increasing globalization and migration, effectively resolving these normative conflicts is becoming a striking priority for many societies in the future.

2.2 Finding Consensus

Despite their potential for negative outcomes, normative conflicts are not an indication that a collective is inherently unfit to live together peacefully. In contrast, they can be fundamental to the formation of social units at different scales. Georg Simmel defines shared consensus on social roles and their supporting norms as necessary features of human society (Simmel, 2009). Similarly, normative conflicts are frequently observed in the literature on group formation and described as a necessary step towards a common group identity. For example, in Tuckman's stage model of group development, the *norming stage* focuses on resolving disagreement and establishing a shared set of behavioral guidelines; it is a crucial step in the formation of an effective group (Tuckman, 1965). Some recent, empirically validated models such as the Normative Conflict Model (Packer and Miners, 2014) confirm this mechanism. According to the model, members strongly identified with the group are more likely to openly express dissent compared to weakly identified members (Packer and Miners, 2014). Dissenters help uncover the causes of the conflict and discuss possible solutions. To form an effective group with committed members, it is necessary to effectively resolve conflicts due to incompatible norms and to find a consensus on which most members agree. Failure to reach such a consensus might result in a lack of common group identity and task effectiveness, leading to the dissolution of the group (Tuckman, 1965).

Interactions between people from different social groups are a steadily increasing occurrence in societies that are socially, economically, and culturally diverse (Arapoglou, 2012). Such diversity is likely to increase in the future, along with changing relations between majority and minority groups due to demographic and socioeconomic changes (Crul, 2016). As ongoing political and societal polarization in Western societies already demonstrate, incompatible social norms associated with different groups have the potential to elicit conflict (Fiorina and Abrams, 2008). For these reasons, we argue that it is crucial to understand the conditions enabling social groups to effectively reach a normative consensus and how this process relates to conflict potential within and between social groups.

3 Network Structure and Group Norm Distributions

Individuals do not adopt norms in isolation; the structure of their social environment is a key determinant of social behavior. The social networks in which we are embedded determine the kinds of people and behavior to which we are exposed, thereby shaping the descriptive norms we hold. Thus, the interpersonal processes which contribute to finding normative consensus (Neumann, 2008), as well as the intergroup and intragroup processes (Hogg and Reid, 2006), are crucially contextualized within networks of social interaction. Consequently, we argue that finding normative consensus is a continuous process of group members mutually exerting social influence (Cialdini, 2007) on each other until a relatively stable equilibrium is reached (Latané, 1981; Flache et al., 2017). This often requires that at least some individuals react to social influence exerted on them by their social networks by changing their norms. For instance, Kalesan et al. (2016) show how networks such as family and friends are the best predictors in forging a culture favoring gun ownership. As for the normative conflict of gay marriage in the USA, a longitudinal time-series study shows how the decision of the US Supreme Court in June 2015 eventually led to an increase in perceived social norms supporting gay marriage independently of individual attitudes (Tankard and Paluck, 2017). In short, the social networks people are embedded in appear to play a crucial role in the process of reaching a normative consensus within and between groups.

In this chapter, we will focus on homophily/heterophily between people from different groups and relative group sizes as determinants of network structure, and on the initial distribution of norms within groups when they come into contact.

3.1 Homophily and Heterophily

Homophily is the tendency to preferentially connect and interact with similar others (McPherson et al., 2001), while heterophily is the tendency to preferentially connect and interact with dissimilar others (Lozares et al., 2014). Homophily has been observed extensively in many social networks, including school friendships (Stehlé et al., 2013), scientific collaborations (Jadidi et al., 2017), and online communications (Mislove et al., 2010). It is likely a manifestation of the *similarity bias*, a fundamental human tendency to like and value others that are similar to the self and to consequently be disproportionally influenced by them (Cialdini, 2007). For example, a controlled experimental study on the spread of a health innovation through social networks varied the level of homophily, showing that homophily significantly increased the overall adoption of new health behavior, especially among those in more clustered networks (Centola, 2010). Similar effects have been shown in diverse health behaviors in large social networks, such as the spread of smoking (Christakis and Fowler, 2008) and obesity (Christakis and Fowler, 2007). Since social influence is exerted through social ties in networks (Aral and Walker, 2011; Lewis et al., 2012) and homophily/heterophily determines how these ties are formed, we argue that it is an important factor in the process of negotiating a normative consensus through mutual social influence.

3.2 Group Size

Almost no collective group is made out of completely homogeneous members. Instead, they consist of demographic subgroups, such as those defined by gender, nationality, or education (McPherson et al., 2001). Mostly, these subgroups are not equally sized, so that people are either part of a majority or minority group (Blau, 1977) with respect to a certain social category. The pervasive influence of majority opinions, customs, and norms is well established in theoretical accounts of group-based social influence (Latané, 1981). The dominant role of the majority has been experimentally validated in numerous studies replicating the seminal work by Asch (1951), both for individual social influence (Horcajo et al., 2010; Kundu and Cummins, 2013) and group influence (Meyers et al., 2000; Cohen, 2003). Greater influence of the majority is generally assumed for acculturation processes of minority immigrants in host countries (Bourhis et al., 1997; Ward et al., 2010). Yet, other studies have demonstrated that under certain conditions, minorities can successfully exert social influence on the majority and consequently redefine the normative consensus in their favor (Hogg and Reid, 2006; Mugny and Papastamou, 1982; Nemeth, 1986). For these reasons, we argue that the sizes of interacting subgroups within a larger society are an important factor in the process of negotiating normative consensus.

3.3 Initial Group Norm Distributions

Agreement on social norms is considered to be a part of the collective identity people derive from the social groups to which they belong (Hornsey, 2008; Hogg and Reid, 2006). Norms vary, however, in how much they align with group membership. Even in the case of German opinions on face veils, a full 15% do not agree with the normative opinion to ban face veils (McKenzie, 2019; Infratest Dimap, 2018). That is, despite sharing group membership, individuals disagree on this norm. Conversely, in the social group of Muslim immigrants in Germany, some will support the norm of face veils, while others will oppose it. People can hold the same norm on face veils even though they are from different social groups, or they can hold different social norms while belonging to the same social group. In terms of our example, there will be some Muslim immigrants agreeing with Germans who oppose face veils. There will also be some Germans agreeing with the Muslim immigrants who do not oppose face veils. In short, even in this case of strong consensus, group membership is not the single determinant of norms held on an individual level. Social norms are often aligned with group membership to a degree, but the two are not synonymous.

This interplay of social group membership versus agreement in moral or normative issues has been shown to be influential in previous studies. For instance, the influence that a group exerts on individuals is not only a function of its size, but also of its unanimity, with stronger pressure towards conformity for more unanimous groups (Asch, 1956). Furthermore, studies have shown that people react more negatively to dissenters from their own in-group (Marques et al., 1988) and consequently punish them harder. The initial distribution of norms within groups thus seems to be important for negotiating a normative consensus, even though it is not necessarily influencing the structure of the social network.

4 Agent-Based Model

Agent-based modeling can be of particular interest to understand social phenomena because it enables researchers to study complex macro-level outcomes that emerge from a clearly defined set of micro-level processes (Macy and Willer, 2002; Flache et al., 2017). In addition, simulations allow us to systematically vary agents' behavioral rules or the circumstances in which they act (Squazzoni et al., 2014). In short, agent-based models help us to gain insight into the emergence of complex systems by systematically testing a variety of different parameters and the combined impact they exert on the emergent system (Macy and Willer, 2002). Previous research has extensively used agent-based models to study phenomena such as spatial segregation (Schelling, 1971), opinion diffusion (Lorenz, 2007), the adoption of innovation (Zhang and Vorobeychik, 2017), and cascade effects (Watts, 2002).

For the purpose of modeling normative conflict in social networks with respect to relative group sizes, homophily/heterophily, and group norm differences, we developed a modular simulation framework based on a network generation algorithm using preferential attachment, group size and homophily/heterophily (Karimi et al., 2018), and Granovetter's threshold model (Granovetter, 1978). We utilized R (R Core Team, 2019) for our model as it appears to be more widespread among the social science community than Python and offers more customizability, better parallelization, and scalability than NetLogo. Consequently, probabilistic processes in our model are implemented using the *sample()* function in R, which relies on the current system time to generate a seed for pseudo-random number generation. All code, documentation, and an animated visualization are available on GitHub (Kohne, 2019) under the MIT License.

4.1 Simulating Norm Conflict

In our agent-based model, we aim to simulate the impact of group size, homophily/heterophily between agents from different groups, and initial group norm distributions on the process of reaching normative consensus and resulting conflict potential. To this end, we generated networks with 2000 agents each, where network structure is determined by one parameter for relative group size (g) and one parameter for homophilic/heterophilic preferences of agents (h) (Karimi et al., 2018). In addition, initial norms for agents were assigned based on three different pairs of binomial probabilities, resulting in three conditions for initial group norm distributions. Once the network structure is generated and agents are assigned their initial norms, each agent is assigned a threshold from a uniform distribution (Granovetter, 1978) and the model simulates normative social influence processes between agents by repeating 50 iterations of Granovetter's threshold model. Once the simulation is complete, we extract the percentage of agents holding each norm for each group, and the number of ties between agents within each group and between the groups. Crucially, we differentiate ties between agents holding the same norm and ties between agents with incompatible norms. Our model thus consists of four subsequent steps: generation of network structure, initialization of group norm distributions, the norm updating process, and the extraction of outcome metrics.

In total, we simulate 150 unique parameter combinations with 20 networks per combination, resulting in 3000 unique networks (for an overview of the parameter space, see Table 1). For each of these networks, we are saving each iteration of Granovetter's threshold model as an individual network object, resulting in 150,000 networks with 2000 agents each. Simulation was carried out on the High Performance Computing Cluster of the University of Cologne on 150 MPI nodes. We opted for 50 iterations of Granovetter's threshold model because it was the highest number of feasible iterations in the maximum computation time limit for

Table 1 Range of parameter values of the simulation in the experiment

Parameter	Description	Value(s)
n	No. of agents in network	2000
m	Minimum agent degree	2
p_1:p_2[a]	Initial group norm distribution	[0.5:0.5][0.6:0.4][0.8:0.2]
t	Individual agent threshold	$U(0, 1)$ [b]
g	Group size	$[0.1, \overset{+0.1}{\cdots}, 0.5]$
h	Homophily/heterophily parameter	$[0.1, \overset{+0.1}{\cdots}, 1]$

[a]Each of the three conditions compares different initial distribution of the majority norm in the majority group (p_1) and in the minority group (p_2)
[b]U:Uniform distribution

the MPI nodes (360 h) of the High Performance Computing Cluster. The simulation took approximately 13 days (315 h) and resulted in approximately 40 GB of output data.

4.2 Generation of Network Structure

To generate different network structures that resemble real social networks and enable comparison of effects of g and h, we implemented the network generation algorithm by Karimi et al. (2018). This algorithm combines the *preferential attachment* mechanism, which has been observed in many large-scale social networks (Barabási and Réka, 1999), with tunable parameters for group sizes and homophilic/heterophilic tendencies of agents in the model. As a point of terminology, we will refer to the group containing more agents as the "majority group" and the group containing less agents as the "minority group."

The network generation model implements an iterative growth process where we start out with a small number of m initial agents for both the majority group and the minority group. After this initial setting, one agent is added to the network at a time. Each new agent has a probability of g to be assigned to the minority group and a probability of $1 - g$ to be assigned to majority group. For example, with a value of $g = 0.4$, each new agent has a probability of 40% to be assigned to the minority group and a probability of 60% to be assigned to the majority group. Each new agent forms m ties to the agents that are already present from previous steps. In this way, the parameter m also defines the *minimum degree* of agents in the network. We keep this parameter constant at $m = 2$ across all our generated networks because it ensures that no agent is isolated in the network. Previous research demonstrated that the choice of m does not change the properties of the network (Barabási and Réka, 1999).

Connecting these m ties from the new agent to existing agents is probabilistic, and relies on the homophily parameter h and the degree of the present agents (Karimi et al., 2018). The parameter h ranges from 0 to 1 and defines the likelihood of agents to form ties to agents from the same group or from a different group $(1-h)$.

A value of 0 represents perfect heterophily (ties will only be formed between agents assigned to different groups) and a value of 1 represents perfect homophily (ties will only be formed between agents assigned to the same group). In addition, agents also have a build-in preference for agents with high degree (preferential attachment), which is interacting with their group preference determined by h. Specifically, the probability p_{ij} of each added agent j to form a tie with a present agent i depends on the degree of the present agent (k_i) and the specified homophily parameter between i and j, h_{ij}, divided by the sum over all existing agents denoted by (l):

$$p_{ij} = \frac{h_{ij}k_i}{\sum h_{lj}k_l} \ . \tag{1}$$

The processes of assigning agents to a group and selecting present agents to connect with are not deterministic, so the same set of initial parameters will generate slightly different network structures each time. To capture this variance, we generate 20 networks per parameter combination and report averaged results. See Fig. 1 for an example, and see appendix for analytical derivations.

4.3 Initialization of Group Norm Distributions

After creating network structures based on the parameters g and h, we initialize a norm as an attribute in each agent. We will use "majority norm" and "minority norm" when we discuss our results with respect to the two different norms in our model. Specifically, majority norm will refer to the norm held by the larger proportion of agents in the larger of the two groups after initializing the network structure. In cases where the amount of agents holding each norm is equal, we simply track one of the two norms over the course of the simulation.

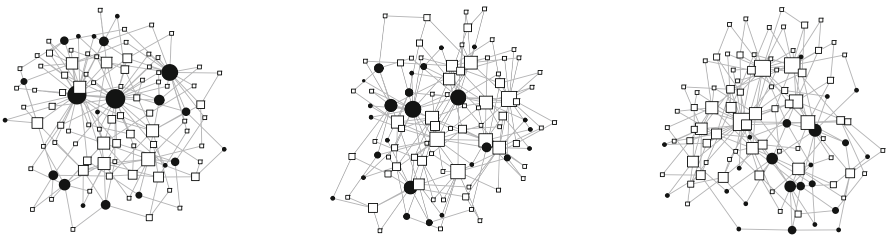

Fig. 1 Generated networks with 100 agents and $g = 0.2$. From left to right, the networks are showcasing $h = 0.2$, $h = 0.5$, and $h = 0.8$. Node size represents logarithmized agent degree. Minority group agents (20%) are represented by black circles, majority group agents (80%) are represented by white squares. When the network is heterophilic (left), the minority group increases their degree rapidly due to the combination of preferential attachment and smaller group size. In the homophilic network (right), the minority group cannot grow their degree by attracting majority group agents

We use a probabilistic process with two different parameters p_1 and p_2 for the initial group norm distributions, where p_1 describes the probability of agents in the majority group to be assigned the majority norm, while $1 - p_1$ describes the probability of agents in the majority group to be assigned to the minority norm. Vice versa, p_2 describes the probability of agents in the minority to be assigned the majority norm, while $1 - p_2$ describes the probability of agents in the minority being assigned the minority norm. For example, with $p_1 = 0.7$ and $p_2 = 0.3$, each agent in the majority group has 70% probability of being assigned the majority norm and probability 30% of being assigned the minority norm. Conversely, each new agent assigned to the minority has a probability of 30% to be assigned the majority norm and probability of 70% to be assigned the minority norm. In this example, we can see that p_1 and p_2 define how closely the assignment of norms is related to the group membership of new agents. If p_1 and p_2 are both 0.5, then there is no connection between group membership and norm—every agent of either group has an equal probability (50%) to endorse either norm. If p_1 is large and p_2 is small, then initial norm proportions are associated with group membership—the majority and the minority group preferentially use different norms. In our model, we will be testing one case where the initial norm distribution is unrelated to group membership ($p_1 = 0.5$ and $p_2 = 0.5$), one where the initial norm distribution is weakly related to group membership ($p_1 = 0.6$ and $p_2 = 0.4$) and one where initial norm distribution is strongly related to group membership ($p_1 = 0.8$ and $p_2 = 0.2$). We thus generate models where (a) 50% of the majority group and 50% of the minority group start with the majority norm, (b) 60% of the majority group and 40% of the minority group start with the majority norm, and (c) 80% of the majority group and 20% of the minority group start with the majority norm.

4.4 Norm Updating Process

After initializing one of the two norms in each agent according to parameters p_1 and p_2, we simulate the adoption of norms over time within each network using Granovetter's threshold model (Lewis et al., 2012; Aral and Walker, 2011; DiMaggio and Garip, 2012). In our simulation, we use a modified version (Granovetter, 1978) where each agent in the model is assigned a threshold value from a uniform distribution [0,1]. A central point in Granovetter's threshold model is the *variability* of thresholds within a group. Once people with lower thresholds adopt a norm, they will raise the proportion of people with that norm, increasing the chance of shifting those who have higher thresholds (Granovetter, 1978). In his seminal work, (Granovetter, 1978) showed these dynamics both with a uniform distribution and a normal distribution of thresholds. In our model, we decided to use a uniform distribution of thresholds because our aim is to understand the role of network structure and initial norm distributions in normative conflict, and not primarily to investigate the effects of the threshold. To clearly understand emergent properties in agent-based models without extraneous mechanisms, it is beneficial to avoid unnecessary complexities (Eberlen et al., 2017). Non-uniform distributions require particular choices: either the single value of the threshold held by all agents or the mean and variance of a normally distributed threshold parameter. Thus, any distribution besides the uniform requires additional assumptions without adding a concrete contribution (Railsback and Grimm, 2019) to our research questions. We use a uniform distribution in our model to control the effect of the threshold distribution (Lee et al., 2015) while testing the effect of network structure and initial norm distribution. We also allow agents to change back and forth between norms as appropriate given their threshold and the norms of their neighbors. This is distinct from some models where an agent can only change once (e.g., learning of a new innovation), and we consider it appropriate for modeling our phenomenon of interest—descriptive social norms.

In the updating process, each agent compares its threshold value to the proportion of its immediate neighbors holding a particular norm. If the proportion of neighbors that are expressing a given norm is equal to or higher than the agent's threshold, the agent will update its currently held norm. For example, if agent j has a threshold of $t_j = 0.6$, it will update to the norm that 60% or more of its neighbors display. Depending on the current norm of the agent, this can mean either switching to a different norm or keeping the agent's current norm. If both proportions fail to reach the threshold (e.g., 50/50 distribution of norms in neighborhood of agent while the threshold value is 0.6), the agent will also keep the current norm. In cases where observed proportions of both norms are equal and exceeding an agents threshold, the agent will choose one of the two norms at random. Each network goes through 50 iterations of the updating process, so all agents update their norms 50 times.

In each iteration of the norm updating process, all agents are updated *asynchronously*, meaning that only one agent is updated at a time and the order in which agents update their norms is randomly shuffled before each iteration of the updating process. Thus, each agent's updating process can affect the updating process of the next agent. We chose this procedure as opposed to having a fixed order for updating agents or updating all agents at the same time because natural social interactions neither occur in a predetermined order nor do all people in a social network exert influence on each other simultaneously. For this reason, we argue that our approach more closely resembles real-life interactions and social influence processes between people.

4.5 Outcome Metrics

After the agent-based model finishes, we extract our outcomes of interest: The degree to which norm distributions change, the degree to which the difference in norm distributions between the two groups changes, and the potential for conflict within and between the groups.

To operationalize the degree to which norm distributions change, the initial proportion of agents holding the majority norm is subtracted from the final proportion of agents holding the majority norm. We subsequently call this *Change in Majority Norm* because it expresses the degree to which the group has adopted the majority norm relative to the group's starting point. If this number is positive, the group's use of the majority norm has increased over the course of the simulation. For example, if the network starts with an 80–20 group norm distribution and ends with 60% of the minority group endorsing the majority norm, the minority group has adopted the majority norm by 40%. If change in majority norm is negative, the group has rejected the majority norm. In a similar example, if the network starts with an 80–20 group norm distribution and ends with 10% of the minority group endorsing the majority norm, the minority group has rejected the majority norm by 10%. This is a group-level outcome: it tells us how the normative consensus within the majority group and within the minority group have changed over time. It is worth noting that the initial norm distribution limits the possible change within the majority group and the minority group. In the 80–20 initial norm distribution, only 20% more of the majority group could hold the majority norm, while 80% more of the minority group could do so.

At a system level, we are interested in the degree to which the difference in norm distributions between the two groups changes. Specifically, we are interested in whether the two groups express the two norms in similar proportions after the last iteration and if they have become more similar in their norm proportions over time. To calculate this, we first calculate the initial group norm difference by subtracting the initial proportion of the minority group holding the majority norm from the initial proportion of the majority group holding the majority norm $\Delta(p)_{initial} = p1_{initial} - p2_{initial}$ (see Sect. 4.3). Then we calculate the final group norm difference by subtracting the final proportion of the minority group holding the majority norm from the final proportion of the majority group holding the majority norm, $\Delta(p)_{final} = p1_{final} - p2_{final}$. We subtract the final group norm difference from the initial group norm difference to define *Change in Group Norm Difference* $\Delta(p)_{final} - \Delta(p)_{initial}$. If this is positive, then difference has increased; the groups have become less similar over the course of the simulation in terms of their norms. If this is negative, then the group norm difference has decreased; the groups have become more similar. Once again, it is worth noting that the initial group norm distribution limits total possible change.

At a dyadic level, we are interested in the potential for interpersonal conflict between and within groups. To look at this, we define *Conflict Ties* as ties connecting two agents with different norms after the last iteration. Crucially, we distinguish between conflict ties of agents from the same group as a proxy for potential intragroup conflict and conflict ties of agents from different groups as a proxy for potential intergroup conflict. In particular, we are extracting the proportion of ties in the majority group that connect agents with inconsistent norms, the proportion of ties in the minority group that connect agents with inconsistent norms, and the proportion of ties between the groups that connect agents with inconsistent norms.

5 Simulation Results

Our results are structured around the three overarching outcome metrics outlined above. For each metric, we consider the aggregated output of our runs by averaging over the values obtained from the 20 simulated networks per parameters combination.

1. **Change in Majority Norm:** Which combinations of parameters increase or decrease the prevalence of the majority norm? In which cases does the majority norm become prevalent among the majority and the minority group? In which cases does the minority norm gain prevalence?
2. **Change in Group Norm Difference:** Which combinations of parameters reduce between-group norm differences? Which make convergence of norms most likely?
3. **Conflict Ties:** Which sets of parameters make it most likely that potential within-group or between-group conflict will emerge? Which make it most likely that there will be little potential for conflict?

5.1 Change in Majority Norm

Our first interest is how the representation of norms within groups changes, using our Change in Majority Norm metric (see Sect. 4.5). Figure 2 displays the results of the simulations, showing how this is influenced by homophily/heterophily, group sizes, and initial group norm distributions.

This visualization highlights several findings. First, the effect of homophily and group size on the results is clearest when the initial group norm distribution is 80–20. That is, when norms are highly aligned with group membership, the influence of network structure is most pronounced. When the initial norm distributions are 50–50 in each group, the change in norm proportion is random—the system is not changing systematically even with varying levels of group sizes and homophily/heterophily. Second, the pattern of results for majority and minority groups are distinct. In the majority group, high heterophily (i.e., a greater proportion of connections to the minority) leads to stronger adoption of the minority norm. Similarly, as the size of the minority group increases, the majority group is more likely to adopt the minority group norm. Within Granovetter's threshold model, this is very reasonable: increased minority group size makes it more likely for a majority group member to be connected to members of the minority group and take on the minority norm.

The minority group adopts the majority norm most when homophily is middling and the minority group is small. The minority group maintains or increases its own norm most when it is relatively large, or when homophily is very high or very low. This suggests the operation of multiple mechanisms at different intersections of homophily and group size (see analytical derivations in the appendix). When the

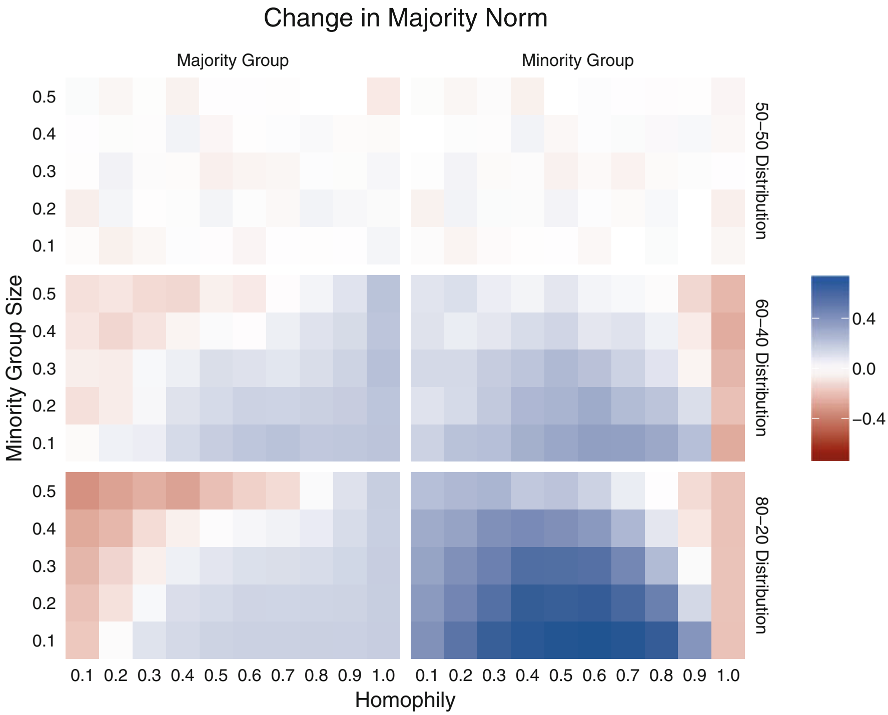

Fig. 2 Change in Majority Norm for majority and minority group. This set of heatmaps displays the influence of network homophily/heterophily, group size, and initial norm distributions on change in the majority norm. Each square represents the degree to which representation of the majority norm has increased or decreased in each group. Darker blue means shift towards the majority norm and darker orange means shift towards the minority norm. When norms are initially distributed equally (50–50, top row), the change in group norm difference is essentially random and does not depend on the properties of network structure and group size. When norms are initially distributed unequally, e.g., 80–20, bottom row, we observe the impact of homophily and group size. For small homophily values, majority members are more likely to change their norm to the minority norm. As homophily increases, the majority and the minority are both likely to adopt the majority norm (until $h = 1$, when the pattern is reversed). In general, as the minority group increases in size, it is more likely to retain its own norm and influence the majority

network is highly homophilic, the minority maintains its own norm because it is selectively attached to members of its own group, thereby avoiding exposure to majority-group influence. When the network is heterophilic and the minority group is small, the minority is also more able to maintain its own norm. This is because this network parameterization results in minority group members becoming hubs: each majority group member connects to minority group members, and there are not many of them. This means each minority group agent has disproportionate influence. With a large minority group, minority agents have a higher likelihood to be attached to other minority agents, again making it more likely that they will maintain their own norm distribution. The results of the simulation are in agreement with our analytical results provided in the appendix.

5.2 Change in Group Norm Difference

Our second point of interest is the degree to which the two groups become more similar in their group norm distributions. To address this, we use our Change in Group Norm Difference metric (see Sect. 4.5). The more negative this number, the more similar the groups have become in their norm distributions; the more positive, the more the groups have diverged in their norm distributions. Figure 3 displays the results of the simulations.

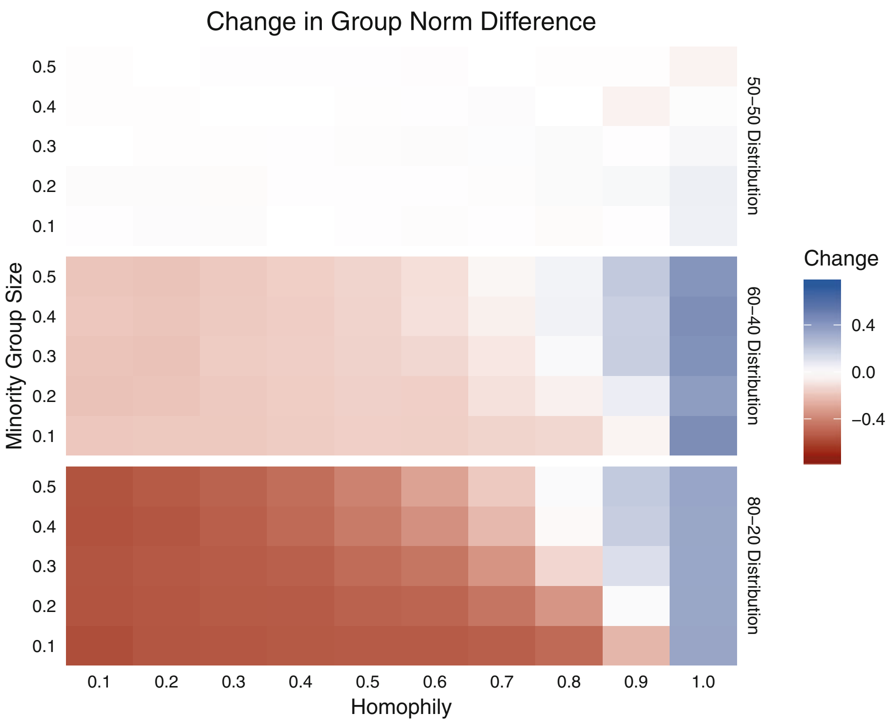

Fig. 3 Change in Group Norm Difference. The more negative this number, the more similar the groups have become in their norm distributions; the more positive, the more the groups have diverged in their norm distributions. In the 50–50 distribution condition, we see that there is no systematic effect of the two groups becoming more normatively similar. In the 80–20 distribution, the network structure results in strong mutual conformity unless homophily and/or minority group size is very high

As with the change in norm proportions, the effects of homophily and group proportion are clearest when the initial group norm distribution is strongly associated with group membership (i.e., 80–20 initial group norm distribution). In this case, we can see there is a strong pattern of the two groups moving towards similar norm distributions (i.e., reduce their differences). This pattern is less pronounced or reversed as homophily increases and minority group size increases. This suggests that heterophily is important for producing between-group norm similarity, while high homophily may actually increase between-group norm difference.

5.3 Conflict Ties

Our third question revolves around the remaining potential for normative conflict, once the simulation has run. For this, we look at the proportion of within- and between-group ties that are Conflict Ties at the end of the simulation. Figure 4 shows the results of our simulation for proportion of within-group and between-group ties that are conflict ties. We display results from the 80–20 initial group norm distribution, where group membership and initial norm distribution are closely connected. As with the prior analyses, the results of the 50–50 initial norm distribution were essentially random, and the pattern in the 60–40 initial norm distribution is similar to the 80–20 case but not as strong.

Comparing the three graphs in Fig. 4, we see that the level of network homophily determines the trade-off between intergroup and intragroup conflict. In high-homophily networks high potential for intergroup conflict remains at the end of the simulation, but there is little potential for intragroup conflict. In contrast, high-heterophily networks have very little remaining potential for intergroup conflict, but slightly higher potential for intragroup conflict.

The role of minority group size also emerges clearly in Fig. 4. For between-group ties and majority-group ties, having a small minority group reduces potential conflict. This effect is relatively consistent across all the levels of homophily, though it is more exaggerated at more extreme ones. Within the minority group, group size does not appear to have as consistent of an effect on conflict ties.

6 Discussion and Conclusion

We see three important strands in our pattern of results. First, they speak to the degree to which the alignment of initial group norm distributions and group membership is crucial for the process of reaching normative consensus. Second, they point towards the impact of homophily and heterophily in balancing between in-group and out-group conflict. Finally, they point towards strategies that could be used to maintain minority norms in minority groups and to avoid large-scale assimilation.

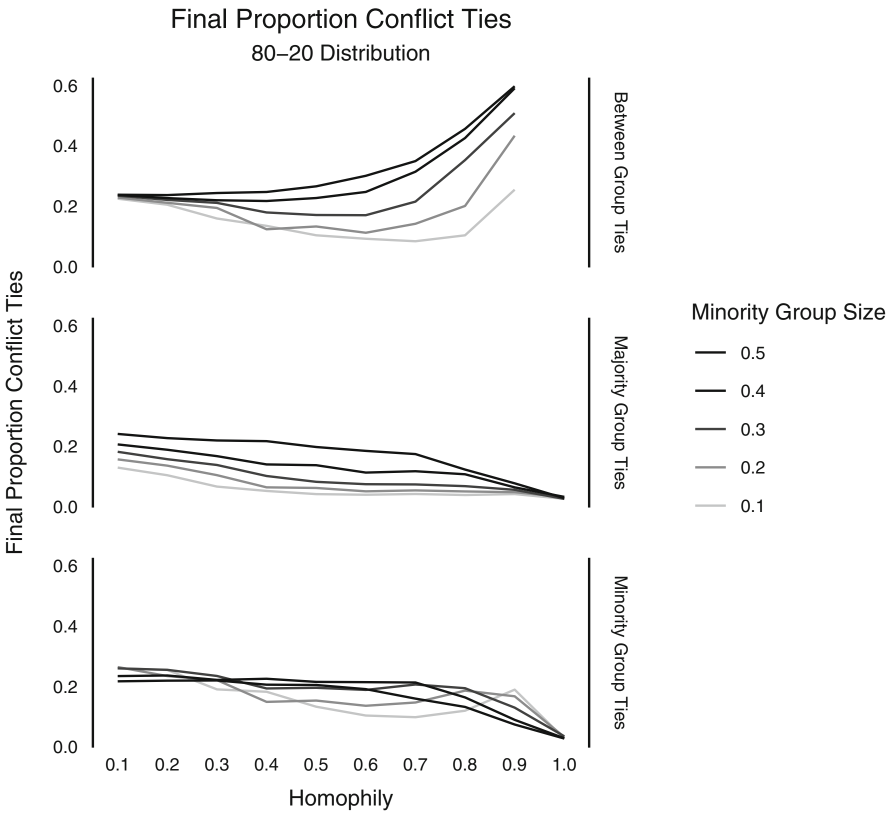

Fig. 4 Final Proportion of Conflict Ties in 80–20 Initial Norm Distribution. We see that highly homophilic networks still have relatively high potential for between-group conflict (top row). In contrast, when there is low homophily, the between-group conflict decreases. A reverse pattern appears for within-group conflict ties (second and third rows). As homophily increases within-group conflict decreases

6.1 The Alignment of Norms and Group Membership

One clear result of our simulation is that, in a system with conflicting norms, substantive change occurs only when the norm is highly aligned with group membership. In our model, this took the form of an 80–20 initial norm distribution, where 80% of the majority group but only 20% of the minority group initially held the majority norm. In cases where the norm was not aligned with group membership (50–50 initial norm distribution, top row of Figs. 2 and 3), we do not observe any clear globally dominant norm at the end of the simulation. Even in cases with a relatively large majority group (minority group only 10% of the network), there was no particular norm change because the social influence of the majority group was evenly split between two norms. When the norm is moderately aligned with group membership (60–40 initial norm distribution), we see intermediate results—not entirely random as with the 50–50, but less clear than when the norm is strongly associated with group membership.

In intergroup situations, we see that group-level and system-level influence arises not out of small pockets of extremely strong beliefs (i.e., the small minority group in an 80–20 initial norm distribution), but rather out of the consistent homogeneous norm of a majority group. There are cases of normative disagreement that take on proportions like this—our headscarf example from the beginning, for instance, showed 81% of Germans in favor of banning the headscarf in public institutions, with only 15% contradicting that opinion. Though such distinct norms are likely to be newsworthy, perhaps there are many instances of intergroup norm non-conflict that receive less attention. Newspapers are unlikely to report that two neighbors from different cultural backgrounds both like to eat dinner with their families, but it may be important for collective cohesion nonetheless.

This also supports prior literature suggesting that groups with consensual norms are most likely to prompt normative change in their outgroup. A recent survey in the USA, for instance, indicated a 50–50 split on whether football players should be required to stand during the national anthem (Vandermaas-Peeler et al., 2018). In this case, Americans as a single majority group are unlikely to exert much normative force on out-group members (e.g., Canadians) about this issue. If we consider subgroups of Americans (i.e., Republicans and Democrats), this norm may be much more strongly associated with group membership and thus more likely to have an effect.

Our model focuses on the shift in a specific norm within a network. This fits our interest in descriptive norms, though real cultural practices might be whole clusters of normative behaviors rather than single binary norms. A contrast between Jewish and Christian people, for example, is not only that they attend different religious services, but also that they can have distinct injunctive norms around weekend hours, food, and marriage that are culturally transmitted. One option is to consider the norm in our model as an aggregate, i.e., not a single behavior, but a cluster of group-based behaviors. Another option is to consider the norm in our model to be the behavior which people notice within a specific context.

6.2 Homophily Balances In-Group and Between-Group Conflict

One of the primary aims of this model was to understand when and how subgroups would conform to each other. In Fig. 3, we see that between-group differences in norms are clearly reduced by the norm updating process, particularly when norms are strongly associated with group membership (i.e., 80–20 initial norm distribution). Except in cases of large minority groups or extremely homophilic networks, there is a meaningful reduction in between-group norm differences: the groups become more similar as the individual agents change their norms. Looking at Fig. 2, it is clear that most of the norm change happens in the minority group—they tend to update their norm to that of the majority group, especially when homophily is intermediate and the minority group not large. In contrast, we see the majority group leaving their norm and adopting the minority norm when the network is extremely heterophilic (i.e., $h = 0.1$) (Fig. 2). This occurs while the minority group is updating to the majority norm. In this situation, heterophily is so strong that the members of the majority group are disproportionately exposed to the norm of the minority group; this allows for strong influence of the minority group even when the minority is quite small. Thus, though the system overall produces mutual conformity, the level of homophily balances which group is changing their norms to accommodate to the other group.

In Fig. 4, homophily again balances group-level and system-level outcomes when considering the remaining potential for conflict within the network. When the network is heterophilic or neutral, few between-group conflict ties remain. In contrast, when the network is very homophilic, we see the potential for intergroup conflict almost doubled. The reverse is true for within-group conflict ties. When the network is heterophilic or neutral, a fair number of within-group conflict ties remain. When the network is very homophilic, this potential intragroup conflict is reduced by at least half. Thus, we see that both in terms of which group changes their norms and the potential conflict that remains, homophily balances between group-level and system-level outcomes.

6.3 Strategies to Maintain Minority Norms

The maintenance of a cultural identity, partially defined by normative practice, can be extremely important. Our simulation lends support to three methods for maintaining minority cultural practice visibly employed by minority groups in reality: isolationism, adopting positions of influence, and increasing the group size of one's minority. Within the model, the minority group was best able to maintain their own norm in extremely homophilic networks, extremely heterophilic networks, and when their group was large.

Extremely homophilic networks in our simulation mimic strongly isolationist cultures in reality. Such isolation can be imposed upon a minority group (e.g., being excluded from mainstream culture), but can also be sought out as a source of cultural affirmation and strength (e.g., resisting assimilation into mainstream culture) (Berry, 2005). This latter motivation has been expressed by groups as different as the Amish in the USA and anti-capitalist leadership in China. The recognition of community-level benefits of culturally affirming and relatively homogeneous environments can be seen in the push to maintain historically black colleges and universities, even as black students in America have increasing access to other institutions (Franke and DeAngelo, 2018). Though isolationism may draw critique as backward-looking, it can be a deep recognition that intergroup contact can fundamentally affect the culture of a minority group.

Extremely heterophilic networks in our simulation, in contrast, are closely related to minority groups which attempt to have their members in positions of overall societal power. Rather than completely preserving group norms through isolation, this strategy attempts to change the larger culture by exerting influence on the majority. This can be observed in efforts to get members of minority groups elected to positions of power, with the explicit goal of increasing minority voice in the government. By holding positions of power within a larger society, minority group members can become hubs to spread their own group norms.

The final strategy we can relate to our results is to increase one's group size. The logic here is fairly straightforward: the larger a group, the greater chance it has of influencing the whole system. We can see this strategy in the tendency of minority group members to define their groups expansively, stressing the similarities with the majority group (Wimmer, 2013), and the converse tendency of majority group members to define their groups strictly (Dovidio et al., 2007).

The three strategies which emerge from our study are far from a complete set; there are many other strategies well outside the scope of our current work. For example, minority groups actively resist norm change (Xie et al., 2010), cultural institutions formally negotiate over cultural practices, and younger generations modify their inherited cultural practices. We leave model-based exploration of these possibilities for future work.

6.4 Limitations and Future Directions

In the effort to construct a parsimonious model from existing theory, we acknowledge that there are many assumptions in this model that could be productively expanded. First, one could incorporate more than two groups or multiple kinds of interpersonal ties. Second, one could make the model more realistic by having a series of inter-correlated norms held by each group, such that individuals have different thresholds to specific norms, or a different weight for norms depending on in-group membership of neighbors. Third, one could integrate psychological theories of preferential information processing to have agents differentially weight the norms expressed by their neighbors based on shared in-group membership. Such modifications would allow us to expand from descriptive to injunctive norms, involving higher-order cognitive processes such as persuasion (Cialdini and Goldstein, 2004) and contrast with personal values (Wei et al., 2016) that could be modeled in agents. Finally, it would be valuable to explore other distributions of thresholds within the network to explore more realistic and complex scenarios.

These further developments would also increase the options for validating this model against real world data (e.g., gathering experimental data or found social network data measuring intergroup norm spread). Thus, continuing to grow this work can increase its contribution to the nexus between networks, social norms, and conflict.

Despite these limitations, the current study provides a novel and meaningful insight by providing a streamlined example of how group size and homophily can affect the adoption and maintenance of group-affiliated norms. We have shown that even in this simplified version of reality, differences in group proportions and homophily have different effects for majority and minority groups, and can affect the degree to which groups eventually adopt similar distributions of norms. We also contribute to the exciting interdisciplinary growth of computational social science by providing a novel agent-based model that includes both structure of social networks and social influence in one framework.

Finally, we hope that this work contributes to existing knowledge on assimilation, acculturation, and between-group conflict over norms. Our simulation demonstrates that assimilation is most likely at low (heterophilic networks) and intermediate levels of homophily. At intermediate levels, the minority group largely conforms to the majority group. This moves the system towards collective harmony, but does so at the cost of the minority group giving up its own norms. At low levels of homophily, when minority group members have a structural advantage within the network (i.e., central positions with many ties), we see accommodation from both directions: the minority members take on the norm of the majority group, but the majority members also take on the norm of the minority group. Taken together, these suggest that collective harmony is maximized when groups are interconnected, and that this is accompanied by the dispersion of minority norms when there is a strong preference for out-group contact.

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Contribution All authors jointly came up with the idea and research questions. J.K. implemented the simulation model, wrote the method part, and contributed to the theoretical background part. N.G. analyzed results and wrote results and discussion. Z.M.K, R.P., and L.P. conducted literature research and wrote the theoretical background part. F.K. provided mentoring, computed analytical derivations, and contributed to results and discussion.

Appendix: Analytical Derivations for Norm Endorsement

In this appendix, we derive the probabilities of norm endorsement in each group using the mean-field approach. This analysis enables us to gain insights on the relationship between the model parameters of homophily, group size, and group norm distribution. In addition, the analytical derivations help us to interpret the outcome of the simulations in Sect. 5.

More specifically, we calculate the probabilities of a minority agent to update to the majority norm and *vice versa*. We use mean-field approximation (also known as the deterministic approximation) which means that we look at the average behavior of the group in an equilibrium state (Marro and Dickman, 2005). That means, we do not consider the changes over time and the heterogeneity of the agents. Nevertheless, the mean-field approach gives us a useful insight on forecasting the overall behavior of the system. Let us assume that the minority is denoted by a and the majority is denoted by b. Two norms are denoted by norm A and norm B. Homophily is denoted by h and group proportion is denoted by g. In order to calculate the probability of a minority agent to update the majority norm (B), we need to estimate the probability of a minority to be connected to majority agents (p_{ab}) and the probability of the minority agent to be connected to minority agents (p_{aa}). Since our agent-based model assumes a preferential attachment mechanism and defines group proportion (g), the probability of two agents to be connected depends on their homophily (h) and the degree of the agent (k). Link formation is a combination of two mechanisms, namely homophily and preferential attachment, and thus the probability of connectivity follows a nonlinear function. To estimate the link probabilities, apart from homophily, we need to estimate the degree growth function (C) of each group of agents. The degree growth determines the attractivity of the agents with regard to their degree. The degree growth in this model follows a polynomial function of order three with one valid solution and it can be calculated numerically (Karimi et al., 2018):

$$C = \left(g \left(1 + \frac{hC}{hC + (1-h)(2-C)} \right) + (1-g) \frac{(1-h)C}{h(2-C) + (1-h)C} \right) . \tag{2}$$

The probability of two agents of group a (p_{aa}) and two agents of group b (p_{bb}) to be connected is

$$\begin{aligned} p_{aa} &= \frac{hC}{hC + (1-h)(2-C)} , \\ p_{bb} &= \frac{h(2-C)}{h(2-C) + (1-h)C} . \end{aligned} \tag{3}$$

In addition, the degree growth function has the following relation to the probability of linkage (Karimi et al., 2018):

$$C = g(1 + p_{aa}) + (1 - g)p_{ba} \; . \tag{4}$$

The probability of a minority agent to update to the majority norm (f_{aB}) depends on the probability of being connected to majority (p_{ab}) and minority (p_{aa}). Thus, for a minority agent, the fraction of neighbors with norm B is

$$f_{aB} = \frac{p_{aa}p_{aB} + p_{ab}p_{bB}}{p_{aa} + p_{ab}} \; . \tag{5}$$

The numerator consists of two parts; the probability of connecting to another minority with norm B ($p_{aa}p_{aB}$) and the probability of connecting to majority with norm B ($p_{ab}p_{bB}$). To estimate the fraction, the nominator should be divided by the total probability of connectivity between the majority to majority and minority. Inserting Eq. (3) into Eq. (5), we find

$$f_{aB} = \frac{(\frac{hC}{hC+(1-h)(2-C)})(p_{aB} - p_{bB}) + (2 - \frac{h(2-C)}{h(2-C)+(1-h)C})p_{bB}}{2 - (\frac{h(2-C)}{h(2-C)+(1-h)C})} \; . \tag{6}$$

Similar relation can be found for the probability of a majority agent to update to the minority norm (f_{bA}):

$$f_{bA} = \frac{p_{bb}p_{bA} + p_{ba}p_{aA}}{p_{bb} + p_{ba}} \; . \tag{7}$$

Figure 5 displays the analytical results derived from the above derivations. It is interesting to note that the update to the norm of other group follows a nonlinear

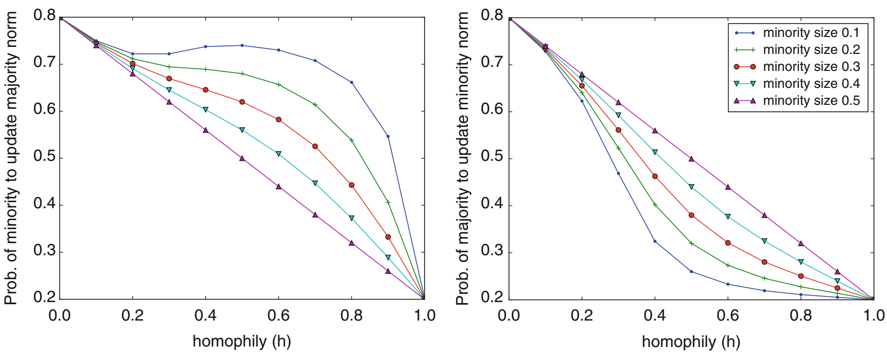

Fig. 5 Analytical results for the probability of minority (left) and majority (right) to update to the norm of the other group. Initial norm proportion is set to 20–80. We observe asymmetrical results as the group balance deviates from 50–50 condition. For small values of homophily $0 \leq h \leq 0.2$ we observe similar behavior for majority and minority. However, as homophily increases, we observe that minority members update their norm to that of the majority with high probability, while majority does not update to the minority norm. The asymmetric relation is more pronounced as the minority group size decreases

and asymmetrical trend both for the minority and the majority. In the intermediate level of homophily ($0.5 < h < 0.8$), while the majority members resist to switch its norm to minority norm, the minority updates to the majority norm with high probability. That would create a higher advantage for the majority norm to persist and stabilize. Only when homophily is very high, the probability of the minority members to update to the majority norm starts decreasing. As the minority size shrinks, the inequality in norm adoption increases.

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On the Fate of Protests: Dynamics of Social Activation and Topic Selection Online and in the Streets

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Abstract This chapter studies individual and network conditions for the emergence of large social protests in an agent-based model. We use two recent examples from Iran and Germany to inform the modeling process. In our agent-based model, people, who are interconnected in networks, interact and exchange their concerns on a finite number of topics. They may start to protest either because of their concern or because the fraction of protesters in their social contacts exceeds their protest threshold. In contrast to many other models of social protest, we also study the coevolution of topics of concern in the not (yet) protesting public. Given that often a small number of citizens starts a protest, its fate depends not only on the dynamics of social activation but also on the buildup of concern with respect to competing topics. Nowadays, this buildup happens decentralized through social media. The model reproduces characteristic patterns of the evolution of the two empirical cases of social protests in Iran and Germany. In particular, our results show that positions of agents with certain concern levels on certain topics within the networks are important for the fate of protests.

Keywords Opinion dynamics · Social protest · Social media · Social network

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1 Introduction

Street protests frequently happen all over the world. In the USA alone, from January 20, 2017 to June 16, 2019, 13,761 protests with 10,827,646 attendees have been recorded (Count Love 2019). Street protests are typical examples of emergent social phenomena that result from the interaction of many heterogeneous and autonomous agents. Changes in the number of attendees and topics of protest are inherent in street protests as the case of Russia from 2007 to 2013 shows (Lankina 2014). By topic of protest, we mean the main issue that protesters address in a protest. After the emergence of a protest, slogans and behavior of protesters, peaceful or violent, influence how others judge it and may constrain more people from joining.

New technologies, specifically social media, have changed our communication. They made cheap and fast interactions among a large number of actors in a decentralized ways possible (assuming that administrators of social media do not intervene in interactions). These technologies have helped to organize protests. A protest announcement can reach millions in no time without central control. Moreover, they have enabled amateur multimedia reporters to broadcast details of the protest in real time.

On the other hand, social media is not only a place for announcing street protests or sharing information about these. Social media is also a place for genuinely digital protest in the form of campaigns and conflicts among users. In this chapter, we address the mutual relationship between street protests and their perception by the public. A significant part of this perception emerges in the media in general and in social media in particular (see Elson et al. 2012 and Anstead and O'Loughlin 2014). Not everyone is active in social media, and users do not publish all their ideas. Nevertheless, social media still captures reasonably how people perceive a street protest, due to the large number of users and their somewhat equal share of power.

The role of social media in the emergence of conflicts has been well studied considering street protests and social media as intercorrelated and interdependent (Ayres 1999; Gerbaudo 2012; Valenzuela et al. 2012; Penney and Dadas 2014; Qi et al. 2016). Hussain and Howard (2013) show that mobile phone usage had a crucial role in the success of the Arab Spring social movements, while social media helped to expand it (Lim 2012; Howard et al. 2011). In the Philippines, during the 2001 protest, again, mobile messaging played a prominent role as the place and time of the protest were coordinated through text messages (Shirky 2011). In the case of Occupy Wall Street, Twitter, Facebook, and YouTube played a significant role (DeLuca et al. 2012). These media are successful in mobilizing people since their decentralized structure allows for large-scale cascades of messages (González-Bailón et al. 2011). They also have a leading role in the first stages of protests. When traditional media start covering these protests, social media effects mix with those of traditional media (González-Bailón et al. 2013).

The majority of the previous studies focused on how social media has helped to mobilize potential attendees of protests. However, only a few have focused on the interplay between street protests and their image in social media and recognized mobile communication as a context for the creation of counter-narratives in street protests. One example is Neumayer and Stald (2014), who studied cases in Denmark and Germany.

We will model the internal dynamics of typical street protests and their relationships with the perception of the broader public who is active on social media. The simultaneous changes in a protest, in terms of the number of attendees and slogans, and the image of the protest in the broader public, in terms of popular topics, are modeled with an agent-based approach. We will use two distinct cases to inform the modeling process one in Iran and another in Germany.

The emergence of social protests has been captured with threshold models of collective behavior by Granovetter (1978) and Kuran (1989). Both models assume that every person has an individual threshold defining the minimal percentage of the protesting population that convinces the individual to join the protest. The rational-choice interpretation of this threshold is that this is the value where expected benefits exceed the expected costs of protest. In that sense, a low threshold stands for a person with strong concerns who is easily motivated to protest, while a person with a high threshold has few concerns. A reasonably simplifying first assumption, also used by Granovetter, is that thresholds are normally distributed with a certain mean value greater than zero. The persons with thresholds of zero or below are the initial protesters who can trigger others also to start to protest and so on until a final number of protestors is reached. For a normal distribution with a standard deviation below a critical value, only a small fraction ends up in protest, while the protest cascades to almost all people when the standard deviation is slightly above a critical value. Granovetter's model assumes that every person has the information about the global fraction of protesters.

Granovetter's and Kuran's model can explain how it comes that suddenly large protest movements emerge. They however do not take into account that individuals might not assess the fraction of protesting people in the whole population but only those in their immediate social networks. Watts (2002) applied the idea of Granovetter's threshold model to an undirected random network and showed that global cascades can be triggered by one protester while other protesters have equal thresholds (e.g., all 0.2) when the average number of links (i.e., association among protesters) is relatively low (between 1 and 6). The cascades, however, do not happen for denser networks. Dodds and Watts (2004) developed this model into a general model of contagion where individuals may receive several "doses" of motivating messages from others that sum up and trigger protesting when a threshold is exceeded. This model also includes compartmental models from epidemiology, such as the SI (susceptible-infectious) and SIR (susceptible-infectious-recovered) models, which are the canonical models for the spread of infectious diseases. In our model, we will use the threshold concept as well as the dose concept. We will assume that people can be activated to protest when a fraction of their social contacts is protesting. We will also assume that social media messages function as doses of concern with respect to particular topics for people who are not yet protesting.

Lohmann (1994) modifies the Granovetter and the Kuran model to focus on participation in a street protest as a costly political action that reveals information on how likely protesters deem political change. Klein and Marx (2018) pursue a similar idea but focus on explicit conversational information exchange between agents and asymmetric learning as a driving factor for the formation of mass movements. In their model, agents have a certain level of grievance and develop expectations of how likely political change is. When two agents meet randomly, one of them can access the other one's attitude. If asked, agents reveal their interest in change. However, since asking has a cost, only those critical of the system try to elicit their conversational partner's attitude. Hence, agents can learn from replies to questions that they ask themselves but also from others asking them or refraining from doing so. This results in asymmetric learning because agents who want change can learn from any interaction while supporters of the status quo only learn from interactions where their conversational partner and not they themselves are given a chance to ask. This means that genuine advocates of change deem change more likely than their peers who are content with the status quo. Moreover, the model shows that agents tend to underestimate the chance for change, while expectations are more accurate for societies with higher spatial or social mobility. Our model implements the idea that expression of one's concern is costly by implementing the possibility of agents sending unpolitical messages instead of expressing their concern. Furthermore, the above-mentioned possibility of social activation honors the fact that people decide whether to join a protest also based on information about the recent number of protesters.

Similarly, Epstein's (2002) model of decentralized rebellion is mainly built on activation but not only triggered by a high number of already activated agents in the neighborhood but also inhibited by repression through the presence of cops. Like the aforementioned models, Epstein's focus is also on fundamental rebellion and hence only captures concern with a single topic (i.e., the current general situation), thereby ignoring the possibility of multiple topics within a protest and agents influencing each other with regard to these topics.

In her investigation of the development of news cycles, Waldherr (2014) touches upon different topics gaining or losing attention within a group of interacting agents. In her model, however, agents are journalists and they are interested in topics rather than concerned about them; thus, attention for a topic has no external consequences like the formation of a protest.

Although our model builds on existing works on protest development as a question of costly choice, social exchange, and information retrieval, it goes beyond previous research by taking into account agents' genuine concern about multiple topics as well as their communicative exchanges on social media. In the following, we analyze two recent cases where protest dynamics and topical changes coevolve and use them to develop our agent-based model.

2 Data

To capture significant similarities and differences in the street protest phenomenon, we deliberately take data from two recent cases of protests from different cultures and political systems: The Iran protests in December 2017 and January 2018 exemplifies a short-term protest that heated up quickly and ended abruptly. In contrast, PEGIDA in Germany since 2014 is a case of long-term motivation of protesters and slow topic shift that can be considered as a social movement. A social movement is a sort of organization with specific goals (Della Porta and Diani 2009, p. 145–150) while a single protest, like the Iran case may not have leaders or definite goals. Protests, in the long run, may turn into a social movement.

2.1 Iran Protest in 2017/2018

Our observations on this case stem from primary data analyses of videos and photographs taken at the street protests depicting protest slogans and Iranian online activity, mainly on Telegram, the most popular social media platform in Iran (Techrasa 2016), with regard to the protest.

On December 28, 2017, in Mashhad, capital of Khorasan Razavi province and the second largest city in the country after the capital city Tehran, a demonstration took place in the main square of the city by the invitation of some hardline fundamentalist/conservative political groups opposing the government of president Rohani. The organizers aimed to put pressure on the president by focusing on economic problems and showing how people are supporting the opposition. However, within hours after the protest started, organizers could not control the crowd and slogans radicalized to the critique of the whole political system. Videos from the demonstrations were shared online to millions of people, and consequently, unlike previous Iranian street movements, protests started in more than 100 cities all over Iran (Rahmani Fazli 2018), with the most intense protests occurring in smaller cities. However, only minor physical conflicts with authorities arose, and there was less systematic oppression by the police in comparison with previous protests, because the government tolerated the protests as the president recognized the protesters' right to express their concerns (Euronews 2018). Demonstrations and their repercussion on social media faded out a week after the first protest.

Albeit this short time frame, the protest experienced various shifts of focus visible in daily changes of protest slogans. Overall, we could identify nine different topics shown in Fig. 1. We identified these nine topics by watching all protest videos posted in influencing Telegram channels (73 videos) during the seven days of the protests in more than 36 cities. In total, 78 different slogans were extracted from these videos. Then, we categorized them into nine topics. Figure 1 also shows in how many cities we found slogans from a given topic. Moreover, topics had different

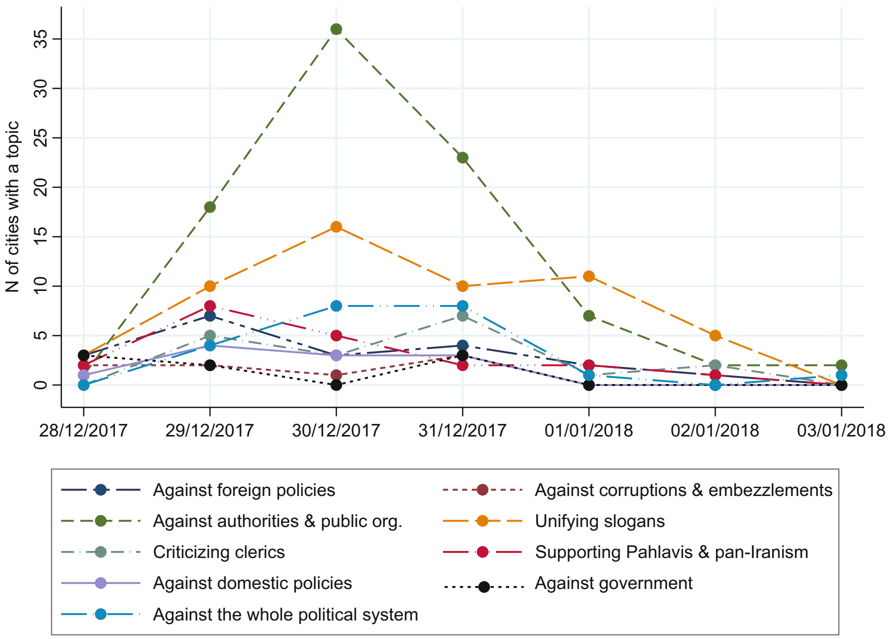

Fig. 1 The number of cities with a topic of protest for the seven days of the protest in Iran

fates along the seven days of protest, as some had uniform popularity and others had more fluctuations in popularity.

Figure 2 shows that different cities had a different number of topics on different days. This underlines the fact that there was not one dominant topic in the protest. This underpins that the movement was decentralized and spontaneous and hence subject to internal dynamics instead of being led by political players pursuing a specific agenda. For example, initial supporters condemned slogans against the whole political regime as some of them are strong defenders of it (Zand 2017). Most political camps in Iran were surprised by the daily developments and hence confined themselves to interpreting events in light of their own goals. This struggle for interpreting the protest was clearly reflected in the first page of political newspapers (Khedmati 2018).

Ordinary non-protesting citizens also interpreted and discussed the developments within families, with colleagues or friends in person and on social media (BBC 2018). Hence, albeit the fact that only about 0.1% of the population joined street protests directly (Rahmani Fazli 2018), a broad debate in society mirrored the protest topics and tensions between them not only during the protest but still a month after it.

We initially aimed to find the popularity of each protest topic on several social media channels, namely Instagram, Telegram, and Twitter, day by day. This could have shown how the street protest and online trends are interrelated and evolve

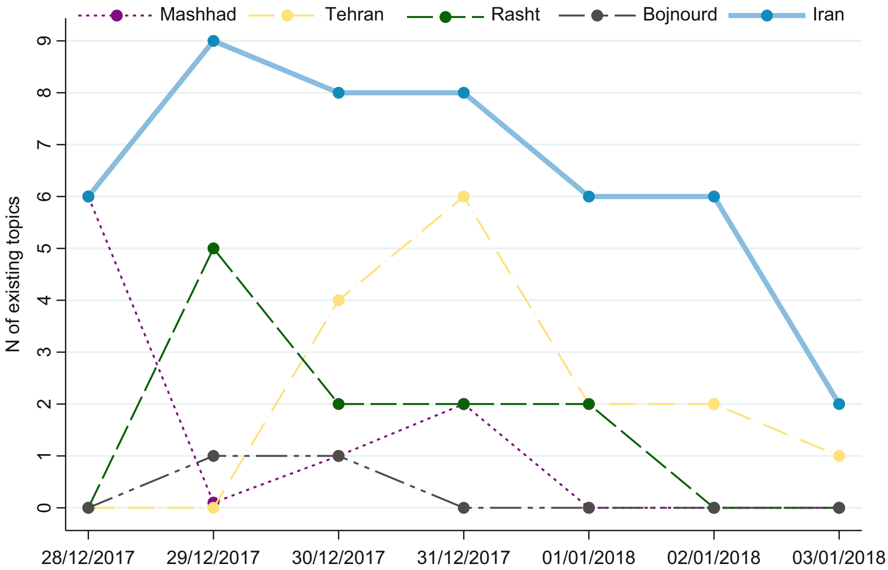

Fig. 2 The number of popular topics in the whole country and four cities during the seven days of protest in Iran

mutually. But tools for analyzing social media turned out to be too expensive and not Persian-friendly enough.

Google Trends, as it is deployed by many scholars (e.g., Choi and Varian 2012; Mellon 2013; Mellon 2014; Minkus et al. 2019) was an alternative for our goal. We searched for the popularity of street slogans on the web, which includes any kind of a text published on the internet (if Google indexes it). This can be a fine proxy of what was important for Iranians during the lifespan of the 2017/2018 protest. Each topic consists of some slogans in the reviewed videos that were gathered from influential Telegram channels. As Google Trends gives indices only for single words or terms, it was impossible to search trends with multiple slogans that constitute one topic. So we searched for single slogans in Iran in Google Trends. Out of 73 slogans, there were data for 10 in Google Trends. The existence of common trends between the number of protesting cities and the Google Trends index shows how hot debates on the internet and in the streets were associated. This is illustrated in Fig. 3.

Figure 3 shows the different patterns of the positive relationship between 10 slogans on the internet and in the streets (in cross-correlation analyses, eight of them had positive relationships). In most cases, the climaxes of online and street topics are the same day or a little retarded or anticipated. It is thus plausible that online and street protests respond to each other. This means that street protests and debates on social media react to each other and can have mutual influence.

The Iran case is an example of protests that start fast and gather people with different topics of interest. In this case, the protest is well-connected to interactions

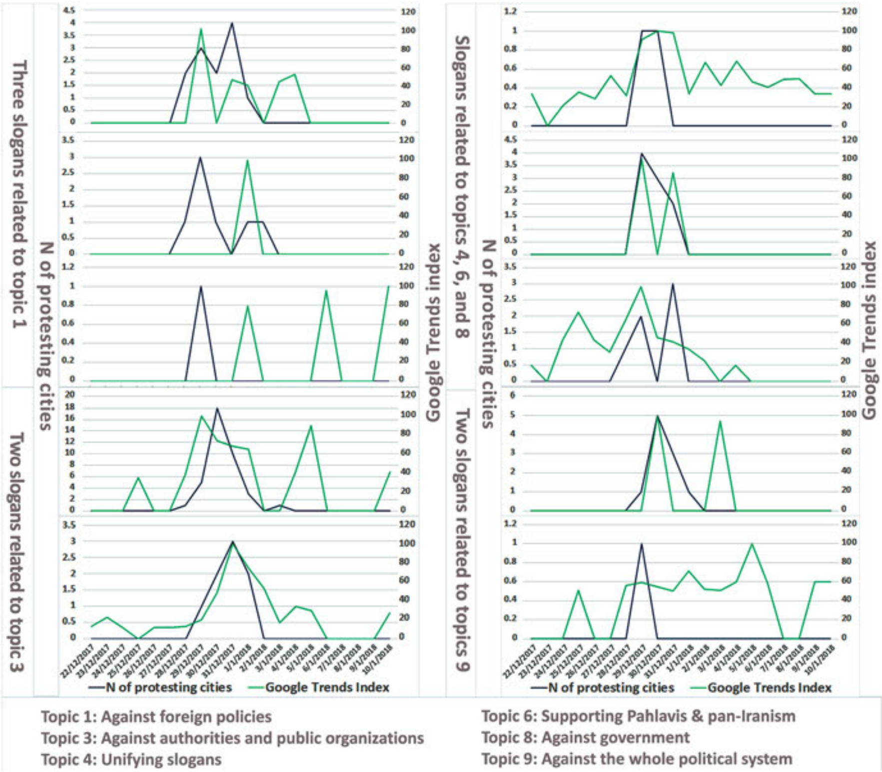

Fig. 3 Examples for the number of protesting cities and Google Trends index during the lifespan of the 2017/2018 Iran protest

among different actors on social media. Change in the popularity of topics in cities and the lateral change in Iranians' online concerns is considerable.

2.2 *PEGIDA, Germany Since 2014 and Ongoing*

The far right-wing populist movement "Patriotische Europäer Gegen die Islamisierung des Abendlandes" (Patriotic Europeans against the Islamisation of the Occident) or short PEGIDA was founded in closed social media groups without party affiliation (Vorländer et al. 2018, p. 2). Soon, a public Facebook page was launched for communication with protesters and general political statements. The page was banned for violation of community standards but immediately re-established (Vorländer et al. 2018, p. 23–27). Weekly street protests started in the city of Dresden in Saxony, Germany, and sparked protests in other German cities. On October 20, 2014, about 350 protesters joined the first PEGIDA street protest

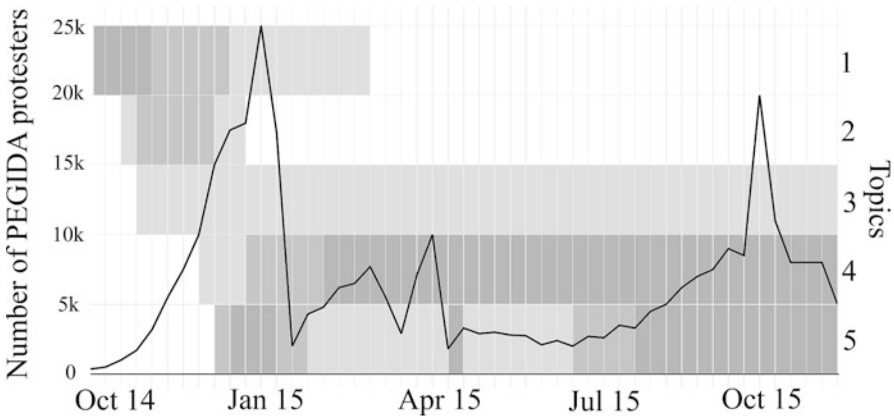

Fig. 4 Number of PEGIDA protesters between October 20, 2014, and November 26, 2015 (Source: Durchgezählt.org) and tendencies in topics lobbied in the protest as found on the PEGIDA Facebook page and elaborated by Rucht et al. (2015) and Vorländer et al. (2016) based on social media communication, slogans at the protest and interviews conducted with protesters. Darker shades mean higher tentative prevalence of the respective topic: 1 = Fear of radical Islam; 2 = critique of Dresden local refugee policy; 3 = anti-feminist sentiment; 4 = fundamental criticism of political establishment and traditional media; 5 = general xenophobia/anti-refugee sentiment

and expressed their worries about public demonstrations in support of different parties in the Syrian civil war and Islamic extremism. However, this developed into a rejection of Islam and Muslims in general over the next weeks. Moreover, PEGIDA criticized first the local Dresden refugee policy and later the German national one (Vorländer et al. 2016, p. 5–7). Figure 4 shows that the number of supporters constantly rose and peaked at 25,000 on January 12, 2015 (https://durchgezaehlt.org). After that, the number of protesters decreased to 2000–3000 and PEGIDA organizers amended its topics by a general critique of the political establishment and also the traditional media. When the so-called refugee crisis in the EU arose in summer and autumn 2015, several hundred thousand refugees arrived in Germany and were sent to (often improvised) shelters across the country (Glorius et al. 2018, p. 113). As a consequence, PEGIDA could then mobilize more people again. This resulted in a second peak of 15,000–20,000 protesters on October 19, 2015. After spring 2016 the figures declined again and remain at the level of about 2000 protesters until now (2019). These protesters still oppose migrants, traditional media, and the German political establishment.

During the protest peak time in December 2014 and January 2015, only few protesters interviewed or surveyed by different research teams (Vorländer et al. 2015; Rucht et al. 2015; Geiges et al. 2015) expressed particular issues with Islam, which at the time was the main message conveyed by PEGIDA organizers on banners at the protest or on social media. Instead, protest attendees were more concerned about refugee policy in general and felt alienated from the political establishment (which partially led to distrust in the political system altogether) and were unhappy with traditional media news coverage of political events.

Overall, PEGIDA in Germany exemplifies a type of protest that starts without connection to existing political actors and with no revolutionary ideas but focuses on a narrow topic; however, people who are generally dissatisfied join the protest and cause a shift of topics towards a more generalized critique of the political establishment. Furthermore, PEGIDA shows that protests can prevail with a small number of supporters and despite not reaching any of its goals directly impact the general political debate (Vorländer et al. 2018, p. 26). Finally, PEGIDA highlights the importance of understanding the interplay of street protests and their social media image as well as interactions of protest leaders and other political actors.

2.3 Stylized Data Facts

Although PEGIDA in Germany and the 2017/2018 protests in Iran seem very different at first glance, our analysis revealed common structural features that a model should capture.

In both cases, topics lobbied in the street shifted away from what organizers of the initial protests intended. This was also noted for the Arab spring by Hussain and Howard (2013) and for Occupy Wall Street in the USA and anti-austerity protests in Greece or Spain by Theocharis et al. (2015). One explanation for these shifts is that protesters have diverse ideas. A few of these ideas can grow more popular and dominate others over time. However, radical shifts do not only occur with regard to topics, but also the number of protesters can drastically increase or decrease either gradually or from one protest day to the next one.

While activity on the street is an important factor for publicity and acknowledgment of a protest, nowadays online space largely contributes to the success of a protest in two ways: Firstly, as spaces for debate, online social networks allow protesters to spread their ideas and develop them further (cf. Lim 2012), as it can, for example, be observed on the PEGIDA Facebook page or in Telegram groups of Iranian protest supporters. Secondly, people can also practically coordinate upcoming street protests by, e.g., sharing information about the time and location, which PEGIDA frequently does prominently by utilizing its page profile and cover pictures for that purpose.

Overall, differences between street protests seem not to be of structural nature, but one should investigate reasons for these differences in specific circumstances of the protest and protesters. However, these specific circumstances can often not easily be empirically accessed, or one may want to predict the fate of future protests based on assumptions about the shape of the specific factors. Hence, our model helps to assess how different circumstances relate to different protest fates.

3 Agent-Based Model

We model the evolution of street protests in terms of individual concerns, social activation, topic selection, and increasing concerns through topic propagation in social media. We only model the activation of protesters and the buildup of concerns and not the dampening and die-out of protests. Before specifying the details, we describe the basic idea.

In our model, several individuals are interconnected in a social network. Each individual holds political concerns of different magnitudes on a finite set of topics. Individuals have different protest thresholds analog to Granovetter (1978). They begin to protest when at least one of their concerns is above the threshold. If this is not the case, they may also join the protest when the fraction of protesting others in their social contacts exceeds the threshold. Thus, individuals can protest because of concerns or because of social activation. The decision to do either is based on the same individual threshold. So, we assume that individuals with a low threshold are more susceptible to both types of activation. They will start to protest already with low concerns or with a low fraction of protesting others. An individual joining a protest decides on one of the topics to protest. A concerned protester selects one of the topics where the concern is above the threshold. Selection is probabilistic with probabilities proportional to concerns. A protester protesting because of social activation has no concern above the threshold and therefore selects a topic from all topics based on probabilities proportional to their concerns. Further on, all individuals, protesting or not, post a message in their social network. Individuals post if they joined a protest and with which topic. Individuals who did not protest post a message unrelated to the protest. The next day people with no concern above threshold read the messages in their social media news feed. Individuals with no concern above their threshold randomly pick one of the messages from their news feed. When this message is protest-related, they increase their concern on the topic of the message. This can be considered a dose of concern analog to Dodds and Watts (2004). People who follow mostly non-protesting others will receive mostly messages that are not protest-related and will thus likely not increase their concerns. This whole process repeats daily and can trigger different fates of protests with respect to the number of protesters and how prevalent the different topics are in the protest. We implemented this model in NetLogo (Wilensky 1999). The model is also provided for reference (Lorenz et al. 2019). It can be downloaded and run in NetLogo, which is free to use.

3.1 Agents, Follower Network, Thresholds, and Concerns

The agents in the model are individuals who are connected in a static directed social network built upon initialization. The network can be interpreted as a follower network where an agent can read the social media posts of the other agents following but not necessarily vice versa. The follower network is created in two parts. First, a directed preferential attachment network is built, representing links to potential “celebrities” at various magnitudes of fame. This is built by successively creating agents whereupon creation each follows a fixed number of other already existing agents (or all other agents for the very first agents), where agents are selected with probabilities proportional to the number of current followers (plus one to give the newest nodes a non-zero probability to become selected). Second, a friends’ network is built. A friend-link is represented by reciprocal follower relations. The friends’ network is a random network, where every possible link is created with a probability selected such that the expected number of friends is a certain integer.[1] That way, we mimic a typical network with mixed properties of social and information networks showing, for example, an in-degree (followers) distribution more skewed and fat-tailed than the out-degree (following) distribution (Myers et al. 2014).

As variables, each agent has a protest threshold which stays constant after initialization and a vector of concern values on a certain number of topics. The topics are the same for all agents; the concern values can change over time. Protest thresholds are real numbers. Any number larger than one represents an agent who will never join a protest for personal reasons but can impact others’ decision to join. Any value of zero or less represents an agent who will always protest regardless of concern or protesting others. Concern values are integers, including zero but less or equal to a certain maximal concern. In a world with five topics, the concern vector [0 2 3 0 7] represents that the agent is most concerned about topic 5 and not at all concerned about topics 1 and 4. Two other dynamic variables of agents are the protest status, which is either “concern,” “social,” or “no,” and their topic of protest on which they post a message in social media. The protest topic is zero if an agent is not protesting, or the topic (represented by the numerical label of the topic) they chose for the protest. As this is chosen randomly with probabilities proportional to concerns, this is usually a topic on which they have a high concern value. The topic of protest represents a protest-related social media post which can be read by followers. A topic of concern with the value zero represents a posting not related to protest.

3.2 Agents’ Activities

In the full model, there are three protest mechanisms: the decision to protest because of concerns above threshold (concern protest), the increase of concern through information from social media (social media concern), and the decision to protest because of many others in the social network protest (social activation).

[1] Besides a random graph the NetLogo model also includes options to build the friends’ network based on a ring or on several cliques for robustness tests. These are not used in this work.

These mechanisms can be independently switched on and off. In the following, we consider that all are switched on.

On each tick (we can think of a day) agents do the following activities.

Step 1. All agents which are not already concerned enough to protest read their news feed and compute the fraction of the people they follow who protested. The news feed represents the list of social media messages from the last day an agent reads. In the model, it is a list of the topics of protest and non-protest-related messages of all agents the agent follows. From the news feed, the agent also extracts the fraction of protesting people.

Step 2. All agents decide if they join the protest.

Step 2.1. (Concern protest) An agent checks if a concern on at least one topic is greater than the individual protest threshold times the maximally possible concern value (a global parameter set to ten in the following). If this is the case, the agent sets the protest status to "concern."[2] We refer to this condition as "concern above the threshold." An agent with protest status "concern" then selects the topic of concern from all the topics that are above the threshold randomly with probabilities proportional to concern values.

Step 2.2. (Social media concern) Agents without concerns above the threshold will read their news feeds and select one topic of concern from this list at random. This can well be zero, representing a message which is not protest-related. In this case, nothing more happens. If it is a protest topic, the agent will increase the concern value on that topic by one. Note that, agents with a concern above the threshold will not increase any concerns anymore, because we assume that an agent only needs one concern above the threshold to join, and we are only modeling the buildup of one particular protest.

Step 2.3. (Social activation) Agents without concerns above the threshold check if the fraction of people followed who protest is greater than the threshold. If this is the case, the agent is socially activated and sets the protest status to "social" otherwise to "no." If the agent protests, one of the topics is selected for the protest at random with probabilities proportional to the concern values. This selection happens even though the concerns themselves are all not above the threshold. The rationale is that for joining a protest, even when only socially activated, one needs a topic of concern.

3.3 Initial Conditions and Stopping Rules

The initialization of a simulation run (setup procedure) is done as follows. First, a fixed number of agents is created. Then, directed links are created using the preferential attachment generator and, as described above, further reciprocal friends'

[2]The protest threshold is multiplied with the maximal concern to match the concern values (from, e.g., $\{0, 1, \ldots, 10\}$) with protest thresholds (from $[0,1]$).

links are created in a random network. Network generation is steered by the parameters *following* and *friends*, which describe the desired average number of directed and reciprocal links an agent should have. Agents' static protest thresholds are random numbers from a normal distribution with mean *threshold level* and standard deviation *threshold-dispersion*. Agents' dynamic concern vectors are *topic-num* integers between zero and *max-concern*. The concern value on each topic is initialized as a binomial random number with probability *initial-concern-level*. This implies that the expected concern on each topic for each agent is *initial-concern-level* times *max-concern*. The three mechanisms of *concern protest* (CP), *social-media-concern* (SMC), and *social activation* (SA) described above can all be independently switched "on" and "off." All "on" specifies the full model.

It turns out that only the five combinations of CP, SA, CP-SA, CP-SMC, and CP-SMC-SA are sensible configurations to distinguish. Just SMC will never spark anyone to protest, and SMC-SA would fully coincide with SA with respect to the protest status of agents. A logical analysis of all model variants shows that an agent can only experience three types of transitions of the protest status: "no" → "concern", "no" → "social", and "social" → "concern". Therefore, the total number of protesters (genuinely concerned or socially activated) can only increase or stay constant. As already mentioned, the decline of protests was deliberately not the aim of the modeling.

Only when social media concern is switched on, the concerns of agents can increase. Thus, it is easy to see that in the CP regime the total number of protesters is reached after one time-step, and in the SA and CP-SA regime, the total number of protesters is reached when the number of protesters stays constant for one time-step. The chosen protest topics may change but the distribution for the probabilistic selection stays constant.

When social media concern is switched on, every agent who is at some point following a protesting agent will successively increase the concern on at least one topic in the long run. Consequently, the agent will turn into a concerned protester unless the agent has a protest threshold above one, which rules out any protest. Thus, in most configurations with social media concern, all agents with thresholds below one end up with protest status "concern." Furthermore, the concerns of agents remain stable once they are concerned protesters. Therefore, also the distribution for the random selection of topics of concern in the whole society stabilizes once all protesters turn to be concerned protesters. We use these insights to define the stopping rules for simulation runs.

4 Simulation Experiment

In our model exploration, we used always the same network generation parameters. We assume that each agent follows five others (directed links in a preferential attachment network) and has five friends (undirected links in a random network). Furthermore, the maximum possible concern is fixed at ten. First, we work with distinct values of the threshold level, initial concern, and threshold-dispersion to represent the cases of Iran and Germany. Afterward, we explore the whole space of the three parameters to gain general insights on the model mechanics that help understand other protests as well as possible future developments in our two example cases. When interpreting the simulation outcome, one should bear in mind that the total population in the model does not necessarily represent everyone in society but is conceptually limited to those active people linked to the protest on social media as well as generally sympathetic about the protest and any of its topics. Moreover, the time-frame is different for different protests based on how dynamical they are.

4.1 The Iran Case in the Model

The empirical observation of the Iran case (see Sect. 2.1) can be translated to nine topics and a low initial-concern-level (0.1), which should mirror the fact that protests broke out suddenly and was not connected to one rising specific concern. The medium threshold level of 0.5 represents the fact that people generally had a sense of urgency and willingness to express their views but at the same time, they would not campaign on the streets lightheartedly. Since the Iran protest evolved dynamically, one should understand a time-step in the model as a few hours in reality, while the population consists of all citizens who consider street protests an appropriate and efficient way of expressing their political opinion, regardless of their political stripe.

Figure 5 depicts a simulation run, exploiting such parameter values. It compares snapshots of the model world to the overall development of the number of protesters and prevalence of topics in the protest. In the model world, non-protesting agents are black, while protesting agents have the color of their protest topic shaded by their concern value on that topic. Agents with protest status "concern" are filled dots, while the protest status "social" is indicated as white-filled circles. Agents are arranged according to the structure in their preference attachment (follower) network, and an agent's size indicates its centrality in that network.

Figure 5 shows that initially, only a few people protest, but numbers steadily increase quickly. The social dimension of the protest is most important after it has gained considerable concern-driven support (starting at step 27); at this point, some people would not yet have joined the protest out of concern but they do join because of social activation. This is crucial here because running the setting without social activation witnesses the protest dying out. However, social activation does not mean that people are not concerned at all and only join because they want to meet their friends on the street. Instead, the presence of people they know may raise one's faith in the protest's success or even a sense of safety when protesting, as Klein and Marx (2018) suggest. Once the protest has consolidated in numbers of protesters, the socially motivated ones also become genuinely concerned (starting from step 36). There are constant minor fluctuations between topics showing that many people are concerned about more than one topic and that slogans in the protest often depend on

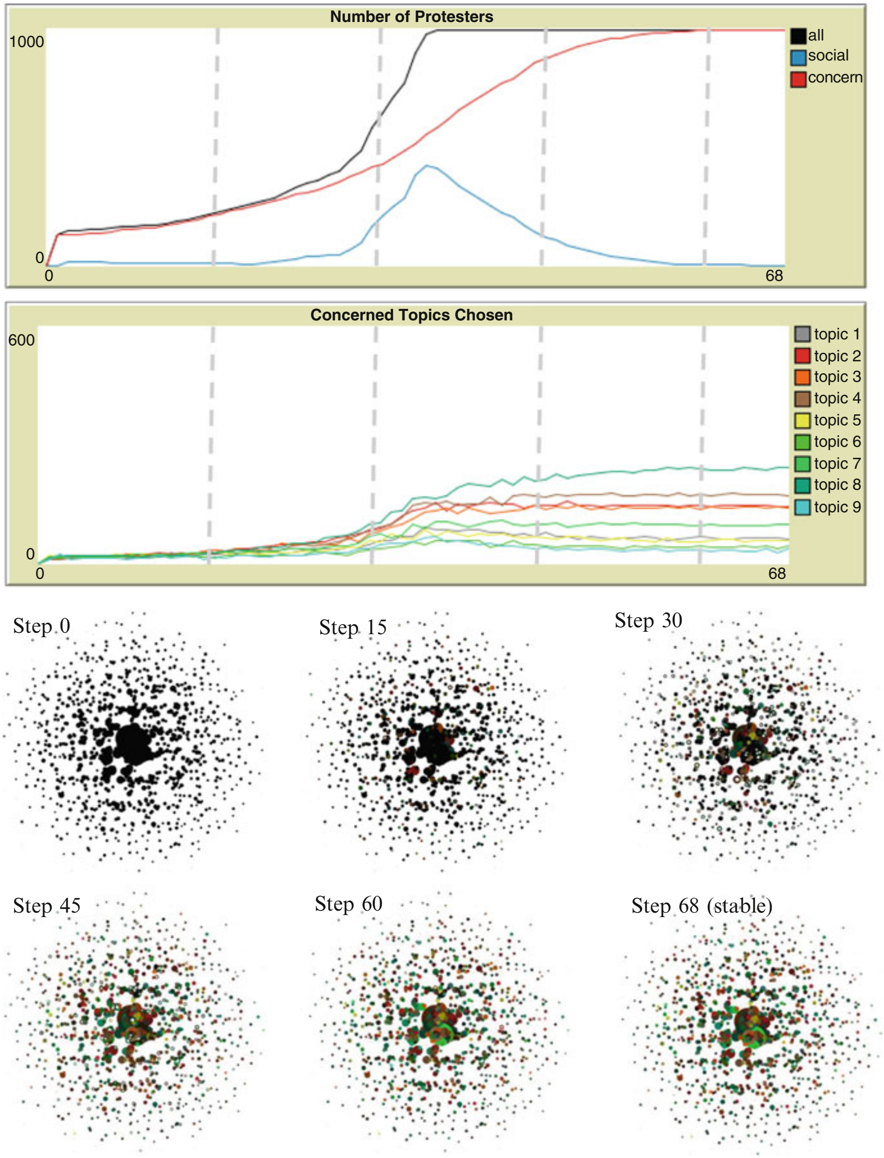

Fig. 5 Simulation run of the Iran case (parameter setting cf. Table 1)

up-to-the-minute news. This amounts to a different focus of protesters in different clusters within the network (comparable to different cities in Iran—not visible in the figure) and at different times.

4.2 The Germany Case in the Model

Representing PEGIDA in the model works with five topics and the same initial-concern-level (0.1) as in the Iran case above but with a higher threshold level of 0.7. This higher threshold represents the fact that issues of the PEGIDA movement are more confined to a single topic area and also less severe for people's everyday lives: In order to lobby a topic in the street protest, an actor has to perceive issues with respect to that topic as particularly severe. One time-step in the model can be identified with one day of the PEGIDA protest, which evolved more slowly than the Iran case. The population also does not represent the whole political landscape in Germany but includes only those possible protesters who sympathize with right-wing ideas or are deeply disappointed with the political and social establishment.

In Fig. 6, one can see one possible situation of how a protest given these input parameters can unfold. The movement takes about 50 steps of only a few people protesting, which corresponds to smaller actions taken by PEGIDA organizers and core supporters prior to focusing on PEGIDA itself. However, after that initial phase, people join quickly and they mostly do that because of genuine concern, which they build up in the meantime, not because of social activation. That again is in line with the empirical findings showing that despite organizers' appeal to moderate views, protesters expressed genuine right-wing sentiment (Vorländer et al. 2018, p. 64–66). Initially, a variety of topics is present within the protest and one of them temporarily becomes the most important one (in reality it was "anti-refugee"). However, later (at step 70) a second topic (in reality it was "critique of the political establishment") emerges and most protesters now (at step 99) regard this as their primary concern. That protesters become part of the same filter bubble (online and offline) also contributes to the focus on a single protest topic. Nevertheless, the first topic still maintains considerable support and is simply outnumbered by new protesters supporting the new one. While social activation has a smaller influence than in the Iran case simulation on the number of protesters, it is the main facilitator for the second topic overtaking the first topic. Additional simulations with the same realization of random events but without social activation show that the overtaking phenomenon does not occur in the case when social activation is turned off. In reality, PEGIDA organizers frequently encouraged protesters to actively reach out to their friends (Rucht et al. 2015, p. 17–18) and while these friends may not have shared a strong anti-refugee sentiment, they held a generally critical opinion of the government and joined for this reason (Rucht et al. 2015, p. 48–51).

4.3 Comparison Between the Iran and Germany Model Simulations

The parameter values for the simulations for the two cases are summarized in Table 1. The similarity of parameter values for the Iran and Germany cases

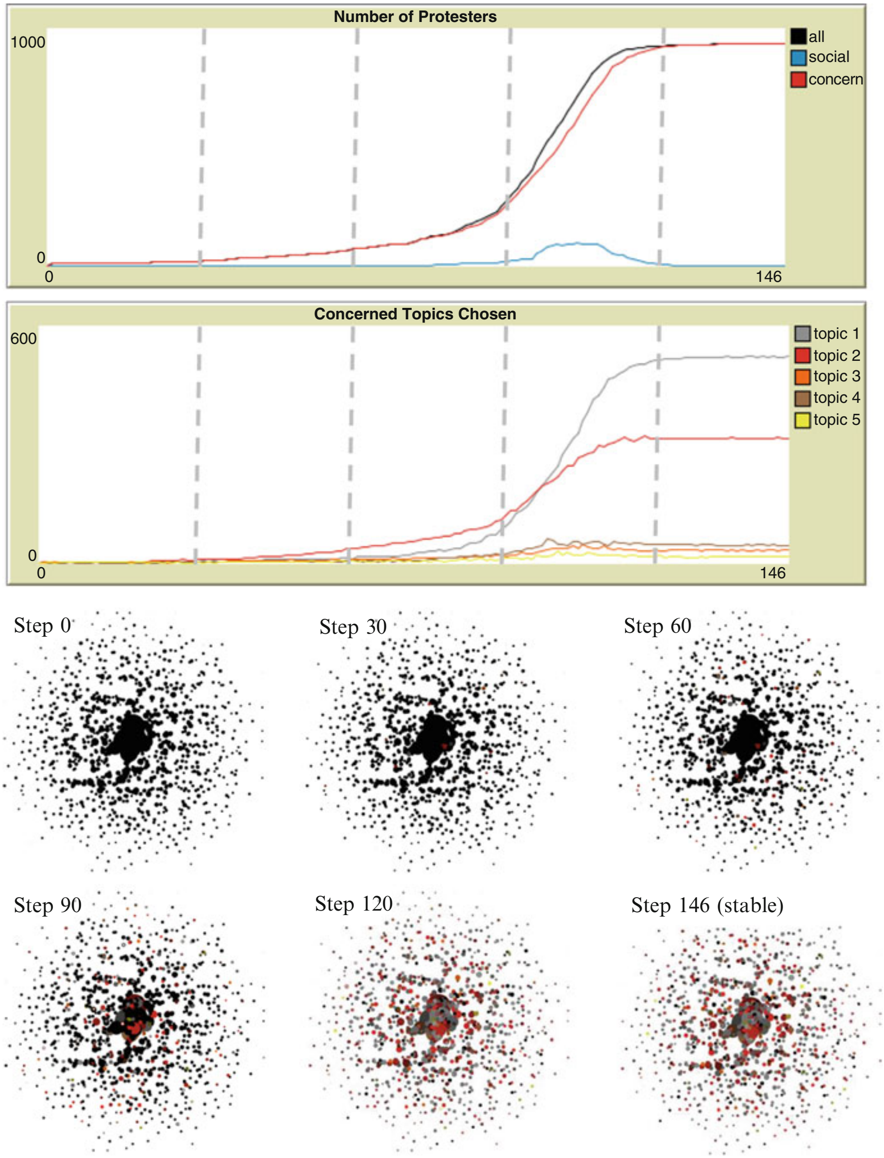

Fig. 6 Simulation run of the Germany case (parameter setting cf. Table 1)

indicates that they are structurally related. The cases differ in the perceived overall importance of the protest cause which translates to a lower threshold level in the model of the Iran case. They also differ in the number of potential protest topics (fewer in Germany). Furthermore, while the specific features of the empirical cases (multiplicity of topics for Iran; single important topic and the crucial role of social activation for Germany) are common for the corresponding parameter values, the effects are not guaranteed to occur under a given setting. That is the case because case-specific features like the layout in the random friendship network or the individual properties of central hubs in the preferential attachment network play an important role in the simulation outcome, too. Such aspects are specific features of a society (Vaisey and Lizardo 2010); the present model suggests that these case-dependent societal aspects can explain why seemingly similar protests experience different fates in empirical cases.

4.4 Parameter Study

In the following, we analyze how the final number of protesters and the distribution of protest topics depend on the three protest mechanisms as well as the threshold level and the initial-concern-level in the society. To that end, we made several simulation runs using NetLogo's BehaviorSpace (cf. Lorenz et al. 2019), setting all other parameters to the Iran case from Table 1. For an *initial-concern-level* of 0.1, we vary the threshold level from 0 to 0.8 in steps of 0.05. Furthermore, we also vary the *initial-concern-level* in steps of 0.05 from 0 to 0.5, for a threshold level of 0.5. We either run the simulation until a natural stopping criterion is reached (cf. Sect. 3.3) or stop it after 1000 time-steps. This ensured that we have reached a final configuration where the number of protesters and the concerns do not change anymore. What remains are stochastic changes in the protest topics selected, because agents may have several topics above the threshold. We computed fifty simulation runs for each configuration using no prespecified random seeds. Based on how often each topic is selected for protest, one can compute an *effective number of topics* $1/\sum p_i{}^2$ where the summation is over all topics and p_i is the number of agents protesting for topic i divided by the total number of protesting agents. This number is analog to the effective number of parties of Laakso and Taagepera (1979).

Table 1 Parameter values for the simulation runs with respect to the two cases

Parameter	Iran case	Germany case
Population	1000	1000
Following	5	5
Friends	5	5
Num-topics	*9*	*5*
Max-concern	10	10
Initial-concern-level	0.1	0.1
Threshold level	*0.5*	*0.7*
Threshold-dispersion	0.2	0.2
RandomSeed	16	17

The randomSeed specifies the sequence of random events used in the NetLogo model (Lorenz et al. 2019)

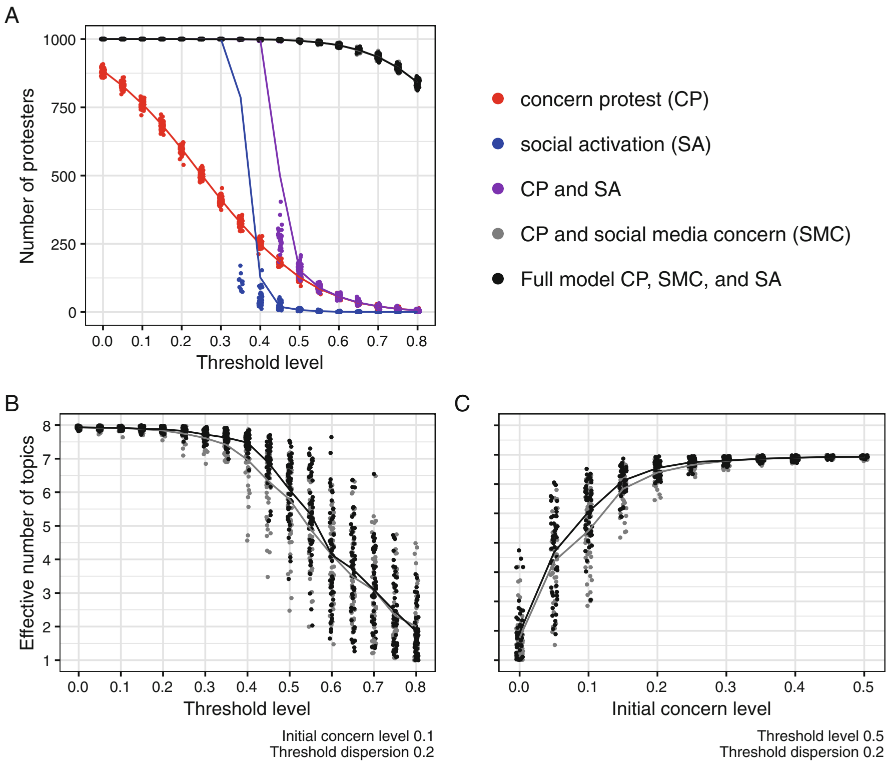

Fig. 7 Results for the parameter study. The threshold level is the mean of the individual thresholds. Note, that the gray dots for "CP and social media concern (SMC)" configuration in Panel A are mostly covered by black dots

Figure 7 shows the results. Dots show data points for individual simulation runs. Lines show the mean value over all simulation runs for this parameter setting.

Panel A shows the number of final protesters with respect to the threshold level. With only concern protest, the number of protesters smoothly declines with a rising threshold level. This is simply explained by initial conditions. With social activation, we have a threshold regime: At a critical threshold level of about 0.35, regimes change from a full protest to almost no protesters. This is similar to Granovetter (1978) and Watts (2002). We have a mixed model with a network as Watts and heterogeneous thresholds as Granovetter. This critical threshold is shifted slightly upwards when concern protest and social activation are combined. When social media concern is added, protest builds up, sometimes quite slowly, until usually all individuals with thresholds below one protest. This is independent of the mechanism of social activation being on or off. For relatively high threshold levels, there is a sizable amount of such individuals who never protest.

Panel B shows the effective number of topics for the same setup. This is only of interest when social media concern is involved. In other cases, without social media, no particular structure of topics evolves. This implies an effective number of topics around eight. An effective number of nine would only occur with perfect equality of all topics. Random fluctuation brings the number to about eight. The same happens with social media when the threshold level is relatively low but changes with higher threshold levels. With threshold levels around 0.5, a hierarchy of topics evolves with an effective number of topics around 5. With even higher threshold levels, this reduces too much lower numbers of effective topics around 2. This essentially means that one topic dominates while others only play a minor or no role.

Panel C finally shows how the effective number of topics changes with increasing initial concerns for a fixed threshold level of 0.5. Panels B and C together show that a larger distance between threshold level and initial concern implies a lower number of effective topics. Only in these cases, social media has time to build a hierarchy of topics before an overall protest emerges. The combination of concern protest and social media with social activation implies a slightly higher number of effective topics. This happens due to the fact that socially activated actors bring new topics to the protest.

5 Discussion

The basic model version introduced in this paper can reproduce different empirically observed fates of protests and describe mechanisms that possibly cause these fates. We were able to show which individual protesters' properties were necessary to get the patterns empirically observed in the Iran and Germany case studies. Combining empirical studies of processes and understanding their possible causes in the model thereby is a key to understand how the relation of individual decisions and exchange online leads to street protests. The die-out of protest, however, was not part of this study.

The parameters explicitly modified in our model only provide necessary conditions for a certain protest fate. Specific features of the society in which the protest takes place are important for its fate too. In the model, these features are the network layouts and especially the positions of agents with certain concern levels on certain topics within the networks. Moreover, this model version is deliberately kept simple and hence cannot capture other aspects of social media interactions and street protests in reality. In an extended model, the protest could be given a more active role in the sense of introducing interaction among protesters in the streets leading to additional concern change or additional messages sent from the protest or individual protesters to the social network. The decision of whether or not to join a protest may need revision to capture real actors' decisions more closely. Finally, one may consider including external influences that, at a pre-defined simulation step or when certain conditions are met, lead to an exceptional emotional dampening for some or all agents regarding a specific topic or across all topics. For example, government reactions, such as suppression or policy change, are not included yet.

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Part III
Computational Research on Violent Conflict

Do Non-State Armed Groups Influence Each Other in Attack Timing and Frequency? *Generating, Analyzing, and Comparing Empirical Data and Simulation*

Simone Cremaschi, Baris Kirdemir, Juan Masullo, Adam R. Pah, Nicolas Payette, and Rithvik Yarlagadda

Abstract Non-State Armed Groups (NSAGs) operate in complex environments, commonly existing as one of the many organizations engaged in one-sided violent attacks against the state and/or the civilian population. When trying to explain the execution and timing of these attacks, most theories look at NSAGs' internal organizational features or how these groups interact with the state or civilian population. In this study, we take a different approach: we use a self-exciting temporal model to ask if the behavior of one NSAG affects the behavior of other groups operating in the same country and if the actions of groups with actual ties (i.e., groups with some recognized relationship) have a larger effect than those with environmental ties (i.e., groups simply operating in the same country). We focus on

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three cases where multiple NSAGs operated at the same time: Afghanistan, Iraq, and Colombia, from 2001 to 2005. We find mixed results for the notion that the actions of one NSAG influence the actions of others operating in the same conflict. In Iraq and Afghanistan, we find evidence that NSAG actions do influence the timing of attacks by other NSAGs; however, there is no discernible link between NSAG actions and the timing of attacks in Colombia. Nevertheless, we do consistently find that there is no significant difference between the effect that actual or environmental ties could have in these three cases.

Keywords Armed groups · Multi-party conflict · Attack timing · Hawkes process · Agent-based model (ABM)

1 Introduction

The escalation of violent attacks from NSAGs, in frequency and number of casualties, is a central threat to international security today. In 2017, while we saw a decrease in the overall number of inter-state armed conflicts, the number of armed actors engaged in one-sided violence increased noticeably (Pettersson and Eck, 2018). Understanding the dynamics of violent attack execution better is essential for both scholarly research and policy-making. Efforts to effectively counter these threats would benefit from a more detailed understanding of the dynamics of their execution.

NSAGs do not operate in isolation. Despite widespread assumptions made by theories of violence (e.g., in civil war research), armed conflict is rarely dyadic (Jentzsch, 2014). The portrayal of conflict both as combat between an incumbent state and a rebel organization, and of armed groups operating and making decisions in isolation, obscures the fact that multiple armed organizations commonly operate in the same conflict settings. To cite just one dramatic example, during the peak of the Syrian civil war, it was believed that as many as 1000 non-state armed groups were commanding about 100,000 fighters (BBC, 2013).

Given the prevalence of conflict settings where multiple NSAGs operate, cooperating and creating alliances (Christia, 2012; Horowitz and Potter, 2014; Gade et al., 2019) and/or competing against each other (Phillips, 2015; Gade et al., 2019), there are good reasons to believe that the behavior of a given group is not (or at least not entirely) independent from the behavior of other groups operating in the same environment. This interdependence might involve, for example, decisions of whether and/or when to commit a violent attack (either as a first mover or in response to others' attacks), as well as decisions to declare a ceasefire and/or sit down in the negotiation table with the government. Nevertheless, as Phillips (2014, p. 336) notes, research often ignores the possibility that armed groups can affect each other in nontrivial ways. We contend that exploring these potential interdependencies in the behavior of Non-State Armed Group (NSAG) in multi-party conflicts is a proper avenue of research to understand various conflict dynamics. Moreover, recognizing and identifying this interdependence might have important implications for both security and peace policy. This is exemplified by the conflict trajectories in Eastern Congo where the enthusiasm that followed the military defeat of the M23 rebel group in 2015 was doomed by the fact that 69 other NSAGs were also operating in the region (Stearns and Vogel, 2015). Similarly, violence has persisted in Colombia after sealing a historic peace deal with the FARC—the most extensive and powerful rebel group in the country's long-standing civil war—as other NSAGs have been fighting to fill in the power voids left by the rebels (Idler and Masullo, 2019).

Does the behavior of one NSAG affect the behavior of other armed groups operating in the same environment? Furthermore, is behavior only affected by the more formal relationships that have captured the attention of the literature, or can it also be affected by the mere fact of operating in the same environment or fighting in the same conflict? In this paper we provide a preliminary exploration of these questions, focusing exclusively on the execution of one-sided violent attacks. To understand violent dynamics, instead of looking within armed organizations (see, e.g. Weinstein, 2007) or at the interactions of armed groups with civilian populations (see, e.g. Kalyvas, 2006) or with the government (see, e.g. Hultman, 2007), we focus on the relational environment in which NSAGs operate and examine how they might influence each other's actions—something that has received relatively less attention in the conflict literature.

Our core contention is that the behavior of a given group is *not* independent of the behavior of other groups operating in the same environment. Specifically, we explore whether there is evidence suggesting that the *timing* of an attack by a given NSAG is affected by the attacks executed by others. If there is some sort of interdependence between attacks, in this preliminary exploration we should at least observe that once an armed organization commits an attack, the probability that another attack will take place increases. Moreover, if what is taking place is in some way related to this form of interdependence, we expect the impact of this additive effect to decay over time.

We are not the first to explore how interorganizational relationships are related to armed group behavior. For example, Asal and Rethemeyer (2008) and Phillips (2014) have looked at how the number of alliances affect group behavior, while others have emphasized on whom the group is connected to, noting that what matters is the quality of the partners and the location of the tie within the overall network (Horowitz and Potter, 2014). In this paper, we consider all the possible connections between all the groups that are present in a given environment (what in social network language would be a "fully connected network" or a "complete graph") and differentiate between *actual ties* (groups with a relationship as defined by the Big, Allied, and Dangerous dataset[1]) and *environmental ties* (groups *simply* operating in the same country). This allows us to explore not only whether there are some

[1] See Sect. 2 for details on the dataset.

interdependent dynamics in the timing of violent attacks, but also whether different types of ties have different effects.

Despite undeniable advances in our knowledge of how NSAGs operate, the study of interdependence between multiple groups operating in the same environment and its consequences on an armed group's violent behavior still requires more sophisticated empirical analysis and better theorization. By combining different methods to generate, analyze, and compare simulation and empirical data, this paper aims to make an empirical contribution to this task. Supportive evidence for interdependent behavior in the timing of violence attacks would constitute a necessary first step to begin exploring these dynamics more deeply, disaggregating data further (e.g., spatially, by the type of attack, armed group, and/or conflict type) and exploring—theoretically and empirically—potential mechanisms.

This paper is structured as follows. In the next section, we present the empirical data that we used and the three cases that we chose to begin exploring whether NSAGs influence each other in attack timing and frequency. In Sect. 3 we introduce the methods detailing the fundamentals of both the analytical estimation from the empirical data and the generative model and simulation. Section 4 presents the main results and, to conclude, Sect. 5 briefly discusses the results, identifying some limitations of this study and delineating a road ahead.

2 Data and Case Settings

The empirical data for our study comes from the Global Terrorism Database (GTD). With information on over 180,000 domestic and international attacks between 1970 and 2017, including kidnappings, assassinations, and bombings, this is the most comprehensive open-source database on terrorist attacks. While including more events than any other available dataset, it rests on clear inclusion/exclusion criteria. It excludes criminal incidents devoid of political or ideological motivations, incidents arising from clashes between opposing armed groups, and incidents perpetrated by the state. In this sense, it allows us to focus specifically on the outcome we are interested in: one-sided violent attacks by NSAGs.[2]

In addition, we use data on ties between armed organizations. These data come from Phillips (2015),[3] which is an extension of the Big, Allied, and Dangerous (BAAD) dataset (Asal and Rethemeyer, 2015). These ties are manually curated based on the Terrorism Knowledge Database, media reports, and legal documents and represent a variety of known incidents of activity between two groups, such as training another group's members, providing safe harbor, or collaborating on attacks

[2]For a detailed description of the data, including the history behind its collection, digitization, and consolidation process, see LaFree and Dugan (2007). For recent updates and to access the codebook and download the data, visit https://www.start.umd.edu/gtd/using-gtd/.

[3]We are grateful to Phillips for sharing these data with us.

together.[4] In this work, we treat the ties between organizations in an undirected manner (i.e., groups in the relationships are coded regardless of who is addressing whom).

For this exploratory analysis, we use three conflicts as our case studies—Afghanistan, Colombia, and Iraq—and restrict the period to 2001–2005. Multiple armed groups were active in each of these conflicts for the period under study, all executed a considerable number of violent attacks, and at least one *actual* tie was observed between two of them. In addition, these three conflicts provide us with variation in dimensions that can prove theoretically relevant: e.g., the macro-cleavage and the stage of the conflict, as well as the profile of the armed group. First, Colombia constitutes a clear example of an irregular, guerrilla type of war that started in the mid-1960s (four decades before our time frame) and pits left-wing rebel groups with Marxist-Leninist ideals against right-wing paramilitaries and the forces of the state. Then, Afghanistan, starting in 2001 (the first year of our time frame), shortly after the 9/11 attacks. Here a coalition of international forces and a new Afghan government faced a local insurgency and multiple armed groups, with fundamentalist, sectarian, and sometimes ethnicity-driven characteristics. Finally, the war in Iraq started in 2003 and ended the Baathist regime in Baghdad. Here, like in Afghanistan, US-led forces were faced with a large-scale insurgency and a number of terrorist organizations targeting the international military presence, civilian population, and aiming to disrupt the ongoing nation-building efforts.

For each of these countries, we carefully cleaned the data to make sure it included a meaningful and internally valid set of NSAGs and ties between them. Based on historical records, secondary sources and first-hand knowledge of each of these conflicts, we excluded organizations that we knew were not operating in the same environment and/or were mostly inactive during the time frame under analysis.[5] Additionally, we merged observations when the same organization was coded as two or three different ones given the use of various names in the sources used to build the original dataset.[6] This process considerably reduced the number of organizations we are working with and explains the difference in the number of observations (both organizations and attacks) relative to GTD and Phillips (2014).

Finally, to account for variation in NSAGs' capacity to execute violent attacks, and inform the parameters in our simulated data with empirical priors (see Sect. 3.2), we estimated the capacity to commit a violent attack for each armed group that made it into our final list. Given that the measurement of our outcome of interest directly involves the number of attacks by each organization, we did not use this information to estimate capacity. Therefore, we relied on two different variables to

[4]For a more detailed description of these data, please refer to the source papers (Phillips, 2014, 2015; Asal and Rethemeyer, 2008).

[5]For example, the IRA was originally included in the data for Colombia from 2001 to 2005.

[6]For example, we merged groups which emanated from name-changes during the conflict and were a continuation of a group and its activities. During the transition, names of these groups were used interchangeably by international news outlets.

Table 1 Descriptives

	Colombia	Iraq	Afghanistan
Armed groups	9	31	8
Actual ties	4	5	2
Environmental ties	32	460	26
Total ties	36	465	28
Attacks	428	181	428

proxy capacity, both from the GTD data: the number of attack types that each group has engaged in and the number of deaths caused by their attacks.[7]

Table 1 summarizes the basic data for the three cases under study after we construct a fully connected network for each country.

3 Methods

To better understand the potential impact of all NSAGs' actions within a country on the timing of the execution of attacks by specific NSAGs, we approached the problem with two distinct methodological strategies. The first consists of using empirical data to estimate the extent to which any NSAG's action is reactive to any and all other NSAGs' actions within the same environment. The second consists of constructing a generative model that implements a basic model of action to explore how much of an impact environmental ties could have and still produce an attack time series that is statistically indistinguishable from the actual historical record. These two tracks combined allow for an exploration of any evidence for latent influence of NSAG's actions on another's actions in the same setting.[8]

3.1 Analytical Estimation

From the empirical data, we analytically estimated possible latent influences from one NSAG's attacks on the timing to another NSAG with a Hawkes process (Hawkes, 1971). A Hawkes process is a self-exciting point process that takes the form of

[7]When combining these two variables, we did not use any weighting as we did not have any theoretical reason to believe that any of the two variables should matter more than the other as proxies of NSAG' capacity to commit an attack. We also considered a large set of variables that provide a good sense of capacity to commit an attack from the Non-State Actors in Armed Conflict Dataset (NSA) compiled by Cunningham et al. (2013). However, as we found that many of the relevant variables in this dataset were highly correlated for the organizations we were working with, we decided to use weights only from the GTD.

[8]All data and code is available at https://github.com/adamrpah/BIGSSS-Terror.

$$\lambda_g^*(t) = \mu_g + \sum_{j:t_{g,j}<t} \alpha_g e^{-\beta_g (t-t_{g,j})} \tag{1}$$

where μ_g is the base rate of "attacking" for a given NSAG; g, α_g is the additive effect that a prior attack has; β_g is how quickly the additive effect from a prior attack decays; $t_{g,j}$ is how long ago the attack was carried out; and λ_g^* is the resultant rate for NSAG g at time t. Without the additive term that accounts for the influence of prior attacks on the future attack probability, a Hawkes process reduces to a Poisson process. Empirically $\lambda_g^*(t)$ is the attack rate for an individual group during the interval of interest.

The mathematical extension of a Hawkes process from a single NSAG reacting to its own past actions (univariate Hawkes) to a NSAG incorporating signals from non-self actors (multivariate Hawkes) is relatively straightforward. We model the multivariate Hawkes process as

$$\lambda_{g_i}^*(t) = \mu_{g_i} + \sum_{g_k \in G} \sum_{j:t_{g_k,j}<t} \alpha_{g_k} e^{-\beta_{g_i} (t-t_{g_k,j})} \tag{2}$$

where the impact of each attack t_{g_k} is integrated with an individual α_{g_k} for each NSAG g_k when we calculate the rate λ^* for a single NSAG g_i at time t. We use the `pyhawkes` package to estimate the parameters for this function, which uses Markov Chain Monte Carlo (MCMC) for the estimation (Linderman and Adams, 2014).

A difficulty with a MCMC approach is with identifying when the parameters have converged. To ensure that our parameter estimation is robust we use the scale reduction factor (Rubin and Gelman, 1992) and continue sampling on all chains until the variation is less than 0.01 on all μ parameters.

The only empirical information that the multivariate Hawkes process requires is the attack time series for each NSAG within a setting. Since all parameters are estimated, there is no reason for the α parameter that controls how much a NSAG reacts to the recent attacks of another NSAG to be larger (or smaller) for actual than environmental ties.

3.2 Generative Model and Simulation

Our generative model implements a modified form of the multivariate Hawkes process (Equation 2) in order to theoretically explore the possible amount of influence of environmental information (attacks by NSAGs with no actual ties) on a NSAG's future attacks in comparison to the influence of the attacks of known NSAGs with which they have an actual tie. Our modified version of the multivariate Hawkes process for the generative model is

$$\lambda_{g_i}^* \leftarrow \mu_{g_i} + \sum_{g_k \in G} \sum_{j:t_{g_k,j}<t} w_{g_k} \alpha e^{-\beta (t-t_{g_k,j})}, \tag{3}$$

Table 2 Parameters of the ABM

Parameter	Range	Description
α	$\{0.05, 0.1, 0.15, \ldots, 0.9\}$	Increase of intensity of impact from an attack
β	$\{4, 4.5, 5, \ldots, 8\}$	Decay rate of attack intensity
ω	$\{0, 0.1, 0.2, \ldots, 1\}$	Weight of environmental ties

where α (the additive impact of past attacks), β (the decay of influence over time), and ω (the edge weight between two NSAGs) are general parameters of the simulation (see Table 2 for simulation parameter ranges).

With Eq. 3, we simulate the multivariate Hawkes process for the set G of NSAGs in the country of interest. Unlike the analytical estimation, here we specify that all NSAGs in G are connected in a fully connected network with weight w_{g_k} for each tie that NSAG g_i has. We set $w_{g_k} = 1$ when $g_i = g_k$ or there is an actual tie between NSAG g_i and g_k from prior work (Phillips, 2015). If there is no actual tie between NSAG g_i and g_k then we set $w_{g_k} = \omega$. Since the magnitude of w_{g_k} is fixed at 1 for actual ties, this allows us to systematically simulate the potential impact of environmental ties on the timing of a NSAG's attacks.

To restrict the potential parameter space, we estimate μ_g for each NSAG from the empirical data. Since μ_g is the inherent rate of attacking for a NSAG it could be, roughly, estimated from the attack time series directly. However, we do not use a NSAG's empirical attack rate so that no direct information about the attacking rate is incorporated into the simulation. Instead, we regress the number of attack types that a group engages in against the log total of casualties that the NSAG inflicts as a proxy for a NSAG's capability to successfully launch attacks. To operationalize this relationship as a rate (μ_g) for each group, we scale the calculated value for each NSAG by the average number of attacks per casualty across all NSAGs and reduce that rate by 20% to account for possible latent influences.[9]

We simulate each run of our model for steps $t \in [0 \,..\, 1865]$, where each step is a day to match the time span in the empirical setting. At each time step t, we enumerate all attacks for each NSAG up to time t and recalculate λ_g^* for each group. For each group, we make a random draw from a Poisson distribution with λ_g^* as the mean and record that random value as the number of attacks at time step t.

To assess whether a set of simulation parameters generate realistic time series for a setting, we perform 500 independent runs for each unique set of simulation parameter values. To statistically test if the simulated data differ from the empirical

[9]The rate reduction of 20% is an arbitrary constant to ensure that $\mu_g \neq \lambda_g^*$. The exact percentage chosen is not important since we are performing a parameter sweep with the simulation. If there is an effect from the attacks of others on the timing of a NSAG's attacks, then a rate reduction that is too small would simply increase the magnitude of the α parameter (and vice versa if the rate reduction was too large). If there is not a systematic effect from the attacks of others, then the landscape of feasible parameter combinations should be rugged (i.e., isolated parameter combinations that duplicate the empirical time series) which would be an artifact of the rate reduction chosen.

data, we test if the inter-event time distribution for each NSAG differs from the empirical inter-event time distribution with the Kolmogorov-Smirnov test. Across all runs for a simulation parameter set with a typical threshold of $p = 0.05$, we would expect 5% of the inter-attack time series to differ by chance alone. Thus, if more than 5% of the inter-event series are significantly different, we conclude that the given simulation parameter set fails to reproduce the empirical data.

4 Results

4.1 Analytical Estimation of Basal and Additive Rates

After estimating Eq. (2) from the empirical data, we can establish the baseline differences between individual NSAGs. Primarily, we aim to further clarify how μ, which represents an individual NSAG's basal rate and capacity to attack, compares to the additive component α, the reactionary attacks in response to attacks from others.

We find a dramatic difference between the magnitude and proportionality of α and μ in our case studies (Fig. 1). In Colombia, the additive effect of another group's attack on a group's own attacking rate is small in comparison to its basal attack rate. FARC stands as a stark outlier in comparison to all groups, with its μ more than two orders of magnitude larger than the additive α effect. This would suggest that the timing of FARC attacks has almost no relationship or influence from prior attacks by any group within the region.

In contrast, in both Iraq and Afghanistan the additive effect α is larger than μ for a majority of NSAGs—with multiple groups having an α value that is two or nearly three magnitudes larger than μ. Under the assumptions of the Hawkes process, this means that the timing for the majority of attacks that NSAGs commit are more in response to the actions of other NSAGs in the region than an independently timed attack.

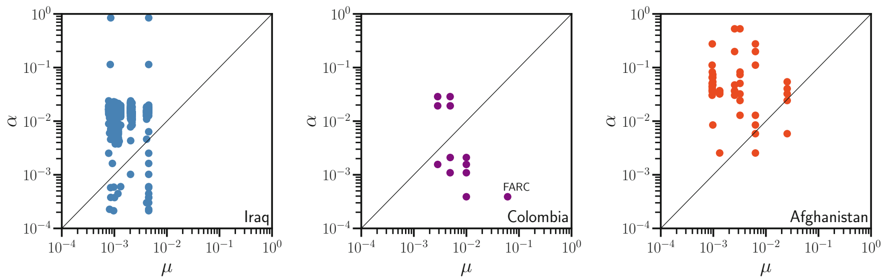

Fig. 1 Comparison of the estimated μ for each NSAG against the α coefficient it has for every other NSAG in the same country. The plotted line is for $\mu = \alpha$

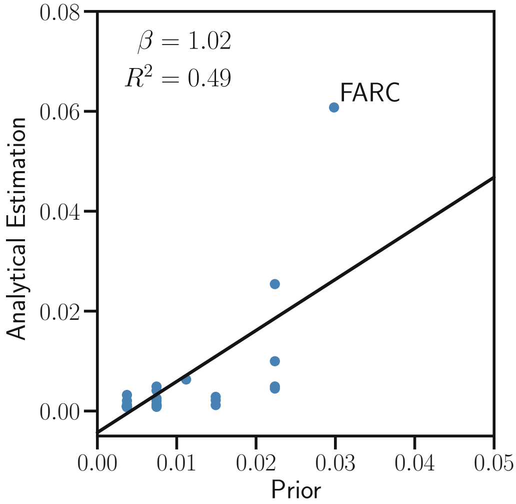

Fig. 2 Comparison of the calculated prior μ to the analytically estimated μ for NSAGs in all three countries

However, if we examine the difference between actual and environmental ties amongst these three settings, we find no significant differences ($p = 0.24$, t-test). If we exclude all ties that originate from Colombia, this result still holds ($p = 0.41$, t-test). This suggests that despite the differences found in the settings in terms of the impact of the additive effect α, whether a tie is actual or environmental is not a major contributing factor.

As a check for the initialization parameters for the generative model, we also compare the analytically estimated μ values with the estimated μ priors for the generative model and find a good agreement overall (Fig. 2, $R^2 = 0.49$). The notable outlier is again FARC, which has an analytically estimated value that is approximately 150% of its calculated prior. This suggests that the estimation strategy is a good, general approximation of a NSAG's μ without the usage of empirical rate-related information.

4.2 Comparison of Inferred Networks to the Network of Actual Ties

To better understand the implications of the inferred α parameters on the entire network of relationships within a country, we explicitly construct an inferred network where α serves as tie strength and compare it to the network of actual ties amongst NSAGs (Fig. 3).[10]

[10]We set a threshold on the strength of α for creating a connection at $\alpha \geq 10^{-3}$.

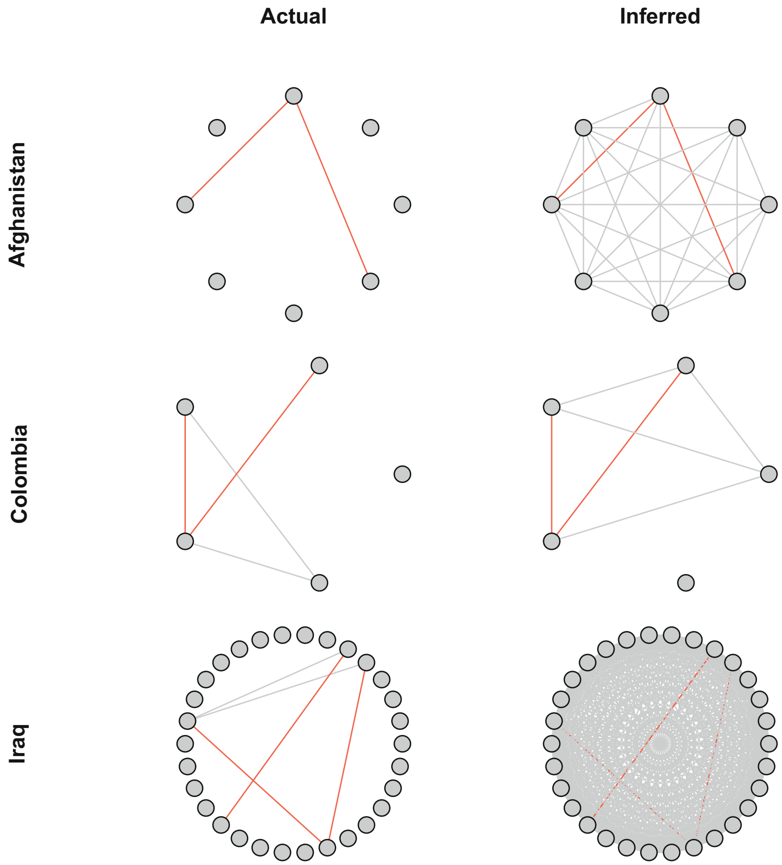

Fig. 3 Actual and inferred networks. Circles indicate NSAGs and lines indicate ties. Lines colored in red indicate the ties present in both the actual and inferred networks

As we would expect from the previous results, the inferred networks for Afghanistan and Iraq are densely connected. Interestingly, we infer no relationship for almost half of the actual ties in Iraq and Colombia, while we capture both of the actual ties in Afghanistan. These results suggest that groups react to a number of other NSAGs within the same country that are not captured through formal known ties and that not all formal known ties are equivalent in nature.

To better quantify how different the inferred network is in each country, we compute the normalized degree and transitivity statistics (Table 3). The normalized degree accounts for the number of ties that a NSAG has given the number of possible ties in the network, which allows for a comparison between countries. We find that in Colombia the normalized degree grows 150% from the network of actual ties to the inferred network, while the growth in degree in Afghanistan and Iraq is over 1000%. This again highlights the difference in countries, with the inferred network

Table 3 Descriptive statistics for observed and estimated networks

	Average normalized degree		Transitivity	
	Actual	Inferred	Actual	Inferred
Afghanistan	0.07	0.93	0.00	0.93
Colombia	0.40	0.60	0.60	1.00
Iraq	0.01	0.98	0.50	0.98

of groups that react to one another barely differing from the known network in Colombia and these two networks drastically diverging in the emerging conflicts in Afghanistan and Iraq.

Transitivity measures the amount of triadic closures, that is, if A is connected to B and B is connected to C, then A is also connected C. In this context, it would imply that if group A reacts to actions taken by group B, then it would also react to actions taken by group C so long as group B also reacts to C. A larger transitivity value in this context would imply that the total volume of attacks in a country is more dynamic since an attack made by one group could start a chain of reactionary attacks from its connected neighbors (given a sufficiently large α). Surprisingly, despite the difference in transitivity for the actual ties networks, all three countries have similar levels of transitivity—meaning that for groups that we have inferred ties for, those ties are closed into triads. In terms of the change from the actual ties network to the inferred ties network, the increase is most notable in Afghanistan. In the observed network, only the Taliban is connected to Jaysh al-Muslimin and Al-Qaeda producing a transitivity of 0, while the inferred network transitivity is 0.93. In Colombia, the magnitude change in transitivity is not as dramatic as in Afghanistan, but it is notable that FARC is isolated from the inferred network which is a contrast to its known ties to the ELN (the second largest left-wing rebel group).

These statistics correspond to the stark visual discrepancies between the actual and inferred network structures. Despite the fact that the actual ties are records of known, shared activities (whether that be training recruits, planning attacks, etc.), we find that the actual network lacks the majority of ties, and the resulting structure, identified in the inferred network. Given our focus on the timing of attacks, this suggests that the "strategic" actual ties do not capture the range of actors and actions that a NSAG may take into account when choosing exactly when to execute an attack.

4.3 Generative Model Results and Correspondence to Analytical Findings

To better interpret our generative model, we plot our sweep through the three parameter ranges for each country, focusing on the parameter region where the model successfully replicates the empirical data (Fig. 4). Once again, Colombia stands out since no parameter combination was able to produce NSAGs time series

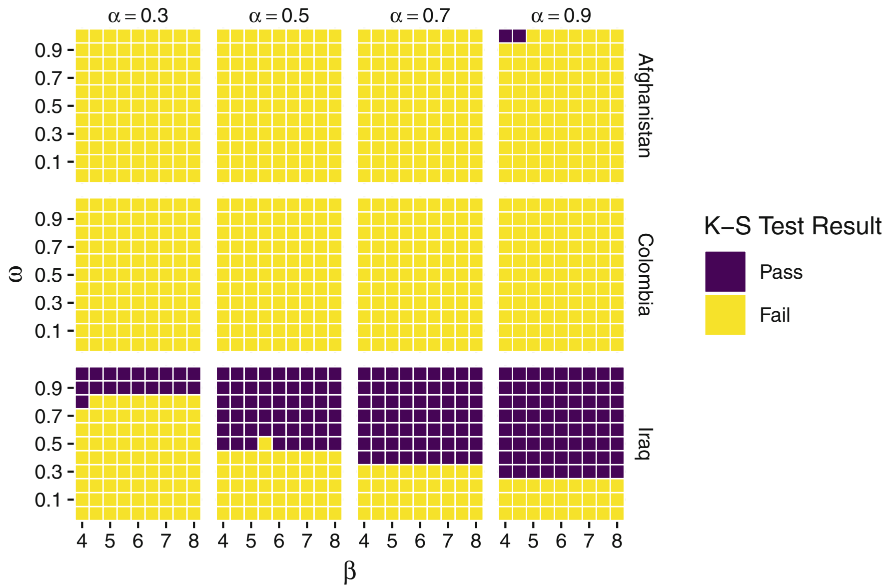

Fig. 4 Generative model results for defined parameter combinations (α, β, ω) in Afghanistan, Colombia, and Iraq. Each cell is the result of comparing the inter-event time series for 500 generative runs against the empirical data with the Kolmogorov-Smirnov (K-S) test. If less than 5% of the runs differ from the empirical data, the cell is marked as 'Pass,' otherwise, it is marked as 'Fail.' Each grid in a column is a different α value (the additive effect from previous attacks), while β (the rate of decay of previous attack effects) on the horizontal axis of each graph. The vertical axis for each graph is ω, which is the relative strength of environmental to actual ties

similar to the empirical data. This is in general agreement with the analytical findings, since FARC has a μ value that is nearly three orders of magnitude larger than any additive effect from another NSAG's actions and conducted more than 50% of the attacks during the study period. Even the ELN, the second most active rebel/insurgent group and the one that conducted nearly 20% of the attacks during the period of analysis, has an estimated μ value that is roughly one order of magnitude larger than the additive effect from any other NSAG's actions.

The results for Afghanistan and Iraq present a different picture, as both cases yielded model parameter combinations that successfully reproduce the empirical data. Since there are only two successful combinations in Afghanistan, the interpretation is straightforward: only when groups react, nearly, as much to the actions of other groups as they do to the actions of their allied groups is the empirical data reproduced. Iraq is similar to Afghanistan in so much as there must be a high additive amount to the rate from each attack in order for the simulation to statistically reproduce the empirical data. There is an expected dependence on the strength of environmental ties—as this link becomes stronger the range of permissible α values grows, to the point that nearly half of the parameter combinations are successful when $\alpha = 0.5$. The primary difference is that in this case not even a weak dependence on how quickly the impact of prior attacks decays seems to play a role. This could be due to the large number of NSAGs operating in this environment and the limited number of attacks that each group committed during the period of analysis (31 NSAGs operated during this period, committing an average of 5.84 attacks). However, the results for both Afghanistan and Iraq confirm the analytical estimates, with both countries having average α values that are larger than the average μ, suggesting that reactionary attacks play a role in the timing of attacks in these two countries.

5 Conclusion

Our preliminary answer to the guiding question of "does the behavior of one NSAG affect the behavior of other armed groups operating in the same environment?" is nuanced. We find clear support in both Iraq and Afghanistan that the actions of other groups affect the timing of attacks; however, no support is found for this notion in Colombia. This mixed result with only three case studies prevents us from drawing any general conclusions on the notion that previous attacks from other groups affect the future timing, and thus frequency, of NSAG attacks within a region.

Quantitatively, it is necessary to expand the analysis to a larger sample with more, if not all, countries with active NSAGs. There are recorded attacks in over 200 countries (without disambiguation for geographical renaming) in the GTD, which would provide enough statistical power to test this hypothesis exhaustively. If the effect were general across countries, then greater insight could be obtained from the estimated magnitude of the impact that prior actions have on the future timing of attacks.

Qualitatively, our initial analysis would suggest that the general stage of the conflict that NSAGs are engaged in is a contributing factor as to whether or not prior attacks influence future attack timings. During the study period, both Afghanistan and Iraq were severely destabilized with the large-scale introduction of foreign forces and joint political instability. In both settings, this resulted in constantly changing circumstances as insurgents, global jihadi movements, foreign powers, and counterinsurgent forces. In contrast, the conflict in Colombia is one that has had the same dominant actors for years before the study period. This is demonstrated by the fact that between 1980 and 2002, hijacking, hostage taking, and kidnapping totaled 76.3% of attacks conducted by FARC, the most dominant actor in Colombia (Eccarius-Kelly, 2012). On the contrary, hostage taking constitutes only 7.2% of attacks conducted by the Taliban, the most dominant actor in Afghanistan. These differences in attack type underscore the qualitative difference in the nature of the conflicts we study here.

Importantly, we find no difference in the relative importance of actual ties to environmental ties. If we examine the results from the analytical model, the mean tie strength does not differ between actual and environmental ties. From the generative model, we find that only as the strength of the additive effect increases can we successfully replicate the empirical data. In Afghanistan, successful reproductions only occur when environmental ties are weighted nearly as much as actual ties. In Iraq, the space of permissible ω values increases as the additive effect α increases—since an increase in the magnitude of the effect compensates for the weakening tie strength. While alliances and rivalries, the basis of our actual ties, have been shown to have long-term effects on group outcomes (Phillips, 2015; Asal and Rethemeyer, 2008), there does not appear to be any relationship to a short-term effect, specifically one on the timing of attacks. While the actions of cooperation, one group training another group or coordinating attacks, does relate to the timing of individual attacks, it does not appear to rise to a systematic level of how attacks are coordinated and executed.

Without expanding the scale of the study, it is not possible to discern if this study is simply further proof of the empirical limits on predicting the timing of NSAGs' attacks (as demonstrated by the failure of the approach in Colombia) or if it is only in specific contexts that prior actions can inform future predictions. We can, at least, state that while formal relationships and the position that a group occupies within that formal structure has a long-term impact, these relationships do not have a systematic impact on daily activities and their timing.

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On the Beaten Path: Violence Against Civilians and Simulated Conflict Along Road Networks

Andrea Salvi, Mark Williamson, and Jessica Draper

Abstract Why do some conflict zones exhibit more violence against civilians than others? In answering this question, the literature has emphasized ethnic fractionalization, territorial control and strategic incentives, while overlooking the consequences of armed conflict itself. This oversight is partly due to the methodological hurdles of finding an appropriate counterfactual for observed battle events. In this chapter, we aim to test empirically the effect of instances of armed clashes between rebels and the government in civil wars on violence against civilians. Battles between belligerents may create conditions that lead to surges in civilian killings as combatants seek to consolidate civilian control or inflict punishment against populations residing near areas of contestation. Since there is no relevant counterfactual for these battles, we utilize road networks to help build a synthetic risk-set of plausible locations for conflict. Road networks are crucial for the logistical operations of a civil war and are thus the main conduit for conflict diffusion. As such, the majority of battles should take place in the proximity of road networks; by simulating events in the same geographic area, we are able to better approximate locations where battles hypothetically could have occurred but did not. We test this simulation approach using a case study of the Democratic Republic of the Congo (1998–2000) and model the causal effect of battles using a spatially disaggregated framework. This work contributes both substantively and methodologically to the literature on micro-foundations of civil war and reactive violence in two main ways: (1) It offers a tentative framework for crafting synthetic counterfactuals with event data. (2) It proposes an empirical test for explaining the variation of violence against civilians as a result of battle events.

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Keywords Violence against civilians · Road networks · Civil war · GIS

1 Introduction

The consequences of violence against civilians (VAC) within the context of civil wars continue to be a debated topic with, at times, contradictory findings. Some argue that the use of violence against civilians is counterproductive to incumbents' goals (Kalyvas 2006; Kocher et al. 2011; Lyall 2017) while others find the opposite (Lyall 2009; Stoll 1993). Departing from this debate, a growing literature has sought to better understand VAC as a dependent rather than independent variable. Consequently, numerous studies have examined factors that may explain VAC, including ethnic fractionalization, territorial control, strategic incentives, and various geographic variables (Fjelde and Hultman 2014; Schwartz and Straus 2018; Raleigh 2012; Wood 2010; Schutte 2015, 2017). This chapter aims to contribute to this body of literature by using a geographic event-based approach to further investigate the occurrence of violence against civilians.

Building on theories of VAC being used as a tactic by warring parties, we proceed to ask the following question: what effect do instances of armed conflict actually have on violence against civilians? We suspect that geographical factors, specifically road networks, are crucial for the logistical operations of a civil war, thus making areas around these road networks more prone to conflict in general. Are actual, observed battles between incumbents and insurgents causing the variation in violence against civilians or does indiscriminate violence simply occur in these more conflict-prone areas, even where battles do not necessarily take place? By addressing this question using georeferenced micro-level data, we hope to increase our understanding about the relationship between conflict waged between combatants and violence experienced by civilians.

This chapter begins with a brief overview of the literature that is both theoretically and methodologically relevant to the present study. Next, we offer our new approach for achieving causal identification in spatial models by using simulated conflict events around road networks. Finally, we present results to demonstrate the feasibility of our approach and then conclude with recommendations for future researchers similarly seeking to use simulation techniques.

2 Conflict and Violence Against Civilians

The existing literature has not reached a consensus on whether armed conflict has any direct effect on the prevalence of violence against civilians. Sullivan (2012) found evidence that insurgent violence may increase the probability of massacres carried out by the state in order to inflict punishment and remove insurgent threats. Fjelde and Hultman (2014) showed that warring parties are more likely to inflict violence against civilians in geographical areas inhabited by the enemy's "ethnic constituency" for a similar reason: to undermine and weaken the enemy and their potential ethnic support base (p. 1233). This follows the findings of Valentino et al. (2004) demonstrating that, particularly in guerrilla wars, combatants target civilians in order to increase their own control and reduce collaboration between local populations and their adversary. The role of rebel strength and capacity has also been investigated with results suggesting that weaker insurgents are more likely to engage in violence against civilians as a means to raise the enemy's cost of fighting (Hultman 2007) or to compel support from the population (Wood 2010). On the whole, existing theories regarding the relationship between conflict and violence against civilians are largely driven by military strategy, whether that be reducing the enemy's base of support, coercing one's own support, or inflicting fighting costs to achieve concessions.

While this literature offers compelling theoretical contributions with regard to the relationship between conflict and VAC, only recently have empirical studies thoughtfully examined the occurrence of armed conflict as a main independent variable. The introduction of georeferenced event-level data has been central in this emerging research agenda. Most notably, Raleigh (2012) utilized a time-location-actor-action model using event data from the Armed Conflict Location & Event Data Project (ACLED) and found a lack of co-occurrence of armed conflict events and instances of violence against civilians in time and space. Instead, a pattern of VAC events emerged around areas occupied by several active groups, suggesting that violence against civilians is not, in fact, "a strategy to gain civilian support or punish civilians" but rather a strategy more often used as a means for competition among violent actors (Raleigh 2012, p. 478). That these results run counter to the prevailing discourse highlights the importance of using event-level data to study the effect of armed conflict occurrence on VAC.

Previous micro-level empirical studies investigating the relationship between conflict and civilian victimization have taken varied approaches to causal identification. In some works, the amount of spatial-temporal correlation between conflict events and VAC is taken as evidence for or against a theory of strategic civilian targeting in war (e.g., Raleigh 2012). However, since the location and timing of conflict occurrence is likely to be driven by strategic behavior related to the civilian population, there is a need to consider whether it is (a) armed clashes that are themselves causing civilian targeting or (b) the underlying conditions that provoke armed clashes that are simultaneously driving levels of violence against civilians. Other studies have addressed similar considerations in the case of indiscriminate violence more broadly (Lyall 2009, 2017; Schutte 2015). In seeking to determine the effect of indiscriminate counterinsurgent artillery fire on subsequent insurgent attacks, Lyall (2009) used a matching technique to compare shelled villages ("treatment") and non-shelled villages ("control") with difference-in-difference estimation. Additionally, Schutte (2015) employed a matched wake analysis (Schutte and Donnay 2014) on spatio-temporal event data to test the "treatment" of indiscriminate violence on civilian collaboration with the incumbent. These studies used improved techniques for causal identification. However, as we describe in the following section, this literature could benefit from designs based around the creation of simulated battle events as a relevant counterfactual to actual occurrence of violence.

3 A New Strategy for Causal Identification: Creating Synthetic Events on the "Beaten Path"

As the foregoing discussion has made clear, existing empirical studies have produced both uncertain and contradictory findings on the effect of armed conflict on civilian victimization. In part, this is a byproduct of the challenges of achieving causal identification using observational data on conflict events. The co-occurrence of armed conflict and violence against civilians in spatial-temporal windows (or lack thereof) cannot provide definitive evidence of a truly causal relationship.

For a more accurate picture, it is necessary to identify and compare a set of counterfactual events against actual observed cases of conflict beyond simple matching or shallow definitions of "plausible areas". These "control" observations would offer an idea of what levels of civilian victimization we should expect in areas that were likely to be sites of conflict, but ultimately did not see any actual battles. In effect, this will allow us to isolate the true effect of the conflict events themselves, while partitioning out the unobservable or unmeasurable variables that are inherently correlated with both the locations of battle events and the likelihood of violence against civilians—such as a location's strategic military importance or its pre- and intra-war social networks. A plethora of studies have applied the logic of simulating conflict events as a way to create control observations with promising results (Lyall 2009; Kocher et al. 2011).

However, the way in which we ought to determine where these hypothetical control events should be located remains up for debate. To study the effect of counterinsurgent violence on rebel responses, Lyall (2009) considers all Chechen villages as plausible control points; similarly, Kocher et al. (2011) examine all hamlets (i.e., small settlements) within the Republic of Vietnam during the Vietnam War. Yet, these approaches make a crucial, unstated assumption about where we should expect to see conflict. In each strategy, it is assumed that battle events can occur in any part of the country, with the likelihood of a given location weighted by relevant spatial covariates.

This assumption has been strained by recent research into the spatial diffusion of conflict. In particular, scholars have identified the significance of road networks in determining where conflict occurs (Zhukov 2012). The availability and quality of roads are among the most crucial logistical constraints for state militaries and insurgents looking to sustain and grow their operations. Moreover, the strategic importance of roads and the settlements that lie along them makes these areas

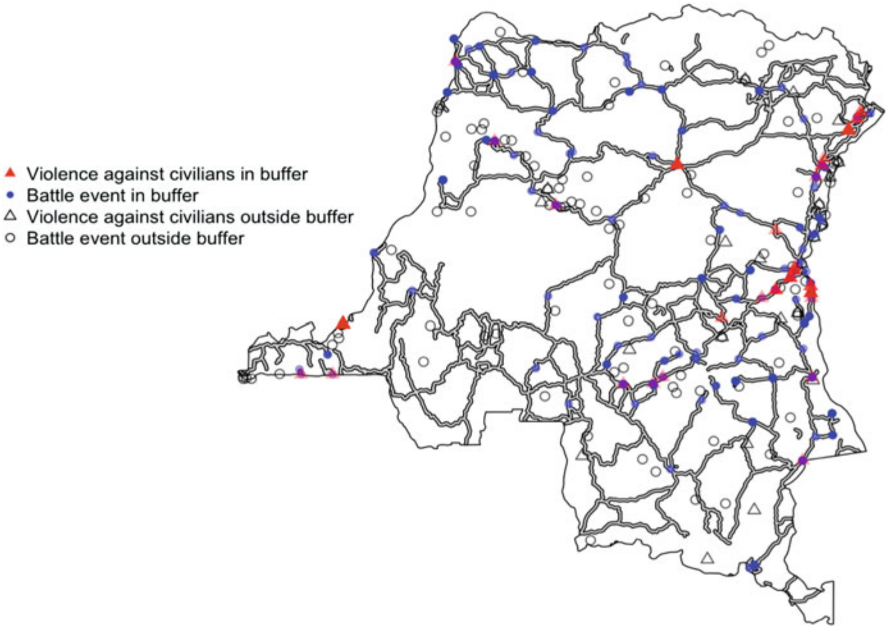

Fig. 1 Observed VAC and battle events in DRC

a hotspot for battles between warring parties seeking to gain an upper hand. Accordingly, the vast majority of armed battles take place in close proximity to roads. Indeed, in the case study of the Democratic Republic of the Congo we describe below, over 62% of all battle events occur within 5 km of a major roadway, despite the actual area of this space capturing less than 14% of the country's total land area.[1] As combatants move further away from the core road network, the costs of sustaining combat operations in more remote areas make it increasingly unlikely that armed actors will have the motivation or capacity to engage in violence (see Fig. 1).

We argue that future efforts to simulate counterfactual conflict events should acknowledge the strong clustering pattern of battles around road networks. There are at least two substantive reasons for that. Firstly, insurgencies tend to display high degrees of mobility. Insurgents—and opposing forces alike—need to quickly move between strategic objectives in order to maximize their impact. For this reason, strategic infrastructure such as roads and bridges are crucial tactical elements. Secondly, major roads normally connect not only major settlements but also strategic infrastructure (ports, airports, energy plants). While data on settlements might offer a viable alternative given that civil wars tend to occur in more populated

[1]Similarly, 70% of events involving violence against civilians occur within this same area around roadways.

areas, they leave out a plethora of other points of interest that can be determinant for warring parties and where civilians tend to “cluster” even when leaving settlements (e.g., after displacement or mass flee). Towards this end, we propose a simple technique for creating relevant “control” battles where none are directly available in the data. Our goal here is to create a set of points that represent locations where armed clashes are likely to occur, but have not actually taken place. Subsequent occurrences of violence against civilians near these hypothetical battle locations can then be compared to the outcomes around locations of actual battles to determine the true causal effect of the battles themselves.

Our proposal involves, first, creating a buffer area around all major roadways in the area under study. Figure 2 suggests that the particular width of the buffer is unlikely to cause any significant difference in our results for widths set at less than 10 km from the roadways. Increasing the buffer width from 1 to 10 km results in a substantial increase in the amount of land area captured in the buffer area while producing only marginal improvements in the number of true battle events captured in that same area. For our analysis, we set the width of the buffer at 5 km on each side of the road (i.e., for a total width of 10 km at any given point).

The buffer is then stored as a vector polygon and overlaid on the overall country polygon using geoprocessing tools that are commonly available today.[2] Then, to create a set of simulated events, we rely on a simple point process model to randomly

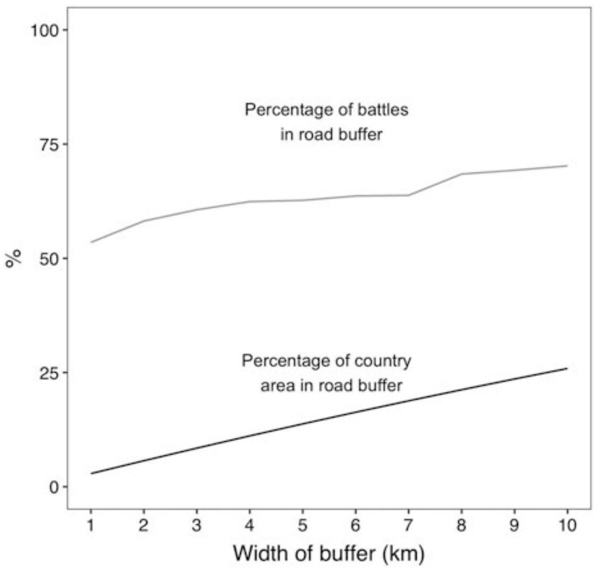

Fig. 2 Coverage sensitivity of road buffer width

[2]In this specific case, we made use of “gBuffer” from *rgeos* (Bivand et al. 2018) package for R due to its high customizability in creating polygons around point data. Other common tools include the “Buffer” function from ESRI ArcMap.

assign locations within this buffer polygon. This is done using a uniform Poisson process within the road buffer windows with intensity (i.e., points per unit area) equaling that of the observed events. This is, of course, an approximation as we assume that each location on the road network to be a candidate for a battle. While this is in line with our theoretical expectation, we recognize that other factors (e.g., population density) might make a certain area more prone to civilian victimization than another on the same road network. Nonetheless, this simplified approach better suits the aim of this paper and, as mentioned above, places emphasis on the importance of roads. Finally, we assign dates to these synthetic events by randomly sampling the dates of actual battles, in hopes of creating a similar temporal distribution of conflict occurrence.

Figure 3 presents an illustration of this technique. In the upper left panel, the locations of observed instances of violence against civilians and battles are plotted in the case study area. The upper right pane adds major roadways throughout the

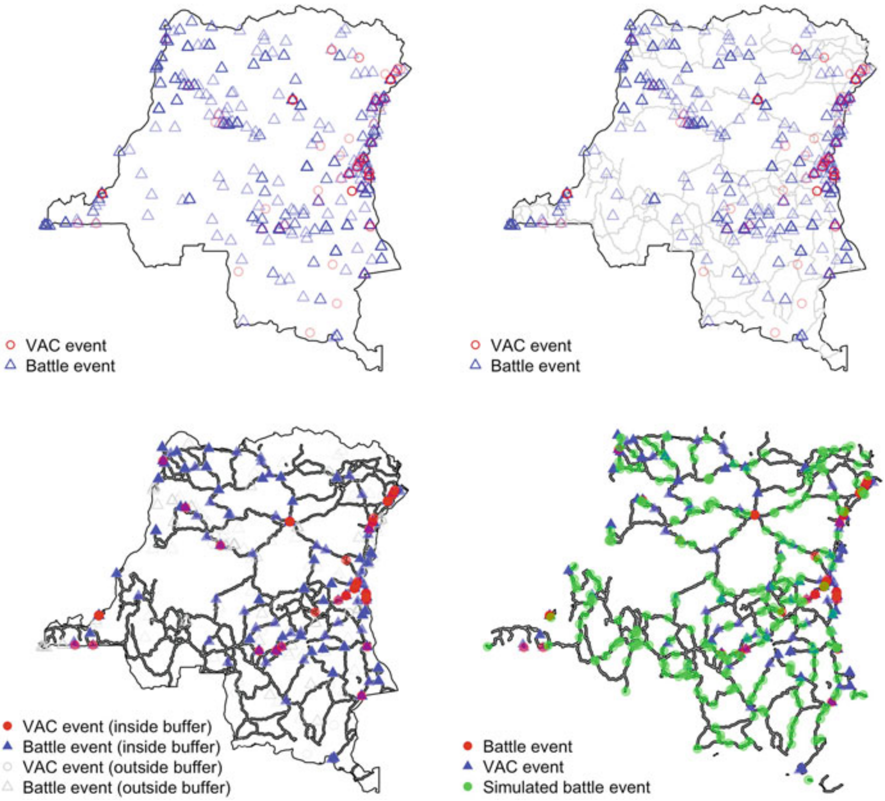

Fig. 3 Demonstration of buffer creation and conflict event simulation. The different shades of red and blue indicate the concentration of events in the same area. Darker colors correspond to areas where more events took place

country. The bottom left panel adds a 5 km buffer around those roadways and then excludes the observed battle and VAC events that occur outside this buffer area. This idea is formalized in the bottom right panel, where those remote events are dropped entirely and the relevant polygon becomes the road buffer area. Finally, in the same bottom right panel, a number of point locations are added within the buffer area to serve as simulated battles events for the modelling stage.

After creating the simulated events within the buffer area and dropping observed events outside this polygon, we proceed to model civilian victimization by taking counts of these two classes of events as our predictors. Here, the number of simulated events act as a control group while the observed events represent a treatment condition.

At this point, since our proposed approach does not fundamentally alter either the dependent variable or the nature of the point-location independent variables, there are numerous spatial models suitable for estimating the causal effect. We discuss our chosen modelling approach, matched wake analysis, in Sect. 5.

Ultimately, we argue that by simulating conflict events only in close proximity to roadways, we are able to offer a more plausible counterfactual when assessing the effects of actual battle events.

4 Data and Case Selection

To test the method described above, we carry out an in-depth analysis of conflict processes in the Democratic Republic of the Congo (DRC) from 1998 to 2000—a period capturing the earlier portion of the Second Congo War—using data from the Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al. 2010). ACLED includes spatially-tagged observations of both battle events and instances of violence against civilians. Each observation is coded using press reports from a range of local and national sources. Previous studies into the relationship between conflict and civilian victimization have made similar use of ACLED data (Raleigh 2012).

In the analysis below, we focus our attention on battle events as an independent variable explaining the occurrence of violence against civilians. In the ACLED data, battle events include any "violent interaction between two politically organized armed groups at a particular time and location" that may or may not result in a change of territorial control (ACLED 2017, p. 8). Here, we exclude what ACLED terms "remote violence," or conflict events where the combatants are not physically present at the location of the violence as a result of using remote technologies such as improvised explosive devices (IEDs) or missile attacks. We removed this category as identifying the planned target of remote violence is not immediate due to the presence of collateral victims (most often civilians). Furthermore, identifying the perpetrator is quite an undertaking and data on this is far from complete. Violence against civilians is defined as "a deliberate violent act perpetrated by an organized armed group against unarmed non-combatants" (ACLED 2017, p. 10). For both of these event types, we remain agnostic about the actors that are engaged in the battles or perpetrating the violence against civilians and include all cases of both rebel and state conflict.

The DRC offers a useful case study to demonstrate our approach for several reasons. First, violence against civilians in the DRC exhibits a strong clustering pattern around road networks. The DRC also has a large country area, which helps to illustrate how small areas around roads are crucial to conflict occurrence. Moreover, it is a case that has experienced persistent conflict over many years, with an ample number of observations of both battle events and violence against civilians. Figure 4 shows a simple comparison between battle events and VAC events in the full ACLED sample (1997–2018) across the whole African continent with the DRC, Sudan, and Somalia having the highest levels of both measures.[3] In the DRC, the magnitude of violence peaked during our temporal window between 1998 and 2000, the first two years of the Second Congo War. Finally, this case is especially informative given the relative mobility with which the conflict unfolded. In particular, the first phase of the conflict was highly "road-intensive." Belligerents sought to move quickly throughout the country to seize strategic locations, movement which frequently occurred via major roadways.

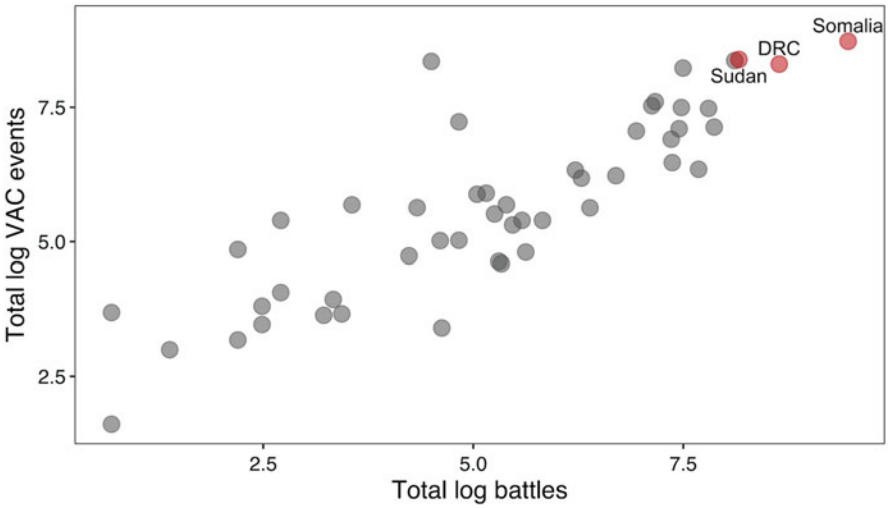

Fig. 4 Battle versus VAC events by country in ACLED Africa data, 1997–2018

[3]For an analysis based on ACLED data on South Sudan, see Kelling and Lin in the chapter "Analysis of Conflict Diffusion Over Continuous Space" of this volume; for an agent-based model simulating the conflict in Somalia, see Duffy et al. in the chapter "Rebel Group Protection Rackets: Simulating the Effects of Economic Support on Civil War Violence".

5 Modeling and Results

In order to test the feasibility of our approach and re-evaluate the causal effect of armed battle events, we rely on Matched Wake Analysis (Schutte and Donnay 2014). This modelling framework combines techniques for causal inference that allow us to evaluate the impact of our treatment on the dependent variable against a control group in a continuous temporal and spatial window. Matched Wake Analysis (MWA) relies on a combination of a Sliding Windows Design, Statistical Matching and Difference-in-Differences approach. This technique has been successfully applied in previous conflict-related empirical studies (e.g., Schutte 2017).

In the MWA framework, all events are first classified as either "treatment" or "control". In our case, these correspond to the observed and synthetic battles, respectively. These georeferenced data are then linked to any number of geospatial covariates through nearest neighbor mapping. A balanced sample is then generated by matching on both the covariates and on pre-treatment trends in the dependent variable using Coarsened Exact Matching (CEM). Finally, a difference-in-differences design is used to estimate the treatment effect (Schutte and Donnay 2014).

Figure 5 provides a graphical representation of this approach showing two units (depicted as cylinders), one with a treatment and one with a control event. The square in the left-side cylinder represents the occurrence of an observed battle event, while the triangle in the right-side cylinder represents a simulated battle. The stars depict single occurrences of VAC, our dependent variable, both as "prior activity" (before the observed or simulated battle, pictured in the lower end of each cylinder) and as "posterior activity" (after the battle, portrayed in the upper end of each cylinder). At the bottom are the relevant spatial covariates on which units are matched.

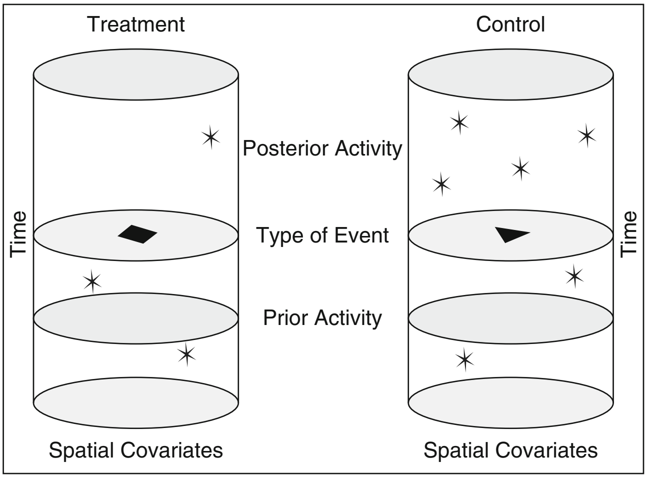

Fig. 5 Demonstration of matched wake analysis. Figure from Schutte and Donnay (2014), reprinted with permission from the authors

In our study, we estimate the following model:

$$n_{\text{post}} = \beta_0 + \beta_1 n_{\text{pre}} + \beta_2 \text{observed battles} + u$$

Here, n_{post} represents our dependent variable: a count of observed instances of post treatment VAC. β_2 represents the average treatment effect of observed battles, while β_1 is the coefficient associated to n_{pre}, which accounts for the effect of pre-treatment levels of violence against civilians. As discussed above, CEM matches samples on the pre-treatment trends in VAC and on other spatial covariates. These control variables have been selected in accordance with the relevant literature on civil conflict discussed above. We include data on population (2000) from Gridded Population of the World (GPW4 2018) and the number of ethnic groups in the area from GeoEPR (Wucherpfennig et al. 2011; Vogt et al. 2015). Furthermore, we compute the distance from the capital city and the elevation[4] associated to each point.

Figure 6 depicts the estimated values of β_2—the average treatment effect of observed battles—for each space and time window.[5] We set the spatial window as a range from 0 to 50 km and the time window as a range from 0 to 50 days. These intervals were chosen in order to capture the effect of battles in a fairly immediate time frame and within a "local" spatial domain. Larger distances or temporal periods would begin to introduce the possibility that variables that are either included in our model or impossible to measure will begin to bias our results. In the 50 day–50 km design, we are still able to test our model over a set of spatial-temporal windows that can help answer our main research questions and produce important policy implications.

As shown in Fig. 6, the treatment effect is positive across the whole window, suggesting that increases in instances of VAC occurred after observed battles took place, as compared to our synthetic battles between belligerents. While this is not surprising from a theoretical standpoint, the distribution of statistically significant effects reveals where we can be more confident about the effect of battle events.

In particular, Fig. 6 reveals a positive and significant effect that depends equally on time and distance from the battle event. The earliest period we see a significant effect on VAC is in areas relatively nearby the battle event. Crucially, however, the effect of battles increases as the distance from the battle location grows. At shorter distances from battles (from 0 to 22.5 km), VAC is likely to increase between roughly 22.5–37.5 days after a battle event. As the distance from the treatment increases (i.e., the interval between 22.5 and 42.5 km), we see an increase in the temporal range in which we would expect to see an increase in VAC (roughly 27.5–42.5 days). After 42.5 km, all time-intervals from 27.5 to 50 days are significant.

[4]Computed and subset from terrain data by USGS and NGA: GMTED2010 (Danielson and Gesch 2011).

[5]The precise values of each cell, along with their associated p-values can be found in Table 1 at the end of this document.

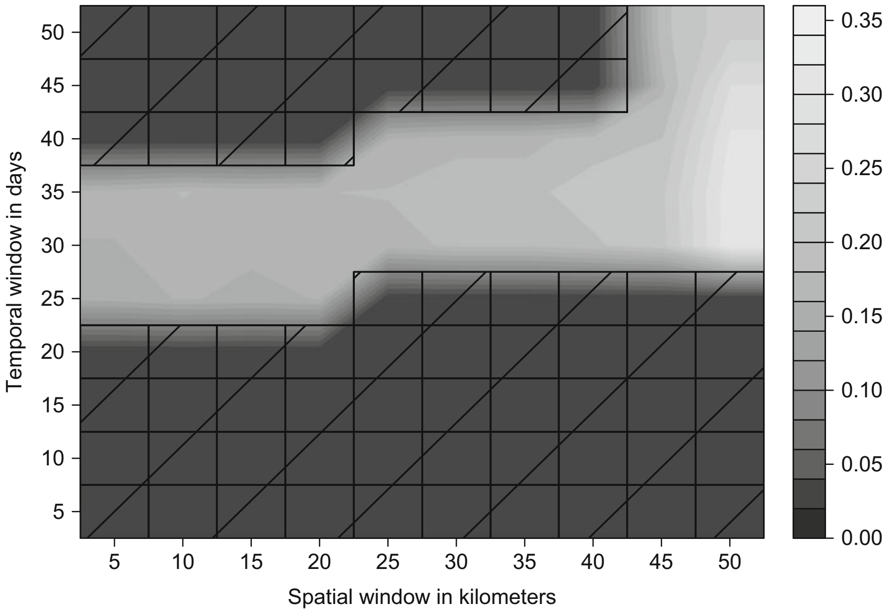

Fig. 6 Results of the MWA analysis of VAC in DRC (1998–2000). The contour plot represents the effect of observed battles on the occurrence of violence against civilians (with the scale on the right indicating the magnitude of the effect). The area not covered with crossed lines correspond to $p \leq 0.05$

This positive correlation between the timing and distance of the effect accords with an intuitive story of conflict diffusion. The results suggest that, after a battle event occurs, belligerents do not engage in VAC in the immediate aftermath. As the existing literature suggests, after taking control over a battle area combatants tend to invest resources in reinforcing their positions rather than seeking out civilians for immediate retribution. Conversely, the losing side will often either retreat entirely—thus not being able to engage in VAC—or adopt a 'wait and see' behavior to determine the stability of the new local power arrangement. Therefore, it is only after roughly 25 days that we see a surge in civilian victimization and only in an area fairly close to the battle location. The belligerents are most likely starting to secure the area with 'pseudo-policing' operations to tighten their clutch on the territory. Quite naturally, as the days pass, violence then spreads spatially as combatants seek to expand their base of control to surrounding populations. It is only at this point that we begin to detect a statistically significant effect in the areas more than 40 km from the battle location.

As for the magnitude of these effects, the average over all significant combinations is 0.21 (Table 1). That is, when comparing the treatment and control groups on average, for every battle event, we should expect to observe 0.21 additional instances of violence against civilians in the particular significant spatial-temporal areas identified above. While actual battles seem to yield more subsequent civilian victimization, the buffer space represents an area of high-risk, where most of the clashes between belligerents and VAC events take place. The moderate, yet positive, effect of the treatment as compared to the control group shows that the synthetic counterfactuals are "plausible" candidate locations for conflict, thus confirming our prior expectations.

Table 1 Combinations of temporal and spatial areas showing the associated cut-points in days and kilometers

Time (days)	Distance (km)	Effect size	P-value	Adjusted R-squared
25	5	0.189	≤0.05	0.0313
25	10	0.202	≤0.05	0.0352
25	15	0.195	≤0.05	0.0335
25	20	0.201	≤0.05	0.0337
30	5	0.199	≤0.05	0.0336
30	10	0.212	≤0.05	0.0379
30	15	0.204	≤0.05	0.0357
30	20	0.21	≤0.05	0.036
30	25	0.211	≤0.05	0.0363
30	30	0.224	≤0.05	0.0394
30	35	0.224	≤0.05	0.0394
30	40	0.237	≤0.05	0.0435
30	45	0.254	≤0.05	0.049
30	50	0.356	≤0.05	0.0583
35	5	0.207	≤0.05	0.035
35	10	0.221	≤0.05	0.0394
35	15	0.213	≤0.05	0.0374
35	20	0.219	≤0.05	0.0376
35	25	0.222	≤0.05	0.0382
35	30	0.235	≤0.05	0.0415
35	35	0.235	≤0.05	0.0415
35	40	0.249	≤0.05	0.0458
35	45	0.257	≤0.05	0.0488
35	50	0.356	≤0.05	0.0588
40	25	0.2	≤0.05	0.0436
40	30	0.211	≤0.05	0.0466
40	35	0.211	≤0.05	0.0466
40	40	0.232	≤0.05	0.0547
40	45	0.24	≤0.05	0.0586
40	50	0.344	≤0.05	0.0638
45	45	0.215	≤0.05	0.0779
45	50	0.321	≤0.05	0.0697
50	45	0.235	≤0.05	0.0835
50	50	0.274	≤0.05	0.1002

Each row records a single window along with the associated size of the effect, p-values, and R-squared

It is important to note that we also tested our buffer model against an "anywhere/anytime goes" model where simulated points were generated across the whole country and conflict timespan. This approach yielded very different results in terms of statistical significance as a result of less efficient artificial counterfactual events. In particular, this baseline model showed an overabundance of significant areas across the whole spatio-temporal window with a less clear pattern in both space and time. This suggests that a less restrictive approach to counterfactual simulation could yield an overidentification of significant results, rather than the more nuanced picture that emerges from our analysis.

6 Conclusion

This chapter has offered a preliminary step towards a new method for identifying the causal effect of armed conflict on civilian victimization. We have proposed the use of simulated conflict events as a method for creating relevant counterfactual events in cases where we can only observe actual instances of violent clashes between armed groups. By leveraging the strong clustering behavior of armed conflict around road networks, our strategy for simulating these "control" events acknowledges the underlying drivers of where true conflict activity is most likely to occur.

Using such an approach on a case study analysis of the Democratic Republic of the Congo, we found that armed battles tend to result in increased levels of violence against civilians across certain spatio-temporal windows. This increase can be observed in the immediate spatial proximity of the battle and reverberates across larger distances as well. Regarding the time component, belligerents seem to consistently engage in VAC after roughly 25 days from the occurrence of a battle event.

While our attention has focused on the consequences of battle events, the framework presented here should extend to a broader class of conflict-related independent variables that tend to diffuse and cluster along road networks. Protests, military base establishments, and remote violence, such as missile or bomb attacks, all exhibit this behavior. The analysis of the causal effects of these events could similarly benefit from a simulation-based approach to identifying relevant counterfactual observations.

There are, of course, limitations to our approach. First, our simulation strategy assumes that the coders of data on battles and VAC events are correctly assigning those events to their exact locations. When conflict events occur in remote areas, it may be the case that either media sources or dataset coders elect to record the location of those events as a nearby settlement rather than the true coordinates. Normally, such a decision would represent a small amount of measurement error, but, in our framework, it is crucial to modelling outcomes. Since most settlements lie along road networks, the assignment of observations to nearest settlements could inflate the amount of conflict occurring within our road buffer polygons, thus biasing estimates of the true causal effect in these areas. Future approaches may encompass a "hybrid buffer" weighted on the basis on existing settlement.

It is unclear whether this type of error occurs in commonly used event datasets. As Eck (2012) has shown, these datasets, when they are created from media sources, tend to be biased towards greater coverage of urban areas in general. The ACLED coding guidelines are fairly robust against coders misassigning observations and the dataset does include a variable indicating the precision of the coordinates (ACLED 2017, p. 25–26). In future applications, this variable could be used to filter out low-certainty observations. However, these checks at the coder-level would not prevent misreporting by the media sources further upstream (i.e., non-local, national, and international media). Thus, our approach is not immune from the literature's ongoing concerns about the precision of spatial conflict data.

Second, our proposed framework makes a strong assumption about where simulated events should be located. A simple implementation of our approach, as shown above, ensures that no simulated events will fall outside the roadway buffer area. A more nuanced approach, which would remain methodologically consistent with our general framework, could involve a probabilistic model to simulate events. Using this strategy, the likelihood that a simulated event is tagged at a given point would decline exponentially as the distance of that point from a major roadway increases. Here, the general principle of roadways as crucial to explaining the spatial distribution of conflict is maintained, while allowing for greater variance in the simulated locations.

Third, by excluding battle events far from roadways (or, downweighting their likelihood of occurring in probabilistic simulations), we run the risk of overlooking a possible interaction effect between armed battle events and their distance from population centers. That is, there is a possibility that battles may provoke greater civilian victimization when those battles occur in remote areas. Combatants may assume that attacks on civilians will be less publicized or less likely to result in retribution if they are done in the hinterland. To our knowledge, this scenario remains untested in the existing literature, but given its relevance to the present research design, we recommend future studies to investigate the possibility of such an interaction effect. Under our current approach, excluding these remote observations precludes the possibility of detecting this type of causal relationship.

With these limitations in mind, we argue that simulating counterfactual conflict events along road networks offers a defensible and advantageous strategy for causal identification in observational events data. Simply put, we want future researchers to understand that they can and should try to find better counterfactuals for battle events. Doing so will require creative thinking about where conflict is likely to occur. Extending this approach to other cases would also help to establish whether these effects are representative of civil conflict dynamics in general or are instead case-specific.

In this chapter, we have proposed one solution of using road buffers as a simplifying condition to simulate counterfactual conflict events; infinitely more options also exist that could fit within our framework. We hope conflict scholars will continue to improve upon our approach and take up with greater zeal the potential offered by synthetic event simulation in conflict studies.

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Analysis of Conflict Diffusion Over Continuous Space

Claire Kelling and YiJyun Lin

Abstract This study illustrates an innovative application of methods in spatial statistics to study the diffusion of conflict events. We investigate how spatial processes of conflict events vary with different characteristics of the events and actors involved in the events. Actor-level attributes have often been ignored in existing empirical studies, which could lead to insufficient modeling of conflict processes and patterns. Due to recent technological and systems advances, conflict events can now be analyzed using data measured at the event (point) level, rather than relying on aggregated units. Our research contributions are twofold. First, through the case of South Sudan, we demonstrate how intensity and covariance functions, defined by the log-Gaussian Cox process model, can be used to explore the complex underlying diffusion mechanism under various characteristics of conflict events. Second, our findings add to the explanation for the process of conflict diffusion. Our analysis reveals that battles with territorial gains for one side tend to diffuse over larger distances than battles with no territorial change, and that conflicts with longer duration exhibit stronger spatial dependence.

Keywords Point process · Continuous space models · Diffusion · Conflict duration · Spatial statistics

1 Introduction

Prolonged civil conflict and war as well as humanitarian crises occur frequently and are widespread in the African continent. This study selects the case of South Sudan as an example to illustrate how our methodological approach can improve understanding of conflict diffusion. Certainly, research findings drawn from a single

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case study are difficult to generalize. Conflict processes in South Sudan, however, fit the methodological goal of this study because varieties of actors have engaged in different types of conflict. This could provide a rich dynamic for how conflict events spread around areas within the country given the capacity of actors. Moreover, lessons drawn from South Sudan could also shed light on the theory of conflict: this country's history of dependence indicates that diffusion of conflicts within a country can unfold even with peaceful agreement among contentious parties.

From South Sudan's independence in July 2011 up to December 2013, President Salva Kiir and opposition leader and former Vice President Riek Machar have successfully integrated rebel groups in the national army and gave money to hundreds of generals and soldiers. Some of these generals and soldiers have become ministers at the national or local level, occupying key roles in the 35 states in which South Sudan is now divided. This problem is further complicated by the fact that there are around sixty indigenous ethnic groups in South Sudan, and that its national income, typically oil, has been used to buy the loyalty of these generals and soldiers. The consequence is that South Sudan has been trapped into prolonged civil conflicts and wars since 2013 (GlobalConflictTracker, 2019), and has also become one of the most conflict-prone countries in the world, which has gained much attention by the international community (CrisisGroup, 2017). The civil conflicts and wars in South Sudan have caused approximately four million people to be internally displaced within South Sudan or to flee to neighboring countries. This phenomenon further exacerbates regional conflicts and humanitarian crises. Humanitarian access has been obstructed by the increasing intensity of active hostilities or inter-communal violence (OCHA, 2018).

The historical conflict process in South Sudan is, therefore, counter-intuitive for the following two reasons. First, it is expected to be extremely difficult to peacefully moderate conflicts in South Sudan due to the presence of multiple factions against the government and the ubiquitous nature of interconnected civil conflicts. Yet South Sudan was able to reach and sign a Comprehensive Peace Agreement (CPA) with Sudan in 2005 in attempt to end the 50 years of violent conflict. Second, the international community believes that working on peace deals between the government and opposition is the main solution to the prolonged conflict. However, such a peaceful agreement quickly failed to resolve local grievances and maintain peace, and the South Sudanese people increasingly believe that violence is a necessary mean to achieve peace (De Vries and Schomerus, 2017). Thus far, the international community is still puzzling over what policy tools can effectively deal with these massive conflict-driven crises. South Sudan's experience calls our attention because false solutions can be made if the international community fails to realize the fact that peace and conflict are two sides of the same coin.

A conventional approach to building conflict theory and testing associated hypotheses has primarily concentrated on national-level institutional characteristics and state motivations or capability of going to war by using country-year aggregate data (Hegre and Nygård, 2015; Hegre, 2014; Maves and Braithwaite, 2013; Hoeffler, 2012; Braithwaite, 2010). This approach has provided insights for understanding the persistent nature of conflict in many countries. However, this approach cannot capture whether and how varying types of conflict and actors involved are spatially linked to each other in ways that exacerbate conflicts within a country over time. On the one hand, country-level institutional characteristics or aggregate economic conditions are often time-invariant or slow-moving factors. As a result, it is hard to justify the condition under which time-invariant variables might influence dynamics of conflict events. On the other hand, although domestic conflict events and the formation of rebel groups were believed to be inevitable in countries where governments are corrupt or political institutions are weak (Collier et al., 2009; Fearon and Laitin, 2003), non-state actors may have different grievances, demands, and means of holding conflict. Therefore, countries could experience distinct and various internal conflict processes and outcomes.

Moreover, conflict scholars have not reached consensus with regard to whether violence against civilians emerges as irrational random attacks, as a consequence of the tension between ethnic groups, or as an instrument for powerful groups to reach their political and military goals (Valentino, 2014, see also Salvi et al. in the chapter "Violence Against Civilians" in this book). Although it is likely that a country's political characteristics can drive civil unrest, many conflict events in Sudan were driven by actors' local demands and grievances. Some of these conflicts diffuse or spread from their initial locations, while other conflicts do not spread out across regions within a country's territory (Raleigh et al., 2010). Thus, country-level factors fail to explain spatial patterns of conflict diffusion within a country, especially due to actor types such as whether they are state, non-state, or civilian actors.

Fortunately, the recent advances in technological systems and methodologies enable conflict scholars to tackle actor-level characteristics as a mechanism by using conflict data at the event (point) level, rather than relying on aggregated units, which can better capture local dynamics and spatial variations in conflict. In this paper, we make use of disaggregated spatial data, together with continuous space models, through which we shift from the conventional monodic, state-based approach to an actor-centered approach to reexamine different types of conflict and test conflict diffusion on the local level. This study also deviates from the traditional approach of analyzing the effect of actor-level characteristics on conflict events at the country level, such as actors' ethnicity, and their capabilities of appealing to violence (Cederman and Gleditsch, 2009; Buhaug and Gleditsch, 2008; Harbom et al., 2008; Toft, 2005), by incorporating the spatial and temporal process of conflict as well as actor-level characteristics at the conflict point level. This analytical strategy fills a gap in the literature, in that it helps to answer what causes some differences in conflict diffusion patterns. In some cases, small conflicts scale up to a violent conflict event, while in other cases they do not and these conflict events may or may not further spread around areas within a country (Hoeffler, 2012; Buhaug et al., 2011). So far, only few empirical works analyze conflict in continuous space (Zammit-Mangion et al., 2012). Our study builds on the literature of conflict point processes over continuous space through detailed analysis of duration length, actor types, conflict types, and temporal elements.

In this study, we analyze five types of conflict events: "Battle—Government regains territory," "Battle—No change of territory," "Battle—Non-state actor overtakes territory," "Riots/protests," and "Violence against civilians." These types of conflict are closely related to the political instability and contentious state accompanied by the history of South Sudan being an independent country since 2011. In some cases, civil conflicts may be smaller episodes of a larger civil war, while others are not. By analyzing these event types in detail, this study captures scenarios where actors have a relatively equal military power (e.g., the first three categories of conflict) versus actors have an unequal capacity to appeal to violence (e.g., the last two categories), and differences in the spatial diffusion mechanism of conflict events by these event types.

By incorporating different types of conflict events and actors involved in conflict, and modeling the conflict process of these events, this study is able to capture differences in patterns of conflict diffusion in South Sudan. This analytical strategy enables us to assess a range of conflict dynamics because large-scale violence encompasses episodes of random killing, violence against civilians as well as the use of selective or indiscriminate violence (Koc-Menard, 2006). These different types of conflict reveal various purposes and/or goals pursued by the actors engaged in conflicts, such as advancing military interests, social identity, or political loyalty (Schwartz and Straus, 2018; Valentino, 2014; Balcells, 2011). We believe it is theoretically meaningful to reexamine different types of conflict based on the actor-level characteristics because actors involved in these events vary with their motivation, strategic behaviors, and capabilities of appealing to violence, which could further lead to distinct conflict processes and patterns. Distinguishing between state, non-state, and civilians as actors is theoretically meaningful because these actors directly determine where and when conflicts might take place as well as the condition under which their motivations, capabilities, and strategic responses might (or might not) lead to full-blown civil war (Cunningham et al., 2013).

Lastly, we study the difference in diffusion mechanisms by the duration of the conflict event. In many ecological and epidemiological models as well as models on crime, the data that is collected is simply an event or observation at a certain point and time (Wang et al., 2016; Liang et al., 2008; Best et al., 2000; Sparks, 2011). However, this may not be true of conflict data, where an event can have a wide range in its duration. Some events merely last for 1 day, while other events persist for several days or weeks at certain time periods. Therefore, we differentiate between conflict events that last only 1 day with conflict events that last longer than 1 day in our study.

The paper is organized as follows. In the next section, we summarize relevant research in three categories: empirical studies on the spread of conflict and wars, methodological studies on models for grid data, and continuous space models. Section 3 summarizes the data we use in this study, and in Sect. 4 we describe the methods and present the results, comparing conflict events based on time, conflict type, and actors involved. We conclude with a summary and some caveats in Sect. 5.

2 Related Work

2.1 Empirical Studies on the Diffusion of Conflict

When it comes to spatial modeling, scholars have often either focused on spatial dependence alone or spatial heterogeneity by using distances between conflict events or borders between cities and states (Anselin and O'Loughlin, 1990). Typically, empirical works on modeling space or location for conflict events have relied on modeling the covariance structure directly, or non-constant error variances in a regression model (Anselin and Baltagi, 2001; Starr, 2003; Ward and Gleditsch, 2002). Thus far, there is no consensus yet with regard to what methods can better identify empirical patterns of conflict diffusion in a robust way, and there are no concrete theoretical linkages pointing out how spatial effects might influence the diffusion of conflict. For example, there could be demonstration effects or diffusion effects. The former refer to the effect derived from either organized or spontaneous collective action. The latter often rely on a larger scale and latent learning process, through which rebel groups learn by observing others. There could also be contagion effects, as rebels move over borders to incite rebellion by their co-ethnics in neighboring countries. Even though methods for robustness tests are available (Bera et al., 2019; Penghui et al., 2015), they are ad hoc. Therefore, it is unclear whether differences in empirical results are due to estimation methods, measurement, data sources, and/or spatio-temporal coverage (Hegre and Sambanis, 2006).

Schutte and Weidmann (2011) model both relocation and escalation diffusion through a joint count statistic. However, they use gridded units for their analysis, and therefore rely on aggregation to areal units. Additionally, although Loeffler and Flaxman (2017) present a strong analysis of diffusion of crime over continuous space, they do not differentiate between these two kinds of diffusion presented by Schutte and Weidmann (2011) or other characteristics of events that are critical to understanding conflict. Therefore we are interested in how the log-Gaussian Cox Process (LGCP) model framework may be parameterized to model diffusion of conflict data, with various characteristics of events that are crucial to understanding the diffusion of conflict events.

2.2 Grid Models

We continue our review of related work by studying the use of grid models to motivate why continuous space models are necessary and feasible to the study of conflict events. In past research, grid squares were often used as the unit of analysis because it allows researchers to specify the scale of the analysis based either on a theoretical framework of expected conflict distributions or on available sub-national data. Gridded squares have been increasingly used in empirical conflict studies due, in part, to the fact that aggregate-level administrative or other types of areal units, such as counties/regions or Census tracts, can mask conflict dynamics (Fjelde and Hultman, 2014; Dittrich Hallberg, 2012; Wood and Sullivan, 2015). Furthermore, the use of sub-state conflict event data offers the opportunity to explore the local distribution of violence over time.

For example, the PRIOGRID data set is an aggregate format of global-scale disaggregate (geo-coded point level) armed conflict events (Tollefsen et al., 2016). PRIOGRID counts of conflict events are the sums of point level conflict events that happened within a given spatial grid cell. This data set has contributed to the emergence of many new studies (Von Uexkull et al., 2016; Theisen et al., 2012; O'Loughlin et al., 2012; Hendrix and Salehyan, 2012). Nonetheless, when using gridded data, the Modifiable Areal Unit Problem (MAUP) represents a significant challenge where the level of aggregation can influence the results of the statistical analysis. The MAUP can significantly weaken and bias a statistical result when smaller areal units are aggregated to form larger areal units. Under this scenario, rezoning or moving boundaries of an area can have significant effects on the results (Wong, 2009).

There is little to no agreement across studies in terms of existing empirical findings using grid cells as the units of analysis, nor can this modeling strategy be used to capture the complex spatial dynamics and diffusion of conflict processes because it is limited by its aggregated nature to a certain resolution of analysis and accuracy. Therefore, we turn our attention to continuous space models where we do not rely on aggregation to areal units, such as grid cells.

2.3 Continuous Space Models

There are few empirical works in conflict studies that analyze conflict events over continuous space. Zammit-Mangion et al. (2012) provides one of the first attempts to model conflict, instead of crime or disease diffusion, over continuous space. However, in their model they do not specifically discuss the parameterization of diffusion, although they suggest it is possible to model diffusion using their model. Instead, they measure volatility and heterogeneous growth and give explicit parameterizations for each. They use a continuous space and discrete time version of the log-Gaussian Cox Process (LGCP) model, as they recognize that conflict data is reported on the day level, instead of at the exact time. They use the Stochastic Integro-Differential Equation (SIDE) approach to estimate the effects of time. The main focus of their study is on prediction, and they did not focus on the interpretations of the parameters.

There is some existing work on measuring diffusion of other types of events in continuous space, where the authors use the Hawkes process to model crime for example (Loeffler and Flaxman, 2017). However, in Loeffler and Flaxman (2017), they study gun crimes, which is a classical example of a point process in which the event happens in an exact instance in time. As stated above, in conflict data the event happens over the span of a day, or sometimes several days or weeks. Therefore, in our approach, we also analyze the difference in diffusion dynamics between events that last longer than 1 day as compared to events that only last 1 day.

We characterize conflict diffusion mechanisms in continuous space across South Sudan for the five types of conflict events discussed above, based on the duration of conflict events and military power of actors involved in conflicts. Thus far, researchers studying diffusion processes of conflict and some other social phenomena, such as crime, often use areal unit models, where events and other kinds of data are aggregated to usually administrative areas or grid cells by either the data provider or the researcher. Therefore, even when point or event level data is available, these processes are not frequently studied in continuous space. Though there have been some studies of conflict events in continuous space (Zammit-Mangion et al., 2012), none has specifically parameterized diffusion in conflict event data in continuous space. Therefore, we tackle the challenge of modeling spatial dependence of conflict events in continuous space.

3 Data

Event or point level data is characterized by an exact location, or coordinates, affiliated with the event and the events sometimes also have date/time affiliations. We refer to these events as points as these will be the "points" in our "point process" statistical methodology and they occur at exact points in space. Using data from the Armed Conflict Location and Event Data (ACLED) (Raleigh et al., 2010), this study examines conflict processes of five event types, including three types of battles (in which armed forces are often involved with different outcomes of territorial integrity), riots/protests (public demonstration and violent protest), and violence against civilians (physical harm to civilians, which can also be committed by rioters and/or to protesters) in South Sudan from 2011 to 2018. ACLED collects this data through news from international, regional, and local media reports as well as NGO accounts (ACLED, 2019).

Our full dataset consists of 4654 conflict events in South Sudan from July 14, 2011 through December 10, 2018. We see in Fig. 1 that there are many more conflict events that occur after 2014. Figure 1 also illustrates the event type over time, where most of these events are battles where there is no change in territory and violence against civilians. The counts of each of these event types for the full time period are presented in the legend of Fig. 1.

In Fig. 2a, we see the spatial distribution of these 4654 events over the country of South Sudan, where most of the events occur in the middle of the country. Each event has an affiliated transparency, so where there are darker colors in Fig. 2a and b, that means there are more events occurring at that location.

In the ACLED dataset, each day of an event is given a separate row in the dataset. If we count each of the days of a given conflict as separate events, then we have a total of 4654 conflict events as stated earlier. However, if we treat events as the same if they share the same location and description and occur within similar time periods,

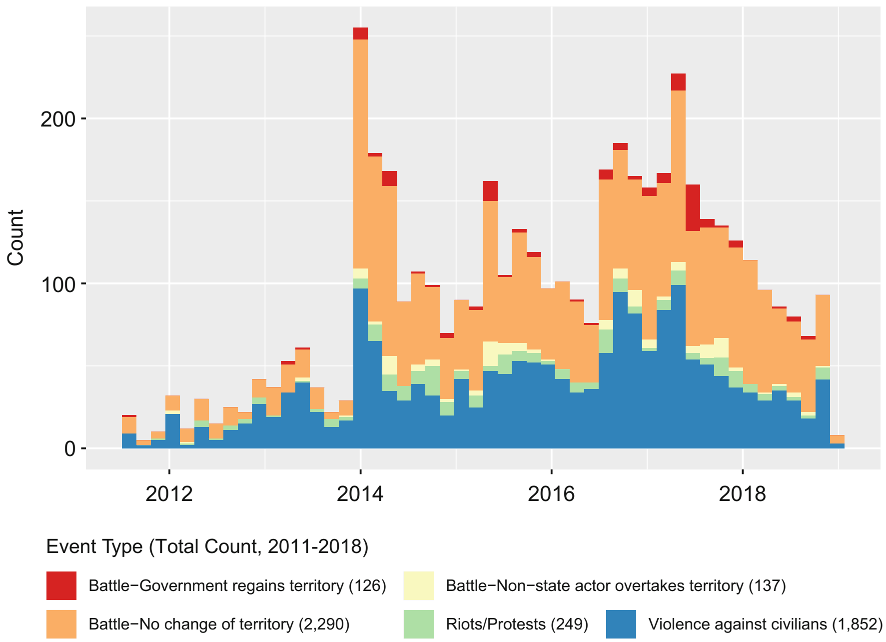
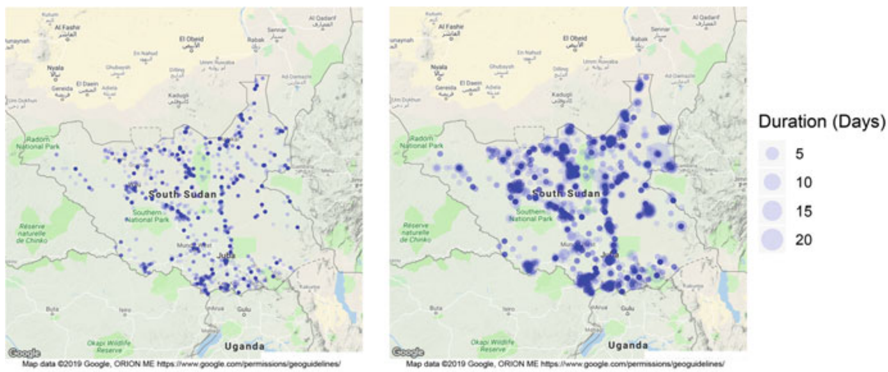


Fig. 1 Frequency of conflict events in South Sudan over time, by conflict event type. The histogram bars are stacked on top of each other by event type



(a) (b)

Fig. 2 Spatial distribution of conflict events over South Sudan. In Fig. 2a, all points, which represent conflict events, are equal size and the darker the point, the more events have occurred at that location. In Fig. 2b, the size of the point represents the duration of the event, and the shading again represents more events at that location. (**a**) Location only. (**b**) With duration

and then assign the duration as the number of days that the event persists, then we only have 4160 unique events in our dataset. When duration is defined in this way, the duration of an event ranges from 1 day to 24 days. Most events last 1 day with

Table 1 We show common actors by frequency of conflict event involvement in South Sudan. We include the actor type that we assigned to each of these actors, in order to provide examples of actors in each category

Actor name	Frequency	Actor type assigned
Military Forces of South Sudan (2011-)	2401	State
Civilians (South Sudan)	1719	Civilian
Sudanese Peoples Liberation Army/movement-in opposition	1536	Non-state
Unidentified Armed Group (South Sudan)	989	Non-state
Police Forces of South Sudan (2011-)	190	State
Protesters (South Sudan)	177	Civilian
Murle Ethnic Militia (South Sudan)	161	Non-state
Unidentified Communal Militia (South Sudan)	156	Non-state
Mutiny of Military Forces of South Sudan (2011-)	144	State
Rioters (South Sudan)	99	Civilian

the mean duration being 1.11 days. In Fig. 2b, we see the duration of these events illustrated by the size of the point. Figure 2b gives a sense of the spatial distribution of the events that last longer than 1 day. For the purposes of our analysis, due to the fact that the vast majority (93%) of conflict events only last 1 day and we would like to treat these events to be independent, we take the first day of the given conflict event and assign each event their duration as a covariate. Therefore, our final dataset for modeling purposes consists of 4160 unique events all of which are assigned their duration as a characteristic of the event, which we will analyze in detail later.

Through the ACLED dataset, we have two actors that are included with most events. There are no events that are missing the first actor and there are only 192 out of the 4160 events in our final dataset that are missing a second actor, i.e., where there was only one actor involved. These are exclusively events where there are only rioters or protesters involved in the event. There may be events with more than two actors involved, but ACLED only provides the first two actors involved. From these 4160 events, we have 285 unique actors in our dataset. We see some of the most commonly occurring actors below in Table 1, along with their assigned actor type.

As mentioned in Sect. 1, it is important to consider the difference in diffusion mechanisms between events that include state and non-state actors as well as civilians/rioters/protesters. To address this difference, we re-code and divide all of the ACLED actors into state actors, non-state actors, and civilians/rioters/protesters. We abbreviate the last category as simply “civilians” going forward. State actors include governments, governmental agencies (e.g., security department or police department), and the military force formed by a government or ruling party. Non-state actors contain a wide range of rebel groups, including identity militias and political opposition organizations. The last group includes civilians, rioters, protesters, and prisoners. The main difference between non-state actors and this category of civilians/rioters/protesters/prisoners is that non-state actors are organized actors with military power and the civilian groups have no military power.

Table 2 We show the counts of conflict events by the actor dyads that were involved for South Sudan from 2011 to 2018. We also provide an example of an actor dyad for each dyad type. For the case of only civilian involvement, these events often did not include a second actor

Actors involved	Frequency of event	Example
State and non-state	1556	Yau Yau Rebels, Government of South Sudan
Non-state and civilian	1161	Dinka Ethnic Militia, civilians
State and civilian	579	Military Forces of South Sudan, civilians
Only non-state	415	Kuei Ethnic Militia, Rup Dinka Ethnic Militia
Only state	230	Military Forces of South Sudan, Police Forces of South Sudan
Only civilian	219	Protesters (one actor)

After this categorization, we then assess the difference in diffusion of conflict events that include different combinations of these kinds of actors, including only state actors, only non-state actors, or only civilians as well as the dyads of these actor types. In Table 2, we show the number of conflict events that fall under each actor dyad. We see that most events involve either non-state and state actors or non-state actors and civilians. We note that at times, as mentioned earlier, there is only one actor involved, which would necessitate this being categorized as only state, non-state, or civilians. However, this only occurs in 4.6% of the events. An example for each kind of event is included below in Table 2.

4 Analysis

4.1 Test for Complete Spatial Randomness

To begin our analysis, first we test for complete spatial randomness, or if our point process of conflict events follows a homogeneous Poisson Process. We perform this test because if the data follows complete spatial randomness, then there is no need for more complicated statistical testing. We define a homogeneous Poisson Process as follows:

Definition 4.1 Homogeneous Poisson Process: Let $N(A)$ denote the number of events in a region A, and $|A|$ the area of this region, then the data/events $X_1, X_2, \ldots, X_{N(A)}$ follow a homogeneous Poisson Process if the following conditions are fulfilled:

1. For some $\lambda > 0$ and any finite region A, $N(A) \sim Poisson(\lambda|A|)$
2. Given $N(A) = n$, the n events form an independently and identically distributed (iid) sample from the uniform distribution on A.
3. For any two disjoint regions A and B, the random variables $N(A)$ and $N(B)$ are independent.

If our data follows a homogeneous Poisson Process, then it also follows **complete spatial randomness** (CSR). The parameter λ is the rate or the intensity of the point process. Before we proceed to build more complicated models, we will test the null hypothesis of complete spatial randomness. We diagnose CSR through Monte Carlo sampling and empirical cumulative distribution functions (ECDF's), which we define below.

Definition 4.2 Empirical cumulative distribution function (ECDF): If $X_1, \ldots, X_n$ are iid with CDF F, then the ECDF is $\hat{F}(x) = \frac{\sum_{i=1}^{n} \mathbb{1}\{X_i \leq x\}}{n} = \frac{\#\{X_i \leq x\}}{n}$. This is an unbiased estimator of $F(X) = P(X_i \leq x)$.

For our use of the ECDF, in this approach, we use Monte Carlo sampling to construct simulation envelopes under CSR. We sample $x_1, x_2, \ldots x_n$ locations uniformly on A and construct $\hat{F}$ as defined above. We use empty space distances where $d(u) = \min_i ||u - x_i||, i \neq j$. We then construct our estimate $\hat{F}_u(r)$ of $F_u(r) = P(d(u) \leq r) = P(\text{at least one point within radius } r \text{ of } u)$. We then compare $\hat{F}_u(r)$ to $F_u(r)$ under CSR.

We conduct this test for CSR and plot the estimates for the F function, the simulation estimate, and the observed F function below in Fig. 3. In these tests, if we see that the observed line is very close to the mean simulated line, then we have evidence for CSR. If the observed line lies outside of the simulation envelope, or the dark shaded area, then we have evidence against CSR. For the pointwise case, the simulation envelopes, or the shaded areas, are constructed by sorting the simulated values and taking the mth lowest and mth highest values (Baddeley et al., 2015). For the simultaneous case, the simulation envelope is slightly more complicated. For each simulation, we calculate the theoretical mean value of F under CSR and we calculate the maximum absolute difference between the theoretical curve and the simulated curve. After the simulations, we take the mth largest absolute deviation from all the simulations, dev_m, and this forms our simulation envelope through $lo = F_{theo} - dev_m$ and $hi = F_{theo} + dev_m$ where F_{theo} is the theoretical mean value (Baddeley et al., 2015). We use two different techniques to estimate the F function: simultaneous and pointwise. We use both the simultaneous and pointwise method because through the use of the simultaneous envelopes, we get a smoother function but a much more conservative estimate of CSR as compared to the pointwise envelopes. In both tests, we have 800 simulations and choose m to be 20.

In Fig. 3, we see the estimates of the F function for both the pointwise and simultaneous methods. We see that even for the more conservative method, the simultaneous envelope, we see strong evidence against complete spatial randomness (CSR), as the observed curve is not close to the mean simulated curve under CSR. Therefore, we conclude that spatial modeling is appropriate for our dataset.

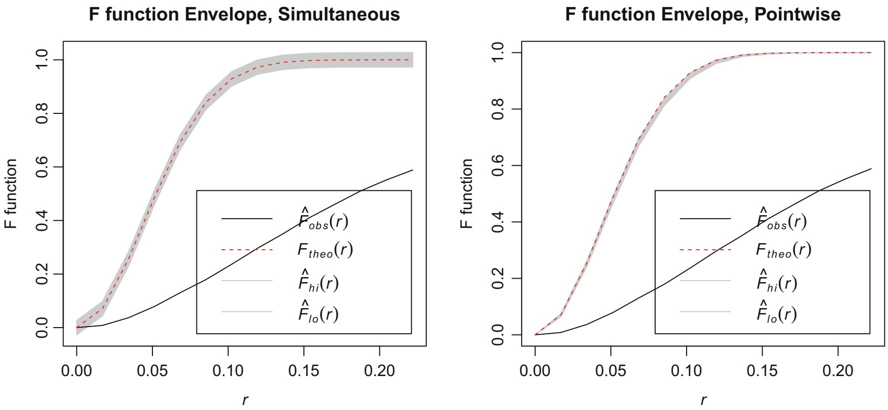
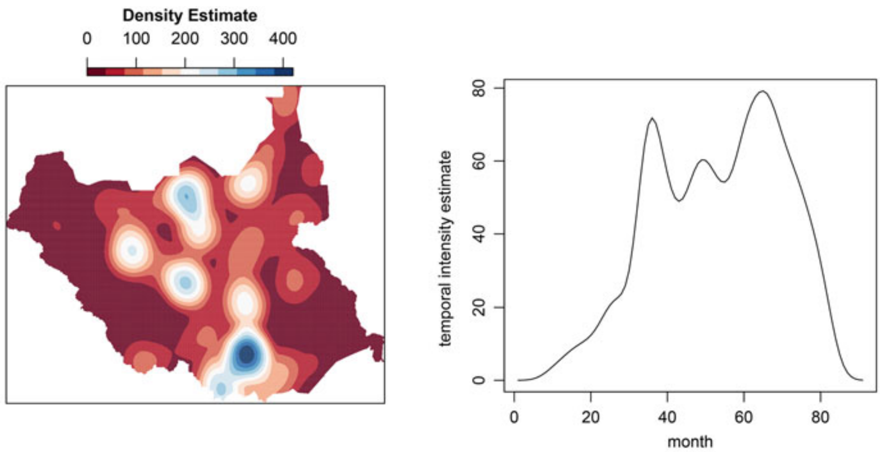


Fig. 3 We diagnose the absence of complete spatial randomness (CSR) through the simultaneous and pointwise simulation envelopes, as the observed curve lies outside of the envelope of the simulated curve

4.2 Continuous Space Model

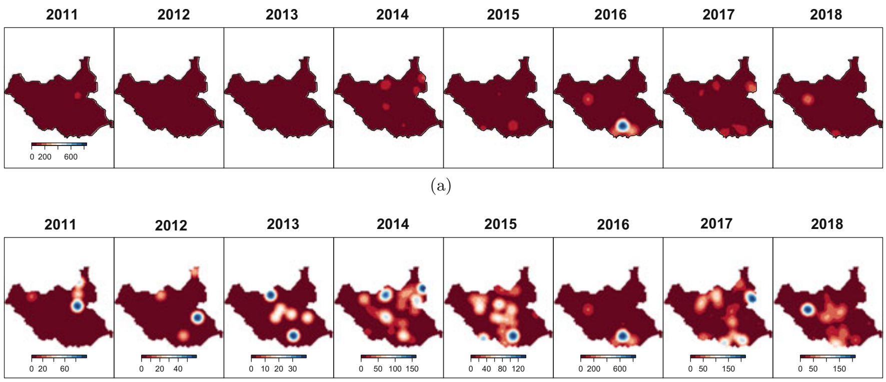
Now that we have established that spatial modeling is appropriate, as the data does not follow complete spatial randomness, we start with a simple continuous space model. First, we treat our dataset as an inhomogeneous Poisson Process with an intensity $\lambda(x)$. We create a kernel density estimate for the intensity $\lambda(x)$ over space and time (Rowlingson and Diggle, 1993). First, we plot the estimate of the spatial intensity over the complete time window as well as the estimate for the temporal trend over the full area through a quartic kernel. In Fig. 4a, we see a high estimate for the kernel density estimate in the southern part of the country, as well as a couple of other peaks. In regards to the time dimension in Fig. 4b, the low count of conflict events at the end of the time window is due to lack of data in the last month of the dataset, as the dataset only covers through mid-December. We also see a low count for the number of events at the beginning of the time window, due to the actual low frequency of events from 2011–2014, as described earlier. The difference between these two low counts at the beginning compared to the end is due to observed low frequencies vs lack of data availability in the time window, respectively. We see a decrease and then increase in conflict in the middle of the dataset.

Next, we plot the estimate of the intensity function over 12 month intervals for our 8 years of data. We note that although time is continuous, we discretize time into years in order to visualize the change in the kernel density estimate over time. In Fig. 5, we see that our spatial kernel density estimate changes over the year-long periods. In Fig. 5a, all of the kernel density estimates use the same scale so we are able to see that there is really only one time period, in 2016, where the conflict events are quite concentrated in space at high levels in that concentration. Otherwise, they are pretty evenly distributed throughout the country at lower levels than 2016. In



(a) (b)

Fig. 4 Through a kernel density estimate for the spatial intensity function, $\lambda(x)$, and the temporal intensity function, we see an estimate of the spatial distribution and temporal trend of conflict events from 2011–2018. (**a**) Spatial intensity function estimate. (**b**) Temporal intensity function estimate



(b)

Fig. 5 Through the kernel density estimate of the intensity function $\lambda(x)$ over space and time, we see how the spatial distribution of conflict events changes over each year in our dataset. Through the common scale, we see there is only 1 year, 2016, with a strong spatial peak relative to the other time intervals. However, if we use a scale determined by each year, we can see where the conflict events are spatially concentrated by year. (**a**) Common scale. (**b**) Scale by year

Fig. 5b, we have a different color scale for each year of the data, so you can see the relative peaks within the given year of data and where the spatial peaks are shifting. Specifically, we see that there is a region in the southern part of South Sudan that often has fairly high conflict rates over the full 8 year conflict window.

However, there are other areas in the country, such as in the north east, which have high conflict events for some periods but not others.

4.3 Gaussian Process

Now that we have seen a preliminary estimate of the intensity function, we will model our continuous space data as a Gaussian Process in order to study diffusion mechanisms in the conflict process. We do this through fitting a log-Gaussian Cox Process (LGCP) through the *spatstat* package in R (Baddeley et al., 2015). In an LGCP model, the intensity function is defined as $\lambda(x) = exp(Z(x))$ at location x where $Z(x)$ is a Gaussian random field in the two-dimensional plane (Moller and Waagepetersen, 2003). The intensity of the LGCP is then governed by the Gaussian Process, $Z(x)$, which has covariance function $C(r)$ where r is the distance between two points. We use an exponential covariance function so that the covariance function takes the following form:

$$C(r) = \sigma^2 e^{-r/\alpha}$$

Through the *spatstat* package in R, we estimate σ^2 and α for our data. We plot the estimate of the covariance function to illustrate the spatial range of our data. Once the covariance function falls below a certain point, which we will specify as 0.1, we call this distance the **effective range** of our events. The reason it is called *range* is because this is the distance at which events still impact each other with nonzero covariance. However, we will never actually observe a covariance of zero, so the reason this is called the *effective* range is due to the fact that the range is small enough, it is effectively 0. A larger effective range suggests that events have a stronger influence or dependence on events for a larger radius around those given events. There is no inherent rule with the choice of the cutoff, as this is a heuristic process. However, the covariance function is most accurate when the radius is small. Therefore, when we specify a smaller cutoff, we are effectively choosing a larger radius where the covariance function is not as accurate. In the figures in this section, the dashed line represents the cutoff point of 0.1.

We note that the number of events in each category does not necessarily affect the value we find for the effective range. In other words, a smaller number of events in one category does not necessarily lead to a higher or lower estimate of our effective range. However, a smaller number of events in the category could affect the precision of our estimate, which we will address in Sect. 5.

First, we compare the effective spatial range for each year of the conflict data in order to make conclusions about the change in diffusion mechanisms over time. In Fig. 6, we plot the effective range through the covariance function estimate for each year. We see that the estimate of the covariance function does change over time in our dataset, but not drastically. We include the effective range over time in Table 3. We see that the effective range decreases from 2011 to 2014 and then increases from

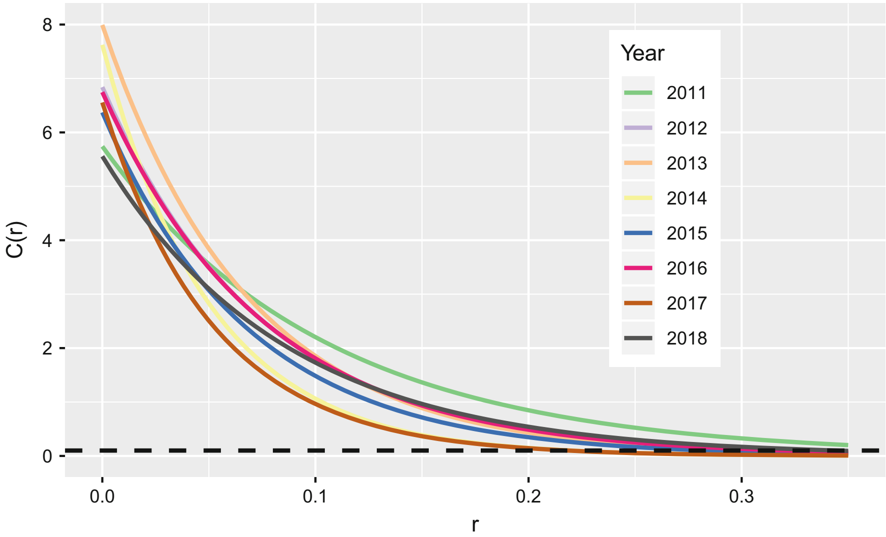


Fig. 6 When we plot the estimate of the covariance function by year, we see lower estimates of the effective range for 2014, 2015, and 2017

Table 3 Effective range estimates by year

Year	Effective range
2011	0.42
2012	0.32
2013	0.30
2014	0.22
2015	0.28
2016	0.32
2017	0.22
2018	0.34

2014–2016 but this increasing trend does not hold through 2018. This implies that between 2011 and 2014, events started to exhibit a weaker dependence structure, where events had a smaller effect on surrounding events than previously. This makes intuitive sense as conflict events were relatively infrequent in the region throughout this time period. Between 2014–2015, the effective range increased, meaning that each event had a stronger effect for more distance, or a larger radius, r, around that given event. This also makes intuitive sense as there were large increases in conflict events during this time period. As stated earlier, there is not necessarily a relationship between more events in a given conflict event group and a higher or lower effective range. However, more events occurring in a certain period of time may suggest that these events would spur more events following them and have a stronger dependence mechanism, and would therefore have a larger effective range. The smaller effective range may also be due to the fact that there are multiple

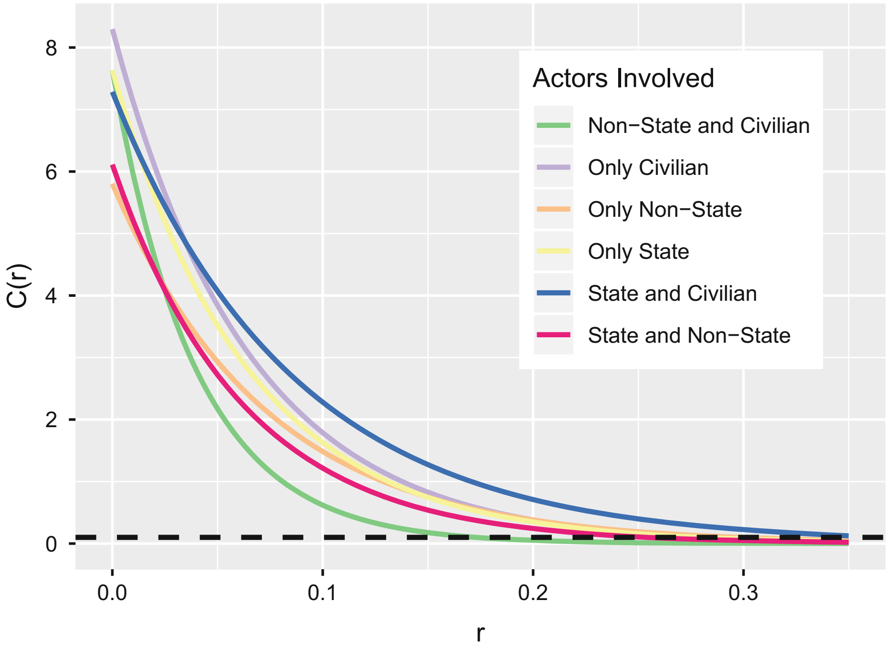


Fig. 7 When we plot the estimate of the covariance function by actor type, we see higher estimates for the effective range for the state actor and civilian dyad and a small effective range when there are non-state actors and civilians involved

Table 4 Effective range estimates by actors involved

Actors involved	Effective range
Only state	0.28
Only non-state	0.30
Only civilian	0.29
State and non-state	0.25
State and civilian	0.37
Non-state and civilian	0.17

clusters of conflict events during these years (2013, 2014, 2015, and 2017), as seen in Fig. 5b.

Next, we compare the effective range of conflict events based on the types of actors that are involved. We see in Fig. 7 and Table 4 that the effective range is highest for events where state actors and civilians are involved. The effective range is quite similar for other conflict events, especially as the radius gets higher. This suggests that the diffusion mechanism might be strongest when there are state actors and civilians involved in the conflict but other actors do not have a large effect on diffusion. This would illustrate that when state actors and civilians are involved, this may spur additional events around it more-so than other conflict events, perhaps due to the contentious nature of these kinds of events.

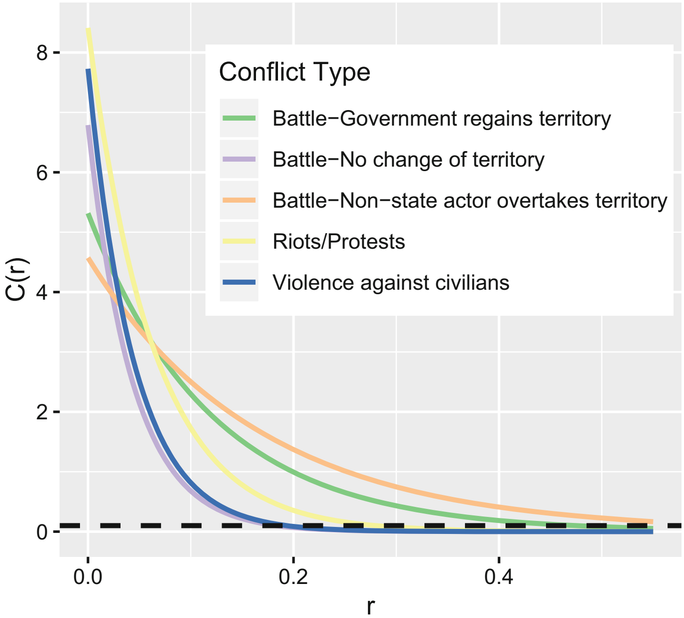


Fig. 8 When we plot the estimate of the covariance function by conflict type, we see a larger effective range for battles where non-state actors overtake territory or when government regains territory

Table 5 Effective range estimates by conflict type

Conflict type-specific	Effective range
Violence against civilians	0.195
Riots/protests	0.28
Battle-government regains territory	0.475
Battle-no change of territory	0.185
Battle-non-state actor overtakes territory	0.635

We also conduct this analysis based on conflict type. We see in Fig. 8 and Table 5 that the event types with the strongest diffusion mechanisms are battles where the government regains territory and battles where non-state actors overtake the territory. It is notable that battles with no change in territory have a relatively weak diffusion mechanism when compared to these other battle types, suggesting that it is necessary to differentiate between these kinds of conflict events. We thus see that these two types of battles, where there is change in territory, may impact the surrounding more than battles where there is no change in territory or violence against civilians. Riots and protests lie in the middle of these conflict event types.

Lastly, we also analyze these events by duration length. We show the difference in the diffusion mechanism for events that last only 1 day compared to events that last longer than 1 day. In Fig. 9 and Table 6, we see that events that last more than 1 day exhibit a much stronger diffusion mechanism through the larger effective range.

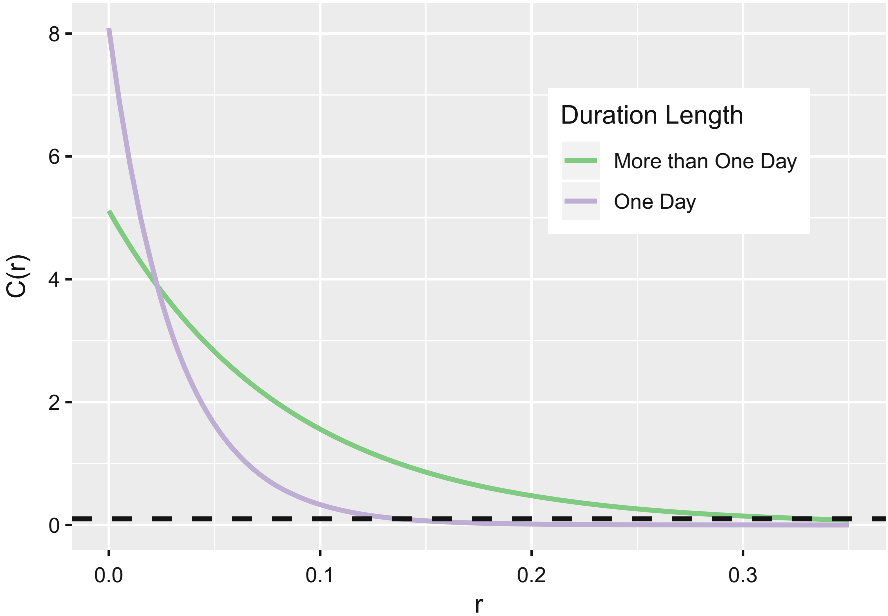


Fig. 9 When we plot the estimate of the covariance function by duration length, we see a larger effective range when the event lasts for longer than 1 day

Table 6 Effective range estimates by duration length

Duration length	Effective range
One day	0.14
More than 1 day	0.335

This makes intuitive sense as these longer events are likely to be larger-scale events in severity, and therefore might spur other events.

Through this analysis, we show that it is important to analyze diffusion mechanisms, such as the effective range of any given event, over time. We have shown that for our dataset, the dependence between events changes over time, and the effective range for conflicts in South Sudan decreased from 2011–2014, suggesting a weaker diffusion or dependence mechanism, but then increased from 2014–2016, as conflict escalated in the region. We have also shown that it is important to take into consideration event types, actor types, and duration of the event when considering diffusion mechanisms between events.

5 Discussion and Future Work

Our results illustrate that it is valuable to characterize the dependence between events when we have rich data in continuous space. We began by characterizing the dependence over time and space through density estimates and formally estimated this dependence through a log-Gaussian Cox Process (LGCP) model and the covariance function. We found that it is important to estimate changes in the diffusion mechanism over time and across actors and conflict types to detect differences in the diffusion process.

The theoretical implication of our empirical analysis is two-fold. First, battles with territorial gains for one side tend to diffuse over larger distances than battles with no territorial change. This implies that the location of an individual conflict event and the clustering of multiple events or locations of events could have significant effects on the subsequent onset or termination of other conflict events. Based on our analysis, the southern part of South Sudan, which is the area around the capital, Juba, has a higher estimated intensity than other surrounding regions. A higher estimated conflict intensity around the southern part of South Sudan is evidence of the spatial interdependence among conflict events. This result reflects a historical conflict diffusion process of mass killings of the Nuer people by Dinka paramilitary groups in the capital, Juba, which were the pretext to the origin of the outbreak of civil war (Sawe, 2017). In the future, we would also like to control for certain demographic and socioeconomic characteristics over space and time, including population, housing, and transportation infrastructure.

Second, modeling spatio-temporal distribution of conflict events will contribute to defining the conjuncture of initial conditions of locations where conflict took place and capturing plausible mechanisms underlying changes on the spatial distribution or pattern of conflict over times. Our analysis shows that conflicts with longer duration exhibit stronger spatial dependence. Throughout the process of being an independent country, conflict events in South Sudan are most spatially concentrated in 2016, when compared to the other years in our dataset. This finding reveals that the long-term unsolved ethnic tension between the government and rebel groups led to the outbreak of large-scale violence against civilians in 2016. Both the government and the rebel groups committed abuses against civilians in and around Juba and other areas. According to the Global Conflict Tracker and Human Rights Watch, the government and the rebel group targeted civilians along ethnic lines, and millions of people were displaced or forced to flee their homes. Military groups committed rape and sexual violence, destroyed property and looted villages, and recruited children into their ranks. The UN even warned that this ongoing ethnic war was likely to transform into genocide (GlobalConflictTracker, 2019; HumanRightsWatch, 2017). Therefore, in future research, it is crucial to investigate how ethnic identity might service as an underlying mechanism reshaping the spatial patterns of conflict.

Third, we have shown that it is important to consider several key characteristics of conflict events when analyzing the dependence structure of these events. For example, we show that temporal analysis, rather than simply a cross-section, may be important in these analyses, which agrees with existing literature that also studies temporal dynamics (Read and Mac Ginty, 2017; Silwal, 2013). This temporal analysis should be expanded in future work. We also illustrate that the types of actors that are involved with conflicts can play a crucial role in determining if that event is likely to influence other events. Specifically, we find that when state actors and civilians/rioters/protesters are involved, this is likely to have a stronger effect on surrounding events, which bridges a gap in the literature (Cunningham et al., 2013). We also find that it is important to consider event types, as battles where there are changes in territories have stronger diffusion mechanisms than other types of conflict events. This adds to the literature, as most studies do not investigate diffusion mechanisms between the types (Wood, 2010; Azam and Hoeffler, 2002; Balcells, 2010). Lastly, we find that events that last only 1 day vs longer than 1 day also have quite different dependence structures, as events that last longer than 1 day have much stronger dependence on events surrounding them. To the best of our knowledge, this study is the first that empirically examines duration using the day-span as the unit of analysis and carefully examines whether the events that persist only 1 day are important. Our results were gathered through the use of continuous space models and point level data, and therefore represent an advancement on most existing methods.

There are some caveats that are necessary in this analysis. Most importantly, in the estimate of our covariance function, there are more points at a smaller radius around a point and less points once you get further away. Therefore, as we get to a larger radius, the covariance estimate is less reliable and we interpret the difference in the covariance function with some caution at larger distances. As mentioned earlier, if there are fewer events in a given category, the precision of the covariance function estimate, and therefore also the effective range estimate, may be affected. One way to assess the variability of these estimates is through a parametric bootstrap where we would simulate multiple realizations from a fitted model and assess the variability in the resulting estimates of the effective range. However, given the computationally intensive nature of these models, we interpret our results with caution, only draw conclusions where there are large differences in the effective range estimates, and suggest this for future work.

In the future, we could consider different formal models for diffusion mechanisms, through the epidemiology literature. However, the log-Gaussian Cox Process methodology provides an easily interpretable mechanism to analyze diffusion in the context of conflict event data. We would also like to incorporate stronger temporal measures of dependence into our analysis, such as through continuous time models, as well as covariate information. An analysis by conflict severity, based on the number of causalities in addition to our analysis of severity by duration of the conflict, could also be an additional important step in this analysis.

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Rebel Group Protection Rackets: Simulating the Effects of Economic Support on Civil War Violence

Frances Duffy, Kamil C. Klosek, Luis G. Nardin, and Gerd Wagner

Abstract Rebel groups engage in a series of economic transactions with their local populations during a civil war. These interactions resemble those of a protection racket, in which aspiring governing groups extort the local economic actors to fund their fighting activities and control the territory. Seeking security in this unstable political environment, these economic actors may decide to flee or to pay the rebels in order to ensure their own protection, impacting the outcomes of the civil war. We present a simulation model (executable at https://gnardin.github.io/RebelGroups) that attempts to capture the decision-making and behavior of the involved actors during protection racket interactions as well as the cooperation and competition between rebel groups to control territory. Our model reveals insights about the mechanisms that are helpful for understanding violence outcomes in civil wars, and the conditions that may lead rebel groups to prevail. Analysis of various scenarios demonstrates the impact that different security factors play on civil war dynamics. Using Somalia as a case study, we also assess the importance of the rebel groups' economic bases of support in a real-world setting.

Keywords Enterprise · Rebel group · Protection racket · Somalia · Civil war · Agent-based model · Simulation

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1 Introduction

How do rebel groups control territory and engage with the local economy during civil war? Charles Tilly's seminal *War and State Making as Organized Crime* (Tilly, 1985) posits that the process of waging war and providing governance resembles that of a protection racket, in which aspiring governing groups extort local populations to gain power, and civilians or businesses pay to ensure their own protection. We present an agent-based simulation model that attempts to capture the decision-making and behavior of the actors involved: rebel groups and enterprises. The model is available online at https://gnardin.github.io/RebelGroups as a web-based simulation and can be run in any modern web browser.

The use of agent-based modeling in civil war research is not a new endeavor. The groundwork is laid by Epstein (2002), who analyzes the conditions under which individuals may mobilize and protest. He examines factors such as the legitimacy of a political system, risk-aversion of potential protesters, police strength, and geographic reach. Several researchers have since expanded upon Epstein's work by focusing on greed and grievances in rebellious movements (Goh et al., 2006), crime (Fonoberova et al., 2018), and network effects caused by the spread of media (Lemos et al., 2016). Our model also builds upon earlier research by focusing on civil war dynamics that could emerge after the initial rebellion. It focuses on the relationships between economic and security factors as determinants of inter-rebel warfare by treating collective rebel groups as well as business enterprises as individual agents.

Conceptually, the opportunity for rebel groups to engage in extortion of local populations most often arises either in a condition of relative anarchy or when the incumbent government is too weak to protect local enterprises itself (Fjelde and Nilsson, 2012). Some scholars theorize that a security dilemma influences actors to support or form rebel groups for protection in order to balance against threats of violence and competition from one another (Posen, 1993). While this theory may capture some of the motivation for enterprises to seek security, it does not explain how this process takes place and why rebel groups, who may face varying degrees of security threats to their own interests, would be motivated to take and hold territory while controlling local populations.

Several scholars address the question of when rebel groups choose to develop a relationship with civilians and when they choose to attack or loot them instead. Weinstein (2006) argues that the presence of outside support and lootable resources increases the likelihood that rebel groups will fail to seek a cooperative relationship with civilian populations under their control, because they can expand economically without extorting local businesses. By contrast, rebel groups that fight on behalf of ideological goals may be more likely to seek the cooperation of local communities, relying on them for provision or extortion of resources and providing protection or other benefits in order to maintain this relationship (Weinstein, 2006). Further, relatively weak rebel groups with rising battlefield costs, which are not strong enough to engage in extortion activities, may also loot civilians rather than engage in a process of periodic extraction from the local population (Wood, 2014). As losses increase, rebels are more likely to desert the rebel group, die in heavy losses, or be expelled as the group can no longer afford to compensate them (Weinstein, 2005).

Therefore, the economic conditions in a conflict territory, as well as the funding characteristics of a rebel group, influence the extortion of local enterprises. These extortion activities have consequences for the behavior of rebel groups in conflict. When two different rebel groups contest territory or seek the extortion of enterprises under the control of another group, we can expect fighting between the rebels (Fjelde and Nilsson, 2012). The groups may seek greater economic gains, continued dominance over an area of territory, or simply to protect and defend the local populations that they themselves extort. These incentives may motivate competition and battles between groups, which depend on the available resources and capabilities. Thus, the extortion racket they develop permits a continued process of expansion aiming at hegemony and protection of the territory.

Those who support a rebel group and benefit from its protection may provide information or intelligence on the group's rivals, or even be recruited to join its ranks which further increases the group's fighting capacity (Barter, 2012; Kalyvas, 2006). Apart from providing temporary jobs as fighters, local populations can also economically benefit depending on the status quo ante. For instance, Leeson (2007) and Powell et al. (2008) find that the statelessness conditions of Somalia between 1991 and 2005 were more favorable for local business actors than the previous predatory regime of Siad Barre. This holds mainly in economic sectors that are less dependent on government authority but suffer due to corruption and forced seizures of assets. Alternatively, if rebel groups are unable to provide protection following extortion or they themselves engage in violent attacks and looting, business actors may choose to support a rival group or even to flee. Whether due to direct attacks or inter-rebel group fighting, an increase in the severity of violence motivates business actors to flee for safety (Barter, 2012; Steele, 2009).

Ultimately, a stable point may be reached at which rebel groups gain enough territory and sufficient trust from the local population to establish themselves as a legitimate governing institution. This shift may come with local adjudication responsibilities and public goods provision. Having established an ad hoc local governing institution, the system transitions away from the competitive security environment and the system is no longer in anarchy. At this point, one group achieves hegemony over all competitors. A stalemate may also be reached if two or more rebel groups balance against each other's power, with neither group gaining the capability to seek the extortion of its opponent's population (Walt, 1985; Waltz, 1979).

As civil war research continues to probe the political mechanisms that fuel local disputes and the origination of violence (e.g., Østby (2008); Cunningham (2013); Cederman and Vogt (2017); Walter (2017)), our agent-based simulation model explores the economic relationships of rebel groups with their local populations. The model captures the extortion of local enterprises by rebel groups, their decisions to expand their controlling territory, as well as the decisions of enterprises whether to report extortion or to flee. We use the model to perform security-related experiments using a theoretical system of three warring rebel groups, examining their impacts on the economy and the importance of their economic bases of support for their sustainability during a civil war. This analysis provides insights for understanding the causes and byproducts of rebel competition in present-day conflicts, such as the case of Somalia. We therefore also apply the model to historical scenarios experienced over the evolution of Somalia's civil war and derive some initial implications from our findings.

2 Theoretical Underpinnings

Intrastate armed conflicts or civil wars require rebel groups to raise revenue and gather resources in order to mobilize and to sustain the offensive and defensive potential necessary for long-term survival. Internally, a rebel group also needs to establish a structured organization to sustain group cohesion until the armed conflict ceases. Both mobilization and structuring incur distinguishable costs on rebel actors (Wennmann, 2009). According to Olson (1993), those rebel groups that are able to monopolize violence in a confined territory and establish themselves as the predominant local institutional structure are able to extract a permanent revenue stream through local taxation. This provides groups with crucial advantages as compared to "roving" actors who survive on incidental and temporary extraction gains.

We assume the interactions of rebel groups in an anarchic environment. No superior actor can alleviate information asymmetries or commitment problems. In their pursuit of survival, rebel groups rely on their own capacities and are unrestricted in their choice of actions. This assumption is prevalent in the study of International Relations, in which states are the highest order actors. It is also popular in civil war studies, in particular in literature on bargaining failures (Spaniel and Bills, 2016; Nygård and Weintraub, 2014) and discussions of the ethnic security dilemma (Roe, 1999; Johnson, 2015). Similarly, Olson (1993) uses the assumption of anarchy as a backdrop of inter-group competition development.

Academic research has also examined different types of rebel revenue streams. Armed actors during the Cold War were primarily financed by external patrons such as the USA, the Soviet Union, Cuba, China, France, and other countries posturing on the world stage (Schmidt, 2013). In the 1990s, in the wake of the fall of the Soviet Union and the ideological contention that accompanied it, the world established new norms of non-intervention, and sub-national armed actors needed to find replacements for their former patrons. Natural resource extraction featured most prominently (Lujala, 2008; Lujala et al., 2005; Collier et al., 2008), in addition to migrant and diaspora remittances (Regan and Frank, 2014; Escribà-Folch et al., 2018) and looting (Wennmann, 2011).

However, rebel groups may still rely on local extraction of funds and supplies. In order to achieve an enduring and consistent revenue stream, rebel groups create protection rackets against business actors operating within the area in which the armed conflict takes place. For example, in the Niger Delta region of Nigeria, local rebel groups kidnap corporate employees and release them in exchange for ransom (Ikelegbe, 2006). Revenues obtained through piracy also often end up in rebel pockets (Daxecker and Prins, 2017). Business elites in Somalia are required by local warlords to pay road taxes in addition to periodical payments in exchange for security (Ahmad, 2015). During civil wars in Sierra Leone and Liberia, rebel leaders instructed foot soldiers to forcibly extract revenues from local civilians, which they did through the manning of crucial local and cross-border trade checkpoints (Reno, 1999). All actions occurred in rebel-held territory and allowed rebel groups to pay for food, arms, and shelter to their members.

2.1 Rebel Group Extortion and Looting

Rebel groups have two potential options for obtaining revenue from local enterprises (Shearer, 2000). First, they may extort enterprises by periodically extracting a proportion of their revenue, which incrementally increases their wealth. The rebel group must take care that the extracted amount does not endanger the sustainability of the enterprise; otherwise, it will be left without a continuous revenue stream in the future. The alternative approach is looting, in which the rebel group seizes all of the wealth of an enterprise. This occurs primarily under three conditions. First, the rebel group behaves like a “roving bandit” and simply pillages the enterprise without any desire to control the territory where it is located (in the model, “territory” is meant not as a specific geographic location but in a metaphoric sense). Second, the rebel group punishes and loots enterprises that pay extortion money to an adversary rebel group. Third, a weak rebel group may find itself in fierce competition with a much stronger rebel group. In order to compensate for the strength of its opponent, it may attempt to collect more wealth over a short period of time through repeated looting.

2.2 Enterprise Fleeing

Enterprises have the inherent desire to create wealth and generate income, even under conditions of civil war. However, assuming no military or defensive capabilities of their own, and assuming no official government protection, they rely on protection provided by armed rebel groups. Cooperation with a group may be beneficial. If a rebel group limits its extortion amount to allow continued revenue earnings and growth, an enterprise can sustain itself and even overcome its competitors who incur losses due to insecurity. However, if an enterprise is depleted of its wealth due to looting, it may decide to flee from the armed conflict rather than attempting to rebuild its business, since it might risk further unwanted extraction or threats to physical safety. For instance, Collier and Duponchel (2013) show that during 10 years of civil war in Sierra Leone from 1992 to 2001, businesses shrunk in size.

2.3 Enterprise Reporting

Enterprises may favor one particular rebel group as determined by the fraction of their extorted revenue. A favored group extracts the least amount of money as compared to its rivals. Assuming a purely economic system, we do not consider shared ethnic identity or other aspects of the group's reputation as influential towards an enterprise's preference. Reporting occurs when enterprises within the territory of one rebel group are extorted by a competing group. We base this logic on the experiences of enterprises who are extorted by mafia groups (see Nardin et al., 2016). An Enterprise may choose to report the extortion attempt to its preferred (main) rebel group based on the amount extracted.

2.4 Rebel Group Fighting and Expansion

Fighting is the attempt of rebel groups to achieve hegemony during a civil war and to eliminate competing groups. We summarize the conditions for rebel fighting under three broad assumptions. First, two groups fight due to a competitive desire for power and expansion. Each group has an inherent wish to expand, and the more powerful a group, the more likely that it initiates fighting in order to conquer other groups. Fjelde and Nilsson (2012) have examined the proclivity of rebel groups engaged in armed conflict with one another, showing that larger capability discrepancies result in an increased probability of fighting. Second, rebel groups may wish to extort funds and resources from enterprises already controlled by a rival group. This broadens the economic base of a rebel group and allows it to recruit more soldiers, which in turn renders the group more competitive. The third influencing condition is enterprise reporting. Once extorted, an enterprise may choose to report to its main rebel group, increasing the probability of fighting by revealing strategic information about the group's whereabouts. A group successfully expands when enterprises are reallocated from the losing to the winning rebel group.

2.5 Rebel Group Cooperation

Under conditions of anarchy, rebel groups may counterbalance against one another in order to achieve power parity, seeking to prevent the achievement of hegemony by any one group. Therefore, two weaker rebel groups may combine forces and cooperate against a stronger group. This closely resembles the logic of balance-of-power in International Relations theory (Walt, 1985; Waltz, 1979). We apply this concept to sub-national actors in a civil war. Cooperation between relatively weak groups becomes more likely the higher the power disparity between an attacking rebel group and its targets. We assume only defensive cooperative behavior; groups only join forces in order to defend against attacks from a stronger group, rather than offensive in which multiple groups combine forces in attacking a larger group. We also assume that the costs of fighting incurred by an attacker are dependent on the combined strength of the cooperating target rebel groups, who may be relatively easy or relatively difficult to defeat. The costs inflicted by the attacker are distributed among the cooperating target groups inversely proportional to their strength.

2.6 Rebel Group Recruitment

Over time, a rebel group hires or "recruits" new rebels to increase its size and maintain its fighting capabilities. The exact number of rebel recruits is determined by the following conditions. First, the cost of hiring and retaining recruits must be deducted from the group's overall wealth. Therefore, the amount of wealth determines how many rebels can be hired in the future. Second, rebels are constrained by recruit availability when seeking new hires. We assume a constraint that limits groups from recruiting new members who number more than a certain percentage of their current size. Rebel groups are unlikely to double or triple in size during the relatively short time periods of intermittent recruitment decisions, although they may substantially grow over the longer term. Third, the power disparity between rebel groups determines the rate of recruitment. The larger the power disparity, the slower the larger rebel group grows. Since an increase in group size increases the probability of winning a fight, the severity of damage to the opponent, and the costs of financing, growth experiences a decreasing marginal return. We assume that once a global power ratio of 4:1 is reached (this means that the largest rebel group has four times more rebels compared to the number in opposition), the hegemonic rebel group pauses recruitment. This choice underlines the marginal benefits a rebel group enjoys by growing in size. Reaching a power preponderance of this scale makes any increase in size minuscule as it becomes highly improbable that the remaining rebel groups will overpower the hegemon. Since the civil war is permanent in this model, the hegemon still attempts to expand and will eventually crowd out the remaining rebel groups.

3 Rebel Group Protection Rackets Model

In this section, we describe in detail the Rebel Group Protection Rackets model (Sect. 3.1), introduce the model variables that define a scenario (Sect. 3.2), and briefly describe implementation details of the model (Sect. 3.3).

3.1 Model Description

Based on the assumptions presented above, we conceptualize an agent-based model of protection rackets in a civil war conflict zone inside a weak or failed state.[1]

Here we adopt the Object Event Modeling and Simulation paradigm, which uses the concepts of *object types*, *event types*, and *event rules* for modeling discrete dynamic systems (Wagner, 2018). The objects of the system being modeled may be passive entities or active entities ("agents"), while the events that happen in this system may represent environment events or actions of an agent. Objects and events are classified by object types and event types, which may define type-specific properties (and operations). Event rules represent causal regularities leading to changes in the states of affected objects and to follow-up events.

Figure 1 shows the information design model for the Rebel Group Protection Rackets model, which is composed of two object types, *RebelGroup* and *Enterprise*,

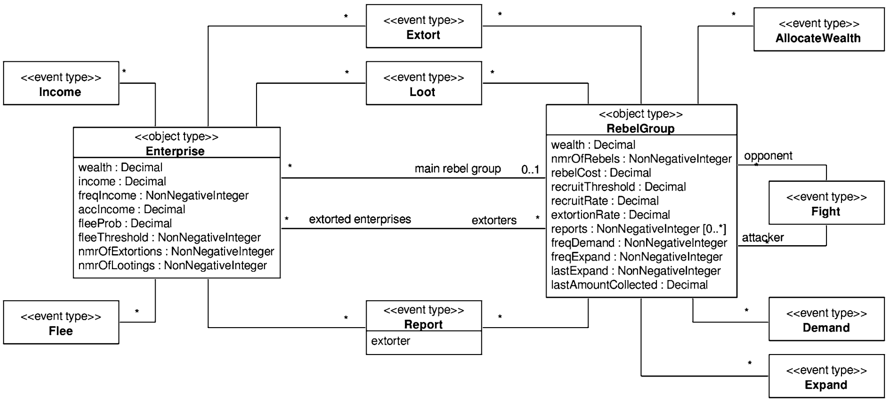

Fig. 1 Information design model for the Rebel Group Protection Rackets model using unified modeling language (UML) class diagram. The * symbol represents association cardinality, e.g., in the `main rebel group` association, one RebelGroup can be the main rebel group of multiple enterprises, but one enterprise can have at most one main rebel group

[1]Notice that this is a stylized fact model; thus, we adopt several simplifications that nevertheless capture the main characteristics of the phenomenon of interest.

and nine event types, *AllocateWealth*, *Demand*, *Expand*, *Extort*, *Fight*, *Flee*, *Income*, *Loot*, and *Report*.

Enterprises represent local businesspersons and liberal professionals who conduct business in a territory that may be under the control of a RebelGroup. Enterprises aim to make enough profit to support their household by avoiding, if possible, the payment of extortion money.

RebelGroups are armed groups that compete among themselves aiming to enlarge their territorial domain[2] by increasing the number of Enterprises under their control. A RebelGroup may have multiple Enterprises under its control (`extorted enterprises`[3] association) and an Enterprise can be under the control of at most one RebelGroup at any moment (`main rebel group` association).

A RebelGroup is composed of a number of rebels (`nmrOfRebels`) that define the size and strength of a RebelGroup. The strength of a RebelGroup can be evaluated in relation to all other RebelGroups (i.e., global strength) or in relation to an opponent RebelGroup (i.e., relative strength). The global strength is calculated as the RebelGroup's number of rebels divided by the total number of rebels of all RebelGroups. The relative strength is calculated as the RebelGroup's number of rebels divided by the sum of rebels of the RebelGroup and its opponent.

RebelGroups and Enterprises interact via a set of events that are generated exogenously (e.g., Demand, Expand, and Income events) or endogenously (e.g., AllocateWealth, Extort, Fight, Flee, Loot, and Report events). *Exogenous* events are recurrently generated based on some defined frequency. *Endogenous* events are caused by some other event. These types of events can be combined to define processes that are composed of an exogenous event acting as process initiator followed by a series of endogenous events. There are three processes in our model: *Income Process*, *Demand Process*, and *Expand Process*.

3.1.1 Income Process

The Income Process is composed of a single exogenous Income event. Each Enterprise is associated with an Income event, which causes the Enterprises to periodically (`freqIncome`) receive an income (`income`) corresponding with their business activities. The income received increases the Enterprise's wealth (`wealth`) and its accumulated income (`accIncome`). The accumulated income represents the revenue received by the Enterprise since the last time it was extorted or looted, and it is used for the calculation of the extortion amount requested by the RebelGroups.

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[2]In the model, "territory" is abstract and it does not mean a specific geographic location.

[3]The Monospace font is used to indicate properties and associations presented in the information design model (Fig. 1).

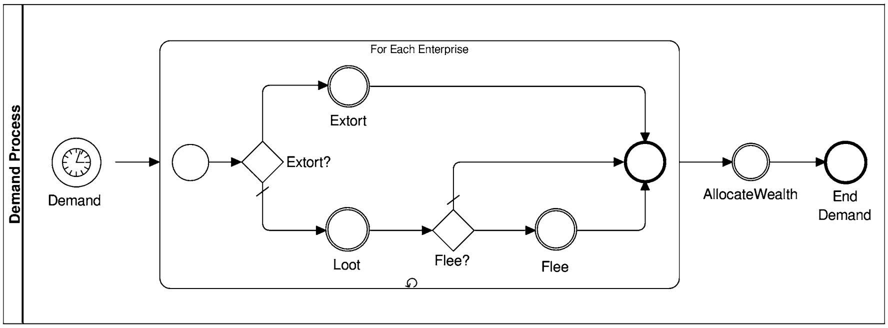

Fig. 2 Diagram illustrating the series of events and their interrelationships in the Demand Process

3.1.2 Demand Process

RebelGroups control portions of the territory and they periodically demand resources from the Enterprises under their control in order to support their fighting efforts.

Figure 2 illustrates the series of events composing the Demand Process that is periodically initiated by the Demand event.

There is one Demand event associated with each RebelGroup, which makes RebelGroups periodically (`freqDemand`) decide whether to extort (Extort event) or loot (Loot event) the Enterprises under their control. The decision whether to extort or loot is individually made by the RebelGroup for each Enterprise, but all Enterprises under the RebelGroup's control are extorted or looted at the same time. The individual decision whether to extort or loot is probabilistically based on the RebelGroup's global strength. Thus, weaker RebelGroups have a greater probability of looting the Enterprises under their control than stronger RebelGroups due to the greater pressure on the former to extract resources quickly to increase in size and become more competitive.

If deciding to extort (Extortion event), RebelGroups request a fraction (`extortionRate`) of the Enterprises' accumulated income (`accIncome`) as extortion payment. Enterprises pay the lesser between the demanded amount and their wealth. This amount is transferred from the Enterprise to the RebelGroup. Thus, RebelGroups increase their wealth (`wealth`) and the value of the last amount collected (`lastAmountCollected`) accordingly, and Enterprises decrease their wealth (`wealth`) by the amount of extortion money paid, reset their accumulated income (`accIncome`) to zero, and increase their number of extortions by one (`nmrOfExtortions`).

When looting occurs (Loot event), Enterprises transfer their total amount of wealth to a RebelGroup. Thus, RebelGroups increase their wealth (`wealth`) and the value of the last amount collected (`lastAmountCollected`) accordingly, and Enterprises reset both their wealth (`wealth`) and accumulated income (`accIncome`) to zero, and increase by one their number of lootings (`nmrOfLootings`). Due to looting, however, an Enterprise may flee (i.e., leave the simulation) with a certain probability (`fleeProb`) or if the number of previous endured lootings is greater than a certain threshold (`fleeThreshold`). If an Enterprise decides to flee (Flee event), the Enterprise is removed from the list of extorted Enterprises and from the simulation.

After all demands are complete, RebelGroups reallocate their resources (AllocateWealth event). First, RebelGroups compensate their rebels, but if they do not have enough wealth to compensate all of them, they reduce their number of rebels by the difference between the wealth and the total compensation divided by the cost per rebel (`rebelCost`).

Additionally, the RebelGroup may recruit or expel rebels if the amount collected since the last wealth allocation was less than the amount necessary to compensate the rebels. The number of rebels recruited (nmrRecruit) or expelled (nmrExpel) by a RebelGroup is defined by

$$\begin{aligned}
\text{delta} &= \frac{\text{lastAmountCollected} - (\text{nmrOfRebels} \times \text{rebelCost})}{\text{rebelCost}}, \\
\text{nmrRecruit} &= \min\left(\text{delta} \times (1 - \text{globalStrength}), \text{nmrOfRebels} \times \text{recruitRate}\right), \\
\text{nmrExpel} &= \min\left(\text{nmrOfRebels}, \text{delta}\right).
\end{aligned}$$

3.1.3 Expand Process

RebelGroups intrinsically try expanding their territorial control over new Enterprises by fighting other RebelGroups or simply extracting resources from these Enterprises.

Figure 3 illustrates the series of events comprising the Expand Process that is periodically initiated by the Expand event.

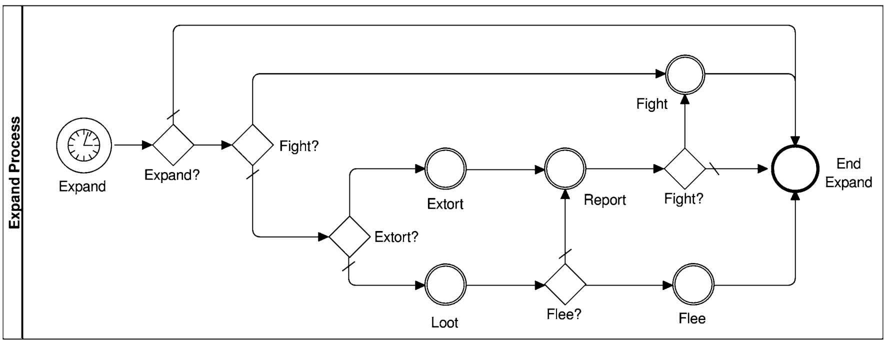

Fig. 3 Diagram illustrating the series of events and their interrelationships in the Expand Process

There is one Expand event associated with each RebelGroup, which makes RebelGroups periodically (`freqExpand`) choose to expand territory if they have rebels and there are still Enterprises not under their control. The expansion decision also depends on a RebelGroup's global strength and the elapsed time since its last expansion. Stronger RebelGroups have greater opportunity to expand their domain, yet weak RebelGroups increase their chance of expanding as time elapses. Thus, the probability of a RebelGroup deciding to expand is defined by

$$\text{expandProb}\,(\alpha, t, t_{\text{last}}) = \frac{1}{1 + e^{-\alpha(t - t_{\text{last}})}},$$

where α is the RebelGroup's global strength, t is the current time, and t_{last} is the last time the RebelGroup expanded (`lastExpansion`).

If the RebelGroup decides to expand, then it evaluates all Enterprises not under its control and chooses one Enterprise randomly with a probability inversely proportional to the Enterprise's wealth (i.e., poorer Enterprises are chosen with greater probability). If the chosen Enterprise is already under the control of another RebelGroup, the expanding RebelGroup decides whether to fight against the Enterprise's main RebelGroup or to simply extort or loot the Enterprise. The probability of a RebelGroup deciding to fight is defined by

$$\text{fightExpandProb}\,(\beta) = \frac{1}{1 + e^{-\beta}},$$

where β is the RebelGroup's relative strength with the main RebelGroup of the Enterprise adjusted to the scale $[-1, 1]$ using the function $f(x) = 2x - 1$.

The decision to fight is unilaterally made by the attacking RebelGroup (Fight event). However, if the opponent is weaker than the attacker, it may form an alliance with another RebelGroup with a probability equal to the difference between the attacker's global strength and its own. If the opponent decides to form an alliance, the alliance is formed with the first randomly chosen other RebelGroup that generates an alliance stronger (sum of both RebelGroups' global strength forming the alliance) than the attacker. If the constraint is not fulfilled with any other RebelGroup, no opposition alliance is formed.

The attacker and its opponent (a single RebelGroup or an alliance) are then categorized based on their global strength as the *strong* and the *weak* RebelGroups. The strong RebelGroup has a probability of winning the fight equal to the relative strength between itself and the weak RebelGroup. If the strong RebelGroup does not win the fight, the weak RebelGroup has a probability of winning the fight equal to the relative strength between itself and the strong RebelGroup.

The fight winner receives a specific number of Enterprises from the loser. These Enterprises are chosen randomly among the loser's list of extorted Enterprises. If the winner or loser is an alliance, then the distribution of Enterprises is determined using the inverse of the relative strengths between the allied RebelGroups.

In a fight, both the attacker and opponent (RebelGroup or formed alliance) suffer losses of rebel numbers. The loss is proportional to the relative strength of the opposing RebelGroup or alliance. The loss among RebelGroups forming an alliance is inversely proportional to their relative strength.

However, if the RebelGroup does not fight to expand, then the RebelGroup decides whether to extort or loot the chosen Enterprise with probability equal to its global strength.

Enterprises extorted by a different RebelGroup than their main RebelGroup always report the action of the former to the latter (Report event). Looted Enterprises, however, decide whether to report or flee.

If a RebelGroup is notified that another RebelGroup is extracting resources from Enterprises under its control, then it decides whether to fight the invader with a probability defined by

$$\text{fightReportProb}\,(\beta, x) = \frac{1}{1 + e^{-\beta x}},$$

where β is the RebelGroups' relative strength adjusted to the scale $[-1, 1]$, and x is the number of reports that the RebelGroup has already received about the invader (`reports`). In the case of a fight, the RebelGroups interact as previously described and the number of reports associated with the invader RebelGroup is reset to zero.

All RebelGroups' decisions to expand and fight are probabilistic and defined based on the sigmoid function of the form $f(x) = \frac{1}{1+e^{-x}}$, where x combines multiple factors relevant to the decision being made. The choice for this function was motivated by (1) its boundedness to the range [0,1]; thus, the result can be directly applied to make a probabilistic decision, and (2) its S-shaped curve that grants a smooth decision transition between extremes, yet it has an initial lag period of slow growth and an end period of reduced growth-rate.

3.2 Scenario and Initialization

A *simulation scenario*, also simply called *scenario*, specifies the initial objects, the initial events, and the initial values of model variables briefly described in Table 1.

An *experiment* is defined on top of a simulation scenario by modifying one or more variable settings according to the definitions of the experiment's parameters. In the initialization of the simulation scenario, the specified number of RebelGroups and Enterprises are created and their properties are initialized using the corresponding model variables value defined in the scenario. Exceptions are those properties that (1) depend on calculations like the RebelGroup's `wealth`, which is set to the number of rebels multiplied by the cost per rebel (`nmrOfRebels` * RG Rebel Cost), and (2) depend on model variables defined as probability distributions like RebelGroup's `freqDemand` and `freqExpand`, and Enterprise's `freqIncome` and `income`, which are set with a number drawn from their respective model variable distribution settings.

Table 1 Model variables defining a scenario

Model variable	Description
Simulation End Time	Length of the simulation run
Random Seed	Random generator's seed
Number Enterprises	Number of Enterprises
Income[b]	Enterprise's income
Income Frequency[c]	Frequency Enterprises receive income
Flee Probability[c]	Probability for looted Enterprises to flee
Flee Threshold[c]	Number of loots Enterprises endure before fleeing
Number Rebel Groups	Number of Rebel Groups
RG Size[a]	Initial number of rebels per Rebel Group
RG Prop. Enterprises[a]	Proportion of the initial number of Enterprises per Rebel Group
RG Extortion Rate[a]	Proportion of the Enterprise's accumulated income to extort
RG Rebel Cost[a]	Cost per rebel
RG Recruit Threshold[a]	Threshold of the Rebel Groups' strength to stop recruiting
RG Recruit Rate[a]	Maximum size increase per wealth reallocation
RG Demand Frequency[a, b]	Frequency Rebel Groups decide racketeering Enterprises
RG Expand Frequency[a, b]	Frequency Rebel Groups decide expanding
Fight Expansion	Number of Enterprises transferred from loser to winner of fight

[a]List with the same number of elements as the *Number Rebel Groups*
[b]Value is the mean and standard deviation defining a normal distribution
[c]Value is the minimum and maximum values of a uniform distribution

3.3 Implementation

We implement our model using the JavaScript-based Object Event Simulation framework OESjs,[4] which is an open-source web-based simulation platform that allows publishing simulation models on the Web and running them in any modern web browser (Wagner, 2017). The Rebel Group Protection Rackets simulation is available online at https://gnardin.github.io/RebelGroups and the source-code is available at https://github.com/gnardin/RebelGroups/releases v1.0.

4 Experiments

This section describes and examines two kinds of civil war experiments, one hypothetical related to security factors (Sect. 4.1) and another resembling the conditions of Somalia since 1992 (Sect. 4.2).

[4]More information about OESjs is available at https://sim4edu.com.

4.1 Security Experiments

We conduct experiments aimed at explaining the dynamics of rebel fighting, their impacts on the economy, and the importance of rebel groups' economic bases of support to their sustainability in the context of a civil war. In particular, we analyze how security factors influence the dynamics of a civil war by varying the initial strength (Sect. 4.1.1) and initial allocation of Enterprises (Sect. 4.1.2).

The hypothetical scenarios in these experiments use combinations of parameter values that represent real-world inter-rebel group configurations. These scenarios are based on 3-actor settings in which three different rebel groups strive for hegemony. Each experiment scenario varies just one parameter value in relation to the baseline, whose values are shown in Table 2. These values were chosen for demonstration purposes with the exception of rebel costs, for which there exists research on the upper and lower boundaries of rebel group expenses as explained in the following paragraphs.

To estimate rebel costs, we neglect the start-up costs of rebel groups and focus only on maintenance costs. Wennmann (2009) calculates different cost ranges depending on the intensity of the conflict. We use present-day Somalia as an example of medium-intensity conflict and apply Wennmann's estimations accordingly. The estimated cost to recruit 1000 rebels ranges between US$2.5 million and US$16.2 million. Al-Shabaab, the current primary militant organization in Somalia, numbered between 7000 and 9000 rebels in 2014 (BBC News, 2017). Because weapon supplies and maintenance costs are relatively inexpensive in this case, we can estimate maintenance costs as US$3.5 million per year. Thus, one rebel should cost US$291 per 30-day period.[5]

Table 2 Baseline input parameter values to the experimental scenarios

Parameter	Value
Simulation End Time	365
Number Enterprises	3000
Income	(200,50)[b]
Income Frequency	1
Flee Probability	50%
Flee Threshold	3

Parameter	Value
Number Rebel Groups	3
RG Size[a]	300
RG Prop. Enterprises[a]	33%
RG Extortion Rate[a]	10%
RG Rebel Cost[a]	US$291
RG Recruit Threshold[a]	80%
RG Recruit Rate[a]	50%
RG Demand Frequency[a]	(30,2)[b]
RG Expand Frequency[a]	(30,2)[b]
Fight Expansion	50

[a]List with number of elements equal to the *Number Rebel Groups* with all element values the same
[b]Mean and standard deviation defining a normal distribution

[5]In the future, these values may be modified to match other empirical cases.

All experiment scenarios are replicated 100 times,[6] each replication using one different random seed. All experiment scenarios use the same ordered set of random seeds. Specifying the random seed permits obtaining the same results as presented in this study, as otherwise probabilistic processes result in deviations.

The analyses of the experiment scenarios are based on a set of output variables: Number of Extortions, Number of Lootings, Number of Expansions, Number of Alliances, Number of Expansion Reports, Number of Fled Enterprises, Number of Recruitments, Number of Rebel Expels, and Number of Rebel Deaths. The results are calculated as the mean and standard deviation of the results of the 100 replications performed for each experiment scenario. Subsequently, we use the Wilcox Rank-Sum test (see Wilcoxon, 1945) to identify whether the change in scenario configurations entails statistically significant effects on the output variables. We chose the Wilcox Rank-Sum test because we cannot assume that the output values are normally distributed.

4.1.1 Rebel Group Strength

The first experiment evaluates the influence of different initial power distributions among Rebel Groups, ranging from an equally balanced to a more hierarchical setting. The experiment is composed of three scenarios that differ in the initial number of rebels of each Rebel Group (see RG Strength in Table 3). In scenario

Table 3 Results (mean and standard deviation) of the Rebel Group Strength experiment that varies the initial power distributions among Rebel Groups, ranging from an equally balanced (RGS1), to one powerful Rebel Group (RGS2) to a more hierarchical setting (RGS3)

	Rebel group strength (RGS) experiment scenarios		
	RGS1	RGS2	RGS3
RG Strength[a]	[300, 300, 300]	[300, 150, 150]	[300, 150, 75]
Number of Extortions	3651 ± 1108.21	3821 ± 1406.26	4043 ± 1337.99
Number of Looting	5122 ± 203.76	5108 ± 230.18	5086 ± 233.04
Number of Expansions	19 ± 4.02	19 ± 3.89	19 ± 4.53
Number of Alliances	0.05 ± 0.22	0.08 ± 0.27	0.1 ± 0.3
Number of Fights	9.8 ± 2.32	9.55 ± 2.17	9.62 ± 2.58
Number of Expansion Reports	6.45 ± 2.95	6.64 ± 2.60	6.27 ± 2.72
Number of Fled Enterprises	2851 ± 127.63	2842 ± 149.19	2823 ± 148.75
Number of Recruitments	2197 ± 908.77	1574 ± 687.67	1413 ± 567.98
Number of Rebel Expels	634 ± 531.22	407 ± 408.46	356 ± 384.31
Number of Rebel Deaths	2199 ± 619	1531 ± 477.43	1329 ± 419.18

[a]Values define the *RG Size* for Rebel Groups 1, 2, and 3, respectively

[6]We also conducted the experiments with 1000 simulations but the results remained almost identical.

RGS1, Rebel Groups have equal strength, measured by the number of rebels associated with them. In scenario RGS2, one Rebel Group has twice the strength of each of the other Rebel Groups. Finally, scenario RGS3 invokes a stricter hierarchy between the Rebel Groups in which the strongest Rebel Group is twice as strong as the second strongest, and the second strongest is twice as strong as the weakest. The selection of these configurations is theoretically motivated, providing insight on the impacts of changes in the variation of individual parameters.

The results suggest that Rebel Group size exerts varying impacts on security and economic outcomes. The number of alliances and fights remain almost identical in all three scenarios and do not significantly differ across the different scenarios. However, recruitment rates are highest for the equal distribution scenario (RGS1), which indicates that power competition is most intense when no Rebel Group dominates from the outset. The Wilcox Rank test is statistically significant for both comparisons RGS1 and RGS2 ($p < 0.01$) and RGS1 and RGS3 ($p < 0.01$). The number of expelled rebels follows the same trend and is also statistically significant for both comparisons ($p < 0.01$). Expelling occurs when the costs of maintaining a large dominant force are too high to bear and capturing enterprises from opponent rebel groups does not pay for its maintenance. Due to fewer recruitments in the hierarchical scenarios (RGS2 and RGS3), the expel numbers fall. Further, the average death rates in the various scenarios differ by a wide margin of almost 1000 fewer deaths in the RGS3 scenario compared with RGS1 ($p < 0.01$). The high intensity of power competition in the first scenario translates into fights with more fighters and hence more fatalities. This is reminiscent of currently ongoing civil wars in Libya or Syria in which the involved rebel group sizes are sufficiently high to perpetuate and intensify the respective civil wars. Lastly, expansion rates do not differ and remain constant at 19 expansion events on average for each scenario, indicating that similar relative strength differences are reached in all different configurations after a short period of time. By contrast, extortion increases and looting decreases in more unequal scenarios but the results are statistically inconclusive.

4.1.2 Enterprise Allocation

This experiment evaluates the effects of different initial allocations of Enterprises among Rebel Groups, from a balanced to a more unbalanced distribution (see Allocation Proportions in Table 4). This experiment is composed of three scenarios in which we vary the initial number of Enterprises under the Rebel Groups' control. In scenario EA1, each Rebel Group starts with approximately the same number of Enterprises. In scenario EA2, Rebel Group 1 has twice as many Enterprises than the other two Rebel Groups. Finally, in scenario EA3, Rebel Group 1 initially has control over almost two-thirds of all Enterprises, while the Rebel Group 2 and Rebel Group 3 have initially thirty and 10% of Enterprises under their control, respectively.

Table 4 Results (mean and standard deviation) of the Enterprise Allocation experiment that varies the initial allocations of Enterprises among Rebel Groups, from a balanced (EA1) to a powerful Rebel Group (EA2) to a more unbalanced and hierarchical distribution (EA3)

	Enterprise allocation (EA) experiment scenarios		
	EA1	EA2	EA3
Allocation Proportions[a]	[34%, 33%, 33%]	[50%, 25%, 25%]	[60%, 30%, 10%]
Number of Extortions	3651 ± 1108.21	3466 ± 1052.23	3836 ± 1239.10
Number of Looting	5122 ± 203.76	5163 ± 169.03	5124 ± 180.96
Number of Expansions	19 ± 4.02	20 ± 3.97	19 ± 3.36
Number of Alliances	0.05 ± 0.22	0.05 ± 0.22	0.04 ± 0.20
Number of Fights	9.8 ± 2.32	9.82 ± 2.39	9.54 ± 2.24
Number of Expansion Reports	6.45 ± 2.95	6.72 ± 2.85	6.21 ± 2.17
Number of Fled Enterprises	2851 ± 127.63	2874 ± 108.96	2852 ± 123.22
Number of Recruitments	2197 ± 908.77	2037 ± 783.10	1714 ± 810.87
Number of Rebel Expels	635 ± 531.22	623 ± 545.54	575 ± 471.30
Number of Rebel Deaths	2199 ± 619	2084 ± 519.54	1793 ± 502.07

[a]Values define the *RG Prop. Enterprises* for Rebel Groups 1, 2, and 3, respectively

The results show that the variation in the output for extortions, recruitments, and deaths is statistically significant in the comparison between EA2 and EA3 ($p < 0.05$) (see Table 4). Since EA1 is not statistically different to each scenario (EA2 and EA3), the argument that there can be a trend discerned in the distribution of enterprises cannot be corroborated. Instead, EA3 appears to constitute an idiosyncratic scenario which reports the lowest deaths and recruitment rates due to its highly unequal access to revenues for rebels. The skewed allocation of enterprises between the different rebel groups put the weakest rebel group at such a disadvantage that fights are less intensive with lower casualty rates. In turn, this does not translate in fiercer competition between the more affluent rebel groups as evident by the low number of recruitments. Having a weak rebel group from the outset changes the dynamics of a civil war by reducing the expected average death toll compared to conditions in which revenue collection is sufficient for each rebel group to engage in active violent competition. From corporate perspective, this scenario (EA3) is most desirable compared to the other two scenarios as higher extortion rates are tantamount to longer survival during the civil war (which is not equal to survive the entire civil war as fleeing rates are very similar).

4.2 *Somalia Case Study*

We now consider the dynamics of a case that resembles the Rebel Group configuration of a historical example: the civil war conditions of Somalia since 1992. Somalia is an applicable case due to its relative level of anarchy since the collapse of a longstanding dictatorship (Leeson, 2007; Powell et al., 2008).

4.2.1 Historical Background

Somalia was led by dictator Mohammed Siad Barre until the Somali Civil War in 1991, in which popular dissatisfaction with Barre's regime resulted in his overthrow. As a result of longstanding interclan tensions that Barre had fueled in his attempt to maintain his grip on power, the country exploded into multiple factions competing among one another for power and spoils. This led to a humanitarian disaster, prompting interventions by the United Nations and the USA (Baumann et al., 2004). However, by that time many militarized groups had proliferated and established bases of support in different areas of the country. The northern region of the country consolidated under the umbrella government of Somaliland, and the southern capital of Mogadishu collapsed into disarray (Leeson, 2007; Powell et al., 2008).

Many organizations emerged in the southern competition for power, some of the most prominent including the United Somali Congress/Somali Salvation Alliance (USC/SSA), the United Somali Congress/Somali National Alliance (USC/SNA), the Southern Somali National Movement (SSNM), the United Somali Party (USP), the Somali National Front (SNF), the Somali Asal Muki Organization (SAMO), the Somali Patriotic Movement (SPM), and the Somali National Union (SNU) (Baumann et al., 2004). Other small, religious-based militias also emerged, alongside local clan militias. Following the attack on U.S. Army personnel during a raid against militia leader General Mohamed Farah Aideed of the USC/SNA that killed nineteen US soldiers, the USA withdrew its troops and numerous attempts by the international community to broker peace subsequently failed (Baumann et al., 2004).

While the northern provisional government of Somaliland presided over a shaky peace, the rest of Somalia remained mired in overall instability and virtual anarchy (Leeson, 2007; Powell et al., 2008). In 2006 the Islamic Courts Union (ICU) managed to consolidate control over most of southern Somalia and implement Sharia law, unifying much of the country and establishing a degree of security. However, opposition organizations aligned with the transitional government challenged the ICU and fought with the support of the USA and Ethiopia, ultimately leading to ICU's withdrawal and defeat. Radical elements of the organization splintered off, forming new militant organizations such as the al-Qaeda-linked al-Shabaab. A new coalition Federal Government of Somalia (FGS) was formed with the support of foreign states, but this government has continually struggled against attacks by al-Shabaab, which holds substantial territory and at one point even controlled the capital city of Mogadishu (Ahmad, 2015).

With the help of international military support, al-Shabaab's territory has been significantly reduced since 2012, yet it regularly carries out bombings and makes grabs for territory. Violence also continues to occur between rival clans and subclans, and other armed militia groups. Due to the ongoing conflict, much if not most of the country lives under relative anarchy of federal or local government control. These conditions make Somalia a prime case for modeling economic opportunism in an atmosphere of insecurity. Al-Shabaab engages in extortionist activity against local businesses in order to finance its war-making activities, and it uses its violent attacks to threaten, intimidate, and punish civilians in order to continue this extortion (Ahmad, 2015). As a result, civilians often flee to neighboring countries, creating a continual refugee crisis. Al-Shabaab also engages in sophisticated information campaigns to recruit new fighters, facilitating its expansion and continual battles against the Western and Ethiopia-backed government.

4.2.2 Data and Experimentation

We perform an experiment simulating three scenarios that each represents one of the three different stages in Somalia's conflict: first, a system with nine Rebel Groups of the same size and characteristics, in equal competition for power; second, a system with nine Rebel Groups but with varying sizes and extortion populations; and third, a system with one primary strong Rebel Group among many much smaller groups. The values used in the model are based on published estimations of group size and extortion of local populations, as well as other rebel and demographic characteristics (Abbink, 2009; Clarke, 1992; UNFPA, 2016). Each experiment scenario varies the RG Size and RG Prop. Enterprises values, while all other values are fixed as shown in Table 5.

All experiment scenarios are replicated 100 times, each replication using one different random seed. The analyses of the experiment scenarios are based on a set of output variables whose values are calculated as the mean and standard deviation of the results of the 100 replications performed for each experiment scenario.

The first scenario (SO1) represents the period immediately following the collapse of the Barre regime, in which multiple groups increased in size and capability in the fight against Barre but had not yet dominated one another. The values for all 9 Rebel

Table 5 Somalia baseline input parameter values to the experimental scenarios

Parameter	Value
Simulation End Time	365
Number Enterprises	3000
Income	(200,50)[b]
Income Frequency	1
Flee Probability	50%
Flee Threshold	3

Parameter	Value
Number Rebel Groups	9
RG Extortion Rate[a]	10%
RG Rebel Cost[a]	US$291
RG Recruit Threshold[a]	80%
RG Recruit Rate[a]	50%
RG Demand Frequency[a]	(30,2)[b]
RG Expand Frequency[a]	(30,2)[b]
Fight Expansion	1

[a]List with number of elements equal to the *Number Rebel Groups* with all element values the same
[b]Mean and standard deviation defining a normal distribution

Group sizes are 500, and 11% for all proportion of Enterprises. The second scenario (SO2) represents the conditions approximately 1 year later once different groups began to compete with one another. The USC/SSA and the USC/SNA emerged as the two primary rival organizations, while the others maintained smaller niches in the fight as well. Here, the first two Rebel Groups have a size of 500 members, while the remaining are comprised of only 200 members. The proportion of Enterprises per Rebel Group are as follows: 18%, 18%, 1%, 14%, 4%, 6%, 14%, 13%, and 3%. These values are determined by the population distributions of the clans that each group claims to represent (Baumann et al., 2004). This assumes that the Rebel Groups each extort only from within their own clans.

The third scenario (SO3 and SO3*) represents a post-ICU Somalia in which al-Shabaab is the primary extortionist Rebel Group, while many other small clan-based militias also compete locally for power. In this case, one Rebel Group is a size of 7000, and the others are all a size of 200, in order to represent the approximate empirical proportionality of different group sizes. The proportion of Enterprises for the first group is 50%, and the remaining are each 6.25%.

The results shown in Table 6 indicate most clearly that observers should expect more extortion to have taken place as power in Somalia became consolidated by a fewer number of groups. This is consistent with our theory that without peer competition, rebel groups are most likely to establish a stable and widespread racket system. In addition to increased extortion, consolidation should also lead to a decrease in other violent activity such as looting and fighting. Although we observe slight decreases in looting and fights across our experiments, these trends are not

Table 6 Experiment results of the Somalia case study

	Somalia (SO) experiment scenarios			
	SO1	SO2	SO3	SO3*
Group sizes and proportions	All equal	Two stronger	One Hegemon	One Hegemon
Number of Extortions	641 ± 32.98	862 ± 75.44	1776 ± 128.64	2958 ± 913.72
Number of Looting	5257 ± 46.05	5256 ± 45	5259 ± 45.36	5178 ± 130.12
Number of Expansions	49 ± 4.45	47 ± 4.07	49 ± 4.18	47 ± 6.96
Number of Alliances	0.68 ± 0.75	0.58 ± 0.70	0.67 ± 0.78	0.43 ± 0.78
Number of Fights	24 ± 4.30	25 ± 4	23 ± 4.04	24 ± 3.99
Number of Expansion Reports	14 ± 4.01	13 ± 3.53	15 ± 3	13 ± 3.84
Number of Fled Enterprises	2999 ± 1.03	2996 ± 5.95	2999 ± 5.03	2938 ± 92.49
Number of Recruitments	2395 ± 307.05	2481 ± 438.79	1497 ± 186.73	6172 ± 1021.36
Number of Rebel Expels	3233 ± 560.02	1778 ± 370.18	8253 ± 343.35	8431 ± 722.15
Number of Rebel Deaths	3660 ± 458.63	3096 ± 379.91	1841 ± 291.42	6008 ± 773.53

SO1 represents the period immediately following the collapse of the Barre's regime. SO2 represents the conditions approximately 1 year later once different groups began to compete with one another. SO3 represents a post-ICU Somalia in which al-Shabaab is the primary extortionist Rebel Group, while many other small clan-based militias also compete locally for power. SO3* is similar than SO3, except that it represents the presence of substantial outside funding comprising about 80% of Rebel Group's revenue significant due to large standard deviation values. We would otherwise expect that, due to the high number of relatively weak groups in scenario SO1, every group should have an incentive to increase its power quickly and primarily loot rather than extort. We observe a very low level of alliances in any of the scenarios, possibly due to high plurality of competition. Overall, these results support our expectations that a greater level of extortion is reached once one group has achieved hegemony, but adjustments to the model may be necessary to lower standard deviations such that other expected patterns become more significant.

A notable pattern emerges during scenario SO3 in which the largest group quickly shrinks in size, with its number of fighters becoming more similar to that of its competitors. Extortion profits are insufficient to continue allocating pay to the proportionally high number of fighters used to represent al-Shabaab in this experiment. Therefore, after only a short period of time, the large group is unable to sustain itself. It does not remain a hegemon, possibly causing an unexpectedly high number of observed incidents of looting, fighting, and fled Enterprises in SO3. This may also be the cause of high numbers of rebel expels and rebel deaths. In reality, a dominant group like al-Shabaab receives a substantial portion of its income from external sources, such as foreign remittances and overseas benefactors (Keatinge, 2014). It also engages in its own trade and business practices in order to raise revenue. These sources of income, which likely enable al-Shabaab to sustain its large number of fighters and widespread activities, are not accounted for in our model.

Therefore, we perform a second simulation of the third scenario (SO3*) in which all parameters remain the same as in SO3, except in order to represent the presence of substantial outside funding comprising about 80% of revenue, we lower the cost per rebel fighter for the hegemon from US$291 to US$50.[7] Our results in SO3* show even greater extortion activity in a system with other revenue sources; the number of extortions is significantly higher than those in the first three scenarios. The number of lootings and fleeing Enterprises is slightly lower, but these results fall within the margin of error and are not statistically significant. Further, the number of fights and the number of Rebel deaths do not decrease as expected in a system with greater stability and control under one hegemon. The model captures greater financial stability, but not greater securitization. These results are consistent with theories that external funding to rebel groups actually increases violence levels and conflict severity (Fearon, 2004; Weinstein, 2006). This impact would therefore counteract economic benefits and explain the lack of decrease in looting, fighting, and deaths.

Data from the Uppsala Conflict Data Program (UCDP) show the highest numbers of civilian and combatant deaths in Somalia at the height of its collapse into civil war in 1991 and 1992 (Croicu and Sundberg, 2017; Sundberg and Melander, 2013). Conflict during this time period, in which a multitude of rebel groups competed among themselves for power, resulted in a critically higher number of refugees

[7] 80% is a rough approximation used to represent outside funding as a substantially larger source of income than extorted funds.

fleeing looting and violence at the beginning of the war than later on (Leeson, 2007; Powell et al., 2008). After 2008, once the Islamic Courts Union (ICU) achieved a monopoly of control over most areas of the country, violence ceased. However, fighting shortly resumed at a lower but consistent level as foreign-backed groups rose to oppose its power and al-Shabaab emerged, using violence to try to reestablish order and intimidate its enemies. Since its inception the group managed to maintain a steady extortion racket in areas under its control (Keatinge, 2014), which is consistent with the results of our model. Although the results do not capture the significant decrease in violence and fleeing from early levels, they do represent how extortion increases with consolidation of power over time.

Our results are also limited in that they provide no insight into the stability or security of the internal practices of a hegemonic group. For example, despite a monopoly on extortion and violence by al-Shabaab in many communities of Somalia, the violent practices exercised by the internationally condemned terrorist organization such as intimidation for extracting extortion, strict policing and law enforcement that utilizes corporal punishment, and acts of terrorism result in an overall instability for civilian residents. Further, their monopoly on power is inconsistent, and clashes rise and fall in frequency as al-Shabaab loses and regains control of territory. Hegemonic control therefore does not necessarily equate to overall improvement in stability and security. However, our model does demonstrate some of the immediate effects of political contestation between different numbers of groups in civil war.

5 Conclusion and Discussion

The experiments using our agent-based simulation model indicate that unequal power distribution between rebel groups leads to less fighting, less rebel recruitment, and lower death rates in a civil war. Unequal enterprise allocation similarly affects extortion, with the highest incidence rate when one hegemon overwhelmingly dominates. Ultimately, wars with unequal power distributions may be more likely to end faster, with fewer fatalities. This finding supports existing research on the effects of rebel group strength parity, which may impede conflict termination due to miscalculations and bargaining failures (Humphreys, 2005, p. 504). It contradicts, however, findings that parity could lead to earlier termination due to the prolonged costs of a stalemate (Zartman, 2000). We also find that a more hegemonic system results in greater economic stability. This does not necessarily result in greater security, as demonstrated by the Somalia case study. Other factors such as external funding of rebel groups and the brutality of their internal practices may cause violent activity despite consolidation of extortion practices.

Our agent-based model provides an important methodological supplement to existing studies of conflict that use quantitative statistical analyses and qualitative case studies. As civil wars are highly complex dynamic systems, the evaluation of individual parameters and their impacts on civil wars must be understood and investigated against the backdrop of continually changing environments. The simulation experiments provide us with expectations for the trajectories of conflicts, depending on various economic and security conditions. The inclusion of probabilistic functions allows us to account for random variation or error that could capture the unpredictability of real-world events. We encourage interested readers to explore various initial settings to develop an understanding of civil war dynamics based on the assumptions laid out in this study (executable at https://gnardin.github.io/RebelGroups).

Future adjustments to the model could include incorporating external influences such as foreign military intervention or outside sources of rebel funding. The difference in results between scenarios SO3 and SO3* in the Somalia experiment demonstrates the potential significance of this addition. Another potential improvement could be the inclusion of spatial data. The model currently does not account for "space" or "territory," which are instead represented through the allocation of Enterprises. Spatial data could be used to place restrictions on Rebel Groups' directions of expansion and initiate balancing. Lastly, since the programming code remains open-source, interested readers can engage in modifications and alter our assumptions. For instance, event types like fighting or expansions can be modified to reflect different understandings of these behaviors. New event types can be created that are not included in the model (e.g., intervention or the provision of foreign aid). Parameters can also be thought to represent rebel group characteristics. For instance, religious and ideologically based rebel groups like Al-Shabaab might have higher expansion rates compared to ethnic based rebel groups in Somaliland.

Apart from its scientific contributions to the field of conflict studies, agent-based models of civil wars have the strong potential to contribute to informed policy-making by allowing users to predict the range of possible ways in which a civil war can evolve. Their usefulness is dependent on successful gathering of data to reflect realistic conditions as closely as possible. It could potentially serve as a useful tool for political decision-making, as model results may provide clues for the expected intensity of wars and their possible impacts on local economies in conflict countries. For instance, an adjusted model that takes foreign influences into account could attempt to simulate the potential outcomes of a currently looming civil war in Venezuela. Using information on the strength of potential rebel groups based on the opposition as well as specifying additional autonomous actors like the army and local groups (colectivos) would allow one to simulate the impact of decisions like the provision of military aid to either group on ongoing civil war dynamics.

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Online Material

This appendix provides a summary of the online material that is made available together with the research conducted in this volume. Interested readers are invited to explore this additional material, to use it to replicate the findings presented in this book, and to adjust it for their own research purposes. Below, we provide a brief description and a link to the respective website (usually a GitHub repository) for each chapter for which such material is available.

Chapter 2: Inventory of Conflict Data

A list of datasets of conflict events and links to the websites where they can be obtained can be found at the end of the chapter "Advances in Data on Conflict and Dissent."

Chapter 4: R-Package *Relational Event Models*

Laurence Brandenberger's R-package for relational event models (REM) can be used to calculate endogenous network effects in event sequences and fit REMs. Using network event sequences (where each tie between a sender and a target in a network is time-stamped), REMs can measure how networks form and evolve over time. Endogenous patterns such as popularity effects, inertia, similarities, cycles, or triads can be calculated and analyzed with the package.

Link: https://github.com/brandenberger/rem

E. Deutschmann et al. (eds.), *Computational Conflict Research*,
Computational Social Sciences, https://doi.org/10.1007/978-3-030-29333-8

Chapter 5: Supplementary Material and Replication Files to *Migration Framing in Political Discourse*

Supplementary materials, replication code, and links to the relevant datasets used in the chapter "Migration Policy Framing in Political Discourse: Evidence from Canada and the USA".

Link: https://github.com/tamos/ValuesInText

Chapter 6: Agent-Based Simulation Model *Simulating Normative Conflict*

The agent-based model developed by Julian Kohne et al. in the chapter "The Role of Network Structure and Initial Group Norm Distributions in Norm Conflict" for simulating norm conflicts in R is available for download on GitHub under the MIT license. The repository includes the necessary functions and documentation to run your own simulation either on a local machine or on an MPI-cluster using SLURM as a workload manager. The online documentation provides an example for running a basic simulation locally and showcases its output graphically.

Link: https://github.com/JuKo007/SimulatingNormativeConflict

Chapter 7: Agent-Based Simulation Model *ProtestFate*

A NetLogo model for the coevolution of protest activation and topic selection online and in the streets authored by Jan Lorenz, Ahmadreza Asgharpourmasouleh, Masoud Fattahzadeh, and Daniel Mayerhoffer.

Link: https://doi.org/10.5281/zenodo.3243818

Chapter 8: Agent-Based Simulation Model *Non-State Armed Groups' Attack Timing*

A NetLogo model that explores the timing and frequency of attacks as the strength of ties between non-state armed groups (NSAGs) varies. Code to statistically analyze empirical attack data with a multivariate Hawkes process and the resulting network of ties between NSAGs.

Link: https://github.com/adamrpah/BIGSSS-Terror

Chapter 9: Replication Code to *On the Beaten Path*

Replication code and links to relevant datasets.
Link: https://github.com/AndrSalvi/onthebeatenpath

Chapter 10: Replication Code to *Analysis of Conflict Diffusion over Continuous Space*

Replication code and links to relevant datasets.
Link: https://github.com/ckelling/conflict_diffusion

Chapter 11: Agent-Based Simulation Model *Rebel Group Protection Rackets*

The agent-based simulation model *Rebel Group Protection Rackets* attempts to capture the decision-making and behavior of the involved actors during protection racket interactions as well as the cooperation and competition between rebel groups to control territory. The model reveals insights about the mechanisms that are helpful for understanding violence outcomes in civil wars, and the conditions that may lead rebel groups to prevail. Analysis of various scenarios demonstrates the impact that different security factors play on civil war dynamics.

Source-code Link: https://github.com/gnardin/RebelGroups
Online Simulation Link: https://gnardin.github.io/RebelGroups

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E. Deutschmann et al. (eds.), *Computational Conflict Research*,
Computational Social Sciences, https://doi.org/10.1007/978-3-030-29333-8