博士論文（要約）

Process, Termination, and Outcome:
A Spatial Analysis of the Causes and Consequences of Violence in Civil Conflicts
(過程，終結，結果：
内戦における暴力の原因と帰結の空間分析)

伊藤　岳

Process, Termination, and Outcome: A Spatial Analysis of the Causes and Consequences of Violence in Civil Conflicts

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Gaku Ito

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Contribution Report

The chapters in Parts II and IV are solely the work of the author. The chapters in Parts I and III are principally the work of the author but include pieces of work conducted in collaboration with Kaisa Hinkkainen (University of Leeds; Chapter 6) and Susumu Yamakage (Aoyama Gakuin University; Chapter 2).

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In memory of my beloved father, grandfathers, and grandmother,
all of whom would have been happy to see me in my steps as
a fellow political scientist.

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Abstract

Civil conflict has been a dominant form of organized violence in human history that can result in massive destruction of the economy, society, and human lives. Besides the causes of initial onset, understanding and preventing civil conflict requires explanation of its two-fold variations. First, violence in civil war varies in the frequency and manner of how it is applied even within single conflicts. Why do the frequency and manner of civil war violence vary across subnational localities? What determines where and how violence occurs in civil conflicts? Second, history tells us that the duration and outcomes vary across civil conflicts. What shapes the duration and outcome of civil conflicts? More importantly, do the micro-level dynamics of battle activities alter conflict duration and outcome at the macro level?

This dissertation investigates these twofold questions at the micro- or subnational-level *causes* and macro- or country-level *consequences* of violence in civil conflicts. Taking the contributions of previous studies as the point of departure, this dissertation departs from the oft-employed single-level approach, which has focused on either micro- or macro-level determinants of the variations observed within civil conflicts. The first part of the empirical analysis in this dissertation explores the micro-level causes of civil war violence. Specifically, it aims to disentangle the impacts of two main classes of determinants of civil war violence found in the previous literature —— the first class includes the set of static factors that are mostly exogenous to conflict dynamics, and the second includes the dynamic factors that are largely endogenous to conflict process. The computational model incorporated with precisely geo-referenced data demonstrates the importance of endogenous diffusion dynamics in determining where and how violence unfolds during civil conflicts. Diffusion dynamics matter in improving our capability to explain and predict insurgent violence, but they matter relatively more in explaining selective violence and less in predicting collective or indiscriminate violence.

The second part of the empirical analysis examines the macro-level consequences of civil war violence by analyzing how the micro-level dynamics of violence translate into the macro-level variations of civil war duration and outcome. Building upon the bargaining model of war, the current study explores the associations between micro-level conflict dynamics and macro-level variations in conflict termination. The two chapters in the second part of the analysis posit that the spatio-temporal dynamics of violence that occur during conflict substantially influence when and how civil conflict ends by altering the severity of the underlying bargaining problems. The core argument is that the relative importance of diffusion dynamics depends on *how* battles diffuse rather than *whether* battles diffuse because different diffusion dynamics affect the expectations and underlying power balance between disputants differently. The empirical results provide strong support for the theoretical claim: while diffusion of battle activities across distant localities substantially lowers the likelihood of conflict termination regardless of outcome types, battle diffusion within proximate localities matters less in altering the prospects for domestic peace.

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Part I

Questions, Argument, and Research Design

CHAPTER 1

Introduction

Violence is not a quantitative degree of conflict but a qualitative form of conflict, with its own dynamics.

Rogers Brubaker and David D. Laitin (1998, 426)

Civil conflict has been a dominant form of organized violence in human history and can result in massive destruction of the economy, society, and human lives. Besides the causes of initial onset, understanding and preventing civil conflict requires explaining its two-fold variations. First, violence in civil war varies in the frequency and manner with which it is applied, even within single conflicts (Kalyvas, 2006). Why do the frequency and forms of civil war violence vary across subnational localities in single conflicts? What determines where and how violence occurs during civil conflicts? Second, history tells us that the duration and outcomes vary across civil conflicts (DeRouen and Sobek, 2004; Kreutz, 2010). Some civil conflicts terminate within months, while others last for years. Some conflicts end through political bargaining, while others end in decisive military victory. Still other conflicts terminate without seeing clear outcomes. What determines the duration and outcome of civil conflicts? More importantly, do the micro-level dynamics of battles significantly influence conflict duration and outcome at the macro level? This dissertation investigates these twofold questions in terms of the micro- or subnational-level *causes* and macro- or country-level *consequences* of violence in civil conflicts. Rather than examining the factors that trigger the initial onset of civil conflicts (e.g., Collier and Hoeffler, 2004; Fearon and Laitin, 2003), this dissertation explores the dynamics of civil conflicts by examining the determinants of violent activities and their cumulative impacts on civil war termination.

Any scholarly attempt to answer these micro- and macro-level questions requires theoretical and methodological unification of oft-divided levels of analysis. Students of civil war often study the micro- and macro-level dynamics of civil conflicts in isolation (Balcells and Justino, 2014; Balcells and Kalyvas, 2014; Sambanis, 2004a).[1] Micro-level studies typically investigate the local dynamics of civil war violence without examining their potential impacts on eventual conflict duration and outcome. Similarly, macro-level research often focuses on structural factors such as rough terrain and the existence of natural resources, while rarely exploring the role that micro-level battle dynamics play in determining when and how civil conflict ends. In other words, the insights into micro-level conflict dynamics have rarely been connected to the macro-level variations in conflict duration and outcome in the literature (Balcells and Justino, 2014; Balcells and Kalyvas, 2014).

[1] As in the study of interstate conflict (e.g., Singer, 1961; Waltz, 1959), civil war study sees three major levels of analysis: micro level, meso level, and macro level (Balcells and Justino, 2014; Balcells and Kalyvas, 2014; Christia, 2012; Justino, Brück, and Verwimp, 2013; Kalyvas, 2006; Roessler, 2011, 2016; Schutte, 2015). Typically, at the micro level, researchers study the interactions between warring parties and civilians and the determinants of subnational variations within civil war violence (e.g., Downes, 2008; Kalyvas, 2006; Weinstein, 2007). At the macro level, in contrast, researchers mainly study the causes and mechanisms of conflict onset, termination, and outcome rather than the microdynamics of violence (e.g., Collier, Hoeffler, and Söderbom, 2004; Fearon, 2004; Fearon and Laitin, 2003). At the meso level, researchers primarily study the interconnectedness between the conflict dynamics at the micro and macro levels (e.g., Balcells and Kalyvas, 2014; Roessler, 2011, 2016; Ruhe, 2015; Wood and Kathman, 2014). This dissertation focuses on the causes of civil war violence at the micro level and its macro-level consequences through the meso-level interactions between warring parties.

The current study aims to fill this gap by answering these micro- *and* macro-level questions about civil war dynamics within a unified framework. The key argument is twofold and stresses the substantial but conditional role of endogenous determinants of civil war violence. First, endogenous or dynamic factors such as recent history of violence, as well as exogenous or structural factors such as physical geography, matter in determining micro-level battle dynamics and macro-level conflict duration and outcome. The second claim is that the relative importance of the dynamic factors varies depending on the nature of the violence, or the manner in which it is perpetrated.

At the micro level, drawing upon the data-driven computational modeling and local-level data of civil war violence, this dissertation disentangles the impacts of endogenous and exogenous factors on civil war violence. Empirical evidence shows how the incorporation of endogenous factors helps us to explain and predict the locations of insurgent violence, and how the relative importance of endogenous factors varies depending on the forms of violence (i.e., selective or indiscriminate violence). At the macro level, with the help of local-level records of violence in dozens of civil conflicts, this dissertation explores the impacts of the spatio-temporal diffusion dynamics of battles on civil war termination. The empirical results demonstrate that while the mere geographical expansion or shrinkage of conflict zones may not have a significant impact on conflict duration and outcomes, the diffusion of battle events across distant locations strongly prolongs civil conflicts regardless of outcome types.

As discussed in detail below, this dissertation provides important theoretical and empirical insights into civil war study by exploring the micro-level causes and macro-level consequences of violence. Violent activities are by definition the primary component of civil and other forms of armed conflict. Disentangling the determinants and mechanisms of violence is of critical importance to explain civil war dynamics. Exchanges of violence can also alter when and how civil conflicts end, by, for example, revealing previously unavailable information and thereby affecting the severity of the underlying bargaining problem that caused the initial onset of inefficient conflict. Any study of civil war termination would remain incomplete at best without exploring these dynamic determinants of conflict duration and outcomes (Balcells and Kalyvas, 2014).

The rest of this chapter briefly reviews the scholarly backgrounds of this study, followed by a summary of the main argument and empirical findings. It then discusses the several key contributions of this dissertation and outlines the structure of the following chapters.

1.1 Background and Subject of Research

A noteworthy aspect of the earlier generation of civil war studies is their focus on the structural or static determinants of civil conflict at the country level. Indeed, initial and widely-cited studies on the determinants of conflict onset (e.g., Collier and Hoeffler, 1998, 2004; Fearon and Laitin, 2003) and conflict duration (e.g., Collier, Hoeffler, and Söderbom, 2004; Fearon, 2004) have explored the role of structural and country-level factors such as state power, economic development, and natural resources, which are largely exogenous to conflict dynamics.[2]

In contrast, the past decade has witnessed a notable growth in scholarly investigation into the micro-level determinants and mechanisms of civil war onset, duration, and outcome. This "micro-level" turn to disaggregate civil conflicts includes both theoretical and empirical moves (Cederman and Vogt, 2017; Gleditsch, Metternich, and Ruggeri, 2014; Ito, 2015; Kalyvas, 2005, 2008, 2012; O'Loughlin and Raleigh, 2008; Weidmann, 2014). Theoretically, civil war researchers have moved toward the specification of the microfoundation of civil war, reflecting a desire to improve the specifi-

[2]For the determinants of durability of peace after civil war termination, see, for example, Downes (2004); Doyle and Sambanis (2006); Findley (2013); Fortna (2004a,b, 2008); Licklider (1995); Mattes and Savun (2009, 2010); Toft (2010a,b); Walter (2002). See Blattman and Miguel (2010); Bleaney and Dimico (2011); Cederman and Vogt (2017); Dixon (2009); Fortna and Howard (2008); Hegre and Sambanis (2006); Hoeffler (2012); Kalyvas (2007); Salehyan and Thyne (2012); Sambanis (2002, 2004b) for an extensive review of civil war study.

cation of the causal mechanisms underlying statistical correlations (Kalyvas and Kocher, 2009, 335-336).[3] Empirically, scholars have increasingly explored subnational variations of civil war violence rather than the aggregated onset or termination of civil war at the national level.

Initial scholarly attempts to explore the micro- or local-level dynamics of civil conflicts have similarly focused on the role that such exogenous factors play during civil conflicts. Buhaug and Gates (2002) and Buhaug and Rød (2006) are among the pioneering empirical studies to explore the local determinants of violence, and both stress the role of geographic factors in shaping conflict geography. Buhaug and Gates (2002) find that geographic factors such as the total land area of the country, adjacency to international borders, and the incidence of natural resources substantially shape the scope of conflict-affected zones and the location of battles. Buhaug and Rød (2006) similarly explore the role of physical geography and demonstrate that the local risk of civil war battles varies depending on the disputed issue. For example, their empirical assessment suggests that the battle activities in territorial conflicts tend to occur in remote and sparsely populated regions, while the battles in governmental conflicts are more likely to occur in densely populated areas near the capital cities (see also, Deininger, 2003).

In contrast, Kalyvas (2006) stresses the role of territorial control exercised by warring parties in shaping the levels and forms of violence applied during civil conflicts. Warring parties employ selective violence in zones of dominant but incomplete territorial control to foster civilian collaboration while deterring support for their opponents. In contrast, the frequency of indiscriminate violence is expected to be inversely related to the level of territorial control. This type of violence, due to the lack of intelligence to discriminate collaborators of the opponents from innocent civilians, tends to be perpetrated where armed groups have very limited levels of territorial control.[4]

[3] See, for example, Donnay and Bhavnani (2016), Gleditsch and Weidmann (2012), Ito (2015), and Weidmann (2014) for an overview of available datasets.

[4] Selective violence refers to violence applied conditional on the past behavior of the

At the macro level, a small but growing body of literature has increasingly explored the determinants of intra-war bargaining in civil conflicts in recent years. Focusing on the local-level dynamics of battle activities, recent studies have demonstrated that battle intensity (Ruhe, 2015), battle locations (Greig, 2015; Greig, Mason, and Hamner, 2016; Ruhe, 2015), civilian victimization (Wood and Kathman, 2014), and acts of terrorism (Fortna, 2015; Thomas, 2014) each invariably influence duration and outcome of civil conflicts.

For example, Greig (2015) argues that the relative locations and movements of battles toward strategic locations such as capital cities reveal previously unavailable information to warring parties and thereby influence their willingness to participate in war-ending diplomacy. Empirical associations show that the locations, movement, and dispersion of battles influence the onset and outcomes of peace talks. Ruhe (2015) also emphasizes the role of battle locations in altering the chances of mediation onset. Intense battle activities are viewed as costly by warring parties only when they occur at locations at intermediate distances from national capitals and thereby alter the chances of mediation success. This is primarily because such geographical battle locations indicate that the situation is at a stalemate rather than that either side is gaining the upper hand over the other. Empirical records follow the theoretical expectation: increasing conflict intensity lowers the probability of mediation acceptance when battles occur in locations close to or very far from the capital, whilst the same increase in conflict intensity is followed by a substantial increase in the probability of mediation acceptance when fighting occurs at intermediate distances from the capital.

targets and is typically observed as violence targeted at collaborators of the opponent. In indiscriminate violence or "reprisals," on the other hand, personalized targeting in selective violence is replaced by collective targeting, typically based on ethnic group affiliation and settled localities, and such instances of violence are often observed as intentional civilian abuse by warring parties during civil conflicts (Kalyvas, 2006). See Steele (2009) and Souleimanov and Siroky (2016) for alternative typologies of violence. See Chapter 4 for a more detailed discussion on this topic. Also note that by "types" of violence, we primarily refer to the selectivity or conditionality of violence on the individual behavior of the targets (Kalyvas, 2006).

The aspects that remain under-examined in the existing literature are twofold, and are amongst the main interests and contributions of this dissertation. At the micro level, the relative importance of each class of candidate determinants remains under-studied. Existing studies tell us that both exogenous and endogenous factors may shape how violence unfolds in civil conflicts, but we know little about how and to what extent each factor helps us to explain and predict civil war violence. Similarly, previous studies tell us little about how and why the relative importance of each class of factors varies depending on the types of violence applied.

At the macro level, the possible impacts of the spatio-temporal dynamics of violence on conflict termination remain under-investigated. Previous studies have explored the role that geographic location and severity of violence and military strategies play in determining when and how civil conflicts end. Yet, one may reasonably wonder whether the spatio-temporal diffusion dynamics of battles may also substantially shape conflict termination, as such dynamics may, for example, reveal previously unavailable information and alter the underlying power balance between belligerents.

Given these critical discrepancies in the current literature, this dissertation explores the causes and consequences of violence, with particular interest in the endogenous logic of civil war violence. It does so by presenting two separate series of empirical analyses, one tackling the question of causes of violence and the other answering the question of the consequences of violence.

1.2 Argument and Main Findings

As noted above, the core argument of this dissertation is two-fold. First, endogenous or dynamic factors such as recent history of violence, as well as structural factors such as physical geography, matter in determining micro-level battle dynamics and macro-level conflict termination. Second, the relative importance of the dynamic factors varies depending on the nature of the violence, or the manner in which it is applied, both in terms of the causes and consequences of violence. It evaluates these claims with the helpf of disaggregated records of civil war violence.

Figure 1.1 uses a path diagram to illustrate the four possible causal pathways through which exogenous and endogenous factors impact the micro-level conflict process and macro-level conflict duration and outcome. A traditional and oft-employed country-year research design that focuses on the role of structural factors is indicated by arrow (1) in Figure 1.1 (e.g., Collier and Hoeffler, 2004; Fearon and Laitin, 2003). Arrow (2) represents the scope of the analysis in the micro-level research on the role of the exogenous causes of civil war violence (e.g., Buhaug and Gates, 2002; Buhaug and Rød, 2006). Arrows (3) and (4) indicate the causal links through which past battle dynamics shape future trajectories of civil war violence at the micro level (arrow 3) and the eventual course of the conflict at the macro level (arrow 4). With the help of data-driven computational simulations and military database of civil war violence in Afghanistan, Chapters 3 and 4 in Part II investigate arrow (3). Utilizing the disaggregated records of wartime violence in dozens of civil conflicts, Chapters 5 and 6 in Part III explore arrow (4) while carefully controlling for the impacts of structural factors on conflict process and termination (arrows 1 and 2) in order to guard against the possible omitted variable bias.[5]

Note that this dissertation is a cumulative collection of several separate studies, with the four empirical chapters consisting of three single-

[5]Note that the focus here is on the causes and consequences of endogenous factors, rather than the effects of exogenous factors. The circumstances in which controlling for endogenous factors when evaluating the effect of exogenous factors on conflict duration and outcome (arrow 1) is advisable include the following: (1) when a post-treatment (concomitant) variable (e.g., conflict process) is a reasonable proxy for relevant but unobserved pre-treatment variables (e.g., rebel characteristics and strategies), or (2) when there remains a substantial imbalance between the treated and control groups with respect to a post-treatment variable even after controlling for pre-treatment variables (Rosenbaum, 1984). Apparently, this illustration corresponds to the classical discussion on the post-treatment variable bias. See Rosenbaum (1984) for a methodological discussion. See, for example, Balcells and Kalyvas (2014) for a focused discussion on the "technologies of rebellion," or the micro-level strategies of conflicts and potential biases induced by the omission of such factors when exploring civil war duration and outcomes.

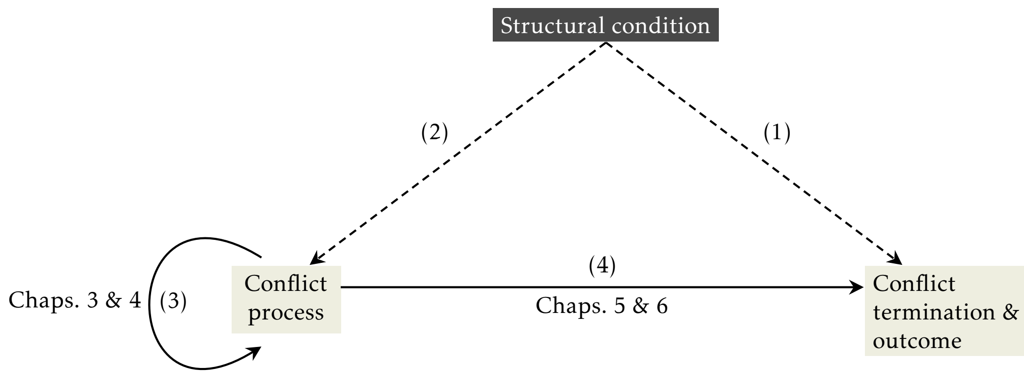

Figure 1.1: Path diagram of the relationships

Notes: Each arrow represents a possible causal relationship between (1) structural conditions and conflict duration and outcome, (2) structural conditions and the conflict process, (3) dynamic factors and the conflict process, and (4) dynamic factors and conflict duration and outcome. Chapters 3 and 4 of this dissertation investigate arrow (3), while Chapters 5 and 6 explore arrow (4).

authored and one co-authored manuscript.[6] The rest of this section provides a brief overview of the backgrounds and main findings of the relevant chapters. Focused reviews of existing studies and scholarly and policy implications are presented in individual chapters.

1.2.1 On the Micro-Level Causes of Violence

The first part of the empirical analysis in this dissertation aims to disentangle the impacts of two main classes of determinants of civil war violence established by the previous literature. The first class includes the set of static factors that are mostly exogenous to conflict dynamics, and the second includes the dynamic factors that are largely endogenous to the dynamics of battles (Braithwaite and Johnson, 2015; Buhaug and Gleditsch, 2008; Schutte and Weidmann, 2011). Building upon these insights of recent micro-level literature, the first two empirical chapters explore

[6]Chapters 3 to 5 are single-authored studies, while Chapter 6 is an edited version of a manuscript coauthored with Kaisa Hinkkainen. Also note that parts of Chapter 2 include three published works, two single-authored and one published articles coauthored with Susumu Yamakage (Ito, 2013, 2015; Ito and Yamakage, 2015).

the relative importance of the endogenous and exogenous determinants of civil war violence.

Modeling the determinants of insurgent violence (Chapter 3) What remains relatively under-investigated in the literature is the relative importance of each class of candidate determinant of civil war violence. There is now a near consensus within conflict research that not only civil conflicts but also violence within individual conflicts cluster in space (e.g., Linke, Witmer, and O'Loughlin, 2012; O'Loughlin and Witmer, 2012; Townsley, Johnson, and Ratcliffe, 2008). While these spatial footprints of violence serve as an important empirical foundation for investigating the drivers of insurgent behavior, there are no largely agreed-upon explanations for the underlying micro-mechanisms.

Among the predominant propositions, two major approaches can be distinguished in the previous literature (Braithwaite and Johnson, 2015; Buhaug and Gleditsch, 2008; Schutte and Weidmann, 2011). The first camp suggests that clusters of insurgent violence stem from the spatial distribution of static, violence-attracting factors such as population size and geographic conditions. The second camp, on the other hand, argues that endogenous conflict dynamics as well as exogenous factors shape the specific course of insurgent violence; the occurrence of violence alters the prospects of future violence.

At first glance, as the first camp advances, the spatial clustering of violence seems to be the product of contagion or diffusion processes. Intuitively, one may reasonably argue that insurgent violence clusters because the activities are spatially and/or temporally contagious. Put another way, the subnational risks of violence are determined not only by slow-moving structural conditions that are largely exogenous to conflict (e.g., rough terrain) but also the faster-moving and endogenous, contagion-like nature of insurgent activities.

The answer is not apparent, however, because empirical records are also consistent with noncontagious mechanism: clusters of insurgent violence need not stem from diffusion at all but can result from heterogeneity in the intrinsic tendency of subnational localities to attract insurgent activities. Clusters of insurgent violence may simply mirror similar distributions of structural covariates, rather than diffusion dynamics.

Although these two mechanisms are conceptually and theoretically distinct, the question of whether and how these two mechanisms impact insurgent behavior remains contested. Perhaps the most fundamental problem is that their expressions in empirical data are often observationally indistinguishable. This methodological challenge makes it extremely difficult to identify the micro-level mechanisms underlying the observed patterns, even when fine-grained micro-level data are available. One might argue that these two mechanisms together shape insurgent behavior. While intuitively appealing at first glance, this explanation would provide little information about the conflict process without a systematic assessment of the relative importance of each mechanism in altering insurgent violence.

Chapter 3 employs the innovative computational modeling approach incorporated with empirical data to disentangle these two mechanisms. The main findings are twofold. First, the computational experiments reveal that while ethnic geography is a leading structural predictor of insurgent violence, a specific type of diffusion process, in which the occurrence of violence in a locality facilitates the geographic spread of insurgents, systematically influences how insurgent violence unfolds. This diffusion pattern is largely consistent with the intra-war bargaining and mobilization incentives of insurgents. Second, the model yields a fair predictive performance and reveals that the incorporation of diffusion dynamics, rather than a standard set of structural correlates of violence, improves predictive performance. This result not only indicates that the model correctly captures the primary drivers of insurgent violence, but also underscores the substantive impacts of the endogenous diffusion dynamics on the conflict process. The flip-side of this finding is that some well-known correlates of civil-war violence may not always have substantive predictive power.

Decomposing the determinants of insurgent violence (Chapter 4) Paying closer attention to the types of violence applied by warring parties, Chapter 4 extends the analysis in the previous chapter to explore the logic of violence in civil conflicts. Chapter 4 argues and demonstrates that the relative importance of endogenous and exogenous determinants depends on the types of violence applied. In recent years, civil war research has increasingly explored the impacts that levels of territorial control (e.g., Kalyvas, 2006), battlefield dynamics, and recent history of violence (e.g., Hultman, 2007; Wood, 2014a), competition among rebel groups (e.g., Wood and Kathman, 2015), organizational configurations of warring actors (e.g., Humphreys and Weinstein, 2006; Weinstein, 2007), relative reliance on local and external sources of support (e.g., Salehyan, Siroky, and Wood, 2014; Zhukov, 2017), and ethnic and physical geography (e.g., Fjelde and Hultman, 2014; Schutte, 2017) each have on the types, locations, and severity of violence perpetrated during civil conflicts. These candidate determinants of civil war violence can be thought of as representing a continuum, with purely exogenous or static factors on the one extreme and purely endogenous or dynamic factors on the other.

Building upon these insights, Chapter 4 presents and tests a nuanced argument: exogenous factors play an important role in predicting indiscriminate violence, because (1) this type of violence is primarily motivated by damage-maximizing incentives, and (2) the locations where warring parties can maximize the pain on their opponents are largely determined by exogenous factors. Consistent with this line of reasoning, the Taliban's spokesman Zabihullah Mujahid, stressing the success of their activities, recently expressed that the suicide attack in Kabul demonstrated that the Taliban "can even attack the parliament in the capital."[7] Strategically important locations such as capital cities are often predetermined, and attacks in these localities satisfy rebels' damage-maximizing incentives.

By way of contrast, endogenous factors matter in determining the locations of selective violence, because (1) the availability of information

[7]Quoted in "2 dead, 31 wounded as Taliban attack Afghanistan parliament." *Fox News*, June 22, 2015. Available at: http://www.foxnews.com/world/2015/06/22/taliban-attack-afghanistan-parliament-with-bombs-gun-fight-ongoing.html, accessed June 30, 2015.

needed to apply violence selectively is largely a function of the levels of territorial control exercised by the warring parties (Kalyvas, 2006), and (2) the use of violence itself contributes to changes in territorial control. Chapter 4 tests this argument with a parsimonious agent-based model incorporated with precisely geo-referenced data from Afghanistan.

1.2.2 On the Macro-Level Consequences of Violence

Micro-level dynamics, macro-level variations, and the bargaining model of war Civil conflicts exhibit substantial variations in how long they last and how they end, as well as how they are fought. As illustrated above, the first part of the empirical analysis focuses on the behavior and decision-making of combatants and troops on the ground to explore the micro-level dynamics of civil conflicts. In contrast, the second part of the analysis departs from the single-level perspective to examine how the costly conflict processes "scale-up" and affect conflict termination (cf. Cederman and Vogt, 2017; Kalyvas, 2012).

Exploring the micro-macro associations requires us to examine the dynamics of intra-war bargaining in the shadow of costly battles. Chapters 5 and 6 build upon the bargaining model of war to explore the associations between micro-level conflict dynamics and macro-level variations of conflict termination. These two chapters posit that the spatio-temporal dynamics of violence that take place during conflict substantially influence when and how civil conflict ends by altering the severity of the underlying bargaining problems.[8]

[8] One might see a discrepancy between the conceptualization of "actors" in the first and second parts of this dissertation. While the former part models the conflict process as a product of the decentralized behavior of multiple actors, the latter focuses on the bargaining process between two relatively centralized warring factions. Yet, these approaches do not necessarily contradict each other given the empirical records of civil conflicts —— local rebel activities are often organized and guided by local commanders and "governors," while bargaining between warring factions almost always involves rebel leaders at the negotiation table. For example, the command-and-control structure of the Taliban can be characterized by a hierarchy led by the central leadership, while tactical-level commanders and district governors often play a critical role in the Taliban's activities at the village and district levels (Johnson and DuPee, 2012, 85–86). The local-level Taliban

Given that war is *ex post* inefficient as it imposes otherwise unnecessary costs on the warring parties, there always exists a bargaining range that can make both sides better off than dividing the disputed good through fighting (Powell, 2006, 177). For example, if both disputants "knew that the attacker could conquer a small piece of territory," as Reiter (2003) argues, then "they would peacefully exchange the territory rather than fight" without paying the otherwise unnecessary costs of fighting (31).

In some situations, however, the disputants fail to reach efficient pre-war agreements due to asymmetric information about, for example, the distribution of power and likely outcome of war, combined with incentives to misrepresent private information (information problem, Blainey, 1988; Fearon, 1995). Pre-war bargaining may also fail when at least one disputant cannot credibly commit not to renege on a pre-war agreement, in the absence of a central enforcement mechanism, due to, for example, a large and rapid shift in the underlying power balance (commitment problem, Fearon, 1998; Powell, 1996, 1999, 2004b, 2006, 2012).[9]

Even after pre-war bargaining breaks down, presumably no rational warring party has the strategic incentive to continue with inefficient fighting once the original bargaining problem has been resolved. In this sense, if the conflict onset comprises a bargaining *failure* caused by a commitment or information problem (Fearon, 1995), then the continuation of the conflict is a bargaining *process* that ends when the original bargaining problem has been resolved through costly use of force (Blainey, 1988; Filson and Werner, 2002; Reiter, 2003, 2009; Schelling, 1966; Wagner, 2000). The perspective of war as a bargaining process can be traced back to the in-

activities are typically organized by tactical-level commanders who lead a *dilgai* (local cadre) or *mahaz* (front), with approximately 10–20 fighters (Johnson, 2013, 8–9; Johnson and DuPee, 2012, 81–82). While the micro-level analysis in this dissertation models the rebels' local-level activities, the macro-level analysis explores the intra-war bargaining at the higher leadership level, reflecting on the local-level battlefield dynamics.

[9] Although many of the bargaining models of war focus on either information or commitment problems, Wolford, Reiter, and Carrubba (2011) proposed a bargaining model that incorporates both credible commitment problem and informational asymmetry (see also, Reiter, 2009).

sights of Schelling (1966, 7, emphasis added):

> War appears to be, or threatens to be, not so much a contest of strength as one of endurance, nerve, obstinacy, and pain. It appears to be, and threatens to be, not so much a contest of military strength as a *bargaining process*——dirty, extortionate, and often quite reluctant bargaining on one side or both——nevertheless a bargaining process.

The bargaining model of war initiation asks why pre-war bargaining breaks down into inefficient fighting; while the bargaining model of war termination asks how inefficient fighting resolves the underlying bargaining problem. As Reiter (2003, 27, emphasis added) briefly articulates,

> [t]he bargaining model of war [termination] sees *war as politics* all the way down. . . . States use both war and words as bargaining tools to help them achieve optimal allocations of goods. Critically, the bargaining model does not see war as the breakdown of diplomacy but rather as a *continuation of bargaining*, as negotiations occur during war, and *war ends when a deal is struck*.

Indeed, it was in this sense that Prussian general Carl von Clausewitz (1832/1989) once described war as the "continuation of politics by other means" (87).

Building upon this theoretical perspective, Chapters 5 and 6 see civil conflict as a costly bargaining process and argue that battle diffusion matters in altering the chances of conflict termination as it influences belligerents' incentive to continue with inefficient fighting. For example, where informational asymmetry causes the pre-war bargaining to break down into mutually-inefficient conflict, the central role of combat activities arguably comprises a reduction in the uncertainty of information (Blainey, 1988; Filson and Werner, 2002; Powell, 2004a; Reiter, 2003; Slantchev, 2003b; see also, Langlois and Langlois, 2009; Slantchev, 2004). Similarly, the credible-commitment account of war suggests that although there generally exists a bargaining range that both disputants prefer over costly fighting, war-avoiding or war-ending bargaining may fail if such agreements are not enforceable due to the temptations of one or more disputants to renege on prior agreements (Fearon, 1995, 2004; Powell, 2004b, 2006, 2012).

Costly conflict can itself contribute to conflict termination as it alters the severity of the underlying bargaining problems. The diffusion of battle activities, a largely non-manipulable product of the underlying capability and resolve of warring parties, reveals previously unavailable information while contributing to fluctuations in the underlying balance of power between disputants. These diffusion dynamics in turn alter the conflict duration, since these information-revealing and fluctuation effects ease or exacerbate the two primary bargaining problems —— informational asymmetry and credible commitment problem —— that cause the pre-war bargaining breakdown and need to be resolved to stop inefficient fighting.

Violence diffusion shapes when civil conflict ends (Chapter 5) The empirical analysis in Chapter 5 yields two main findings: the *distant* diffusion of battle activities (diffusion of battles across geographically distant locations) substantially lowers the likelihood of conflict termination, whereas the effect of *proximate* diffusion (diffusion of battles across geographically contiguous areas) remains indeterminate. Additionally, the expansion or shrinkage of conflict-affected zones themselves have little impact on the chances of conflict termination. Put differently, the empirical analysis indicates that it is not *whether* or not battle activities diffuse, but *how* battles diffuse that matters in influencing the underlying bargaining problems and prospects for domestic peace.

Theoretically, Chapter 5 argues that diffusion of battle activities matters in determining conflict termination by altering the severity of the underlying bargaining problems. Successful rebel campaigns across a wide geographical range can effectively inflict damages on the incumbent and its supporters, thereby undermining popular confidence in the state's capacity (Hultman, 2009; Kydd and Walter, 2006; Thomas, 2014). Such battlefield dynamics, while revealing previously unavailable information, contribute to fluctuations in the government's capability and bargaining position and thereby exacerbate the commitment problem. Reflecting on battlefield outcomes, the temporarily weakened government may commit to giving concessions to the rebels that reflect its deteriorating bargaining position in these instances. The same government, however, cannot credibly commit to the agreement because, once fighting stops, it will likely regain its capability, primarily due to the disarmament and demobilization of rebel forces (Fearon, 2004; Walter, 1997). In the post-conflict period, the government would face strong temptations to exploit its enhanced bargaining position and renege on the prior policy concessions. Given that "nothing stops it from overturning or undermining the arrangements" in the absence of enforcement mechanisms, the common knowledge that the shock is temporary renders the government's commitments not to renege incredible (Fearon, 2004, 290, 294).

Indeed, the disarmament of rebel forces is often cited by the incumbent as the necessary condition for negotiations, even when its capability fluctuates due to battlefield outcomes. For example, although the Shiite Houthi rebels now control the capital and much of the north, former Yemeni Foreign Minister Riad Yassin recently expressed that

> [t]he Houthis and (former President Ali Abdullah) Saleh's militias must implement the UN resolution and *surrender their weapons*, and *only then* the dialogue and political process can begin, with the participation of all Yemeni parties (Stuster, 2015, emphasis added).

Aware of this likely future pathway, the rebels are likely, at best, to be unwilling to accept a negotiated settlement over the disputed goods, which in turn can cause intra-war bargaining to break down into a continuation of inefficient fighting. In other words, the rebels are likely to be less, rather than more, willing to agree to stop fighting when they are more successful in the battlefield because the more temporarily powerful rebels are, the larger the expected size of the post-conflict power shift and rebels' fear of such a shift becomes. Just as the fear of the weak causes the onset of civil war (Fearon, 1998), rebels' fear of a post-conflict power shift, even with their currently enhanced bargaining position, in turn impedes mutually-efficient war-ending agreements.

Violence diffusion shapes how civil conflict ends (Chapter 6) Chapter 6 extends the analysis in the previous chapter to explore the empirical relationships between spatio-temporal battle dynamics and the specific outcomes of civil conflicts. The analysis presented in this chapter demonstrates that the escalating diffusion of combat activities across distant locations lowers the likelihood of conflict termination with *both* rebel-favorable (i.e., negotiated settlement and rebel victory) *and* government-favorable conflict outcomes (i.e., low activity and government victory) for different reasons.[10]

The escalating diffusion of violence across geographically distant locations lowers the likelihood that a civil conflict will end in a rebel-favorable outcome due to the rebels' fear and reluctance to accept negotiation offers from the incumbent. As the credible-commitment story of war termination illustrates, although battlefield success indicates fluctuations in government capability and enhances rebels' current bargaining position, the fear of the post-conflict power shift induced by the likely disarmament and demobilization of rebel forces prevents rebels from ending inefficient conflict (Walter, 1997, 2002).

Simultaneously, however, the same diffusion patterns of battles negatively impact the probability that a civil conflict will end in a government-favorable outcome. This is primarily because the incumbent is likely to have difficulties in restoring the monopoly of violence through coercive means when the rebels are relatively successful in the battlefield. In other words, the same pattern of battle diffusion has a negative impact on both rebel-favorable and government-favorable outcomes but for different reasons: the likelihood of rebel-favorable outcomes decreases primarily due to the underlying bargaining problem, while the likelihood of government-favorable outcomes decreases primarily for military reasons. Particular

[10] The coding rule of conflict outcome follows Fortna (2015) and Greig, Mason, and Hamner (2016). See Chapter 6 for a detailed discussion.

forms of battle diffusion prolong civil conflicts primarily by hampering credible negotiated settlements while undermining the chances of decisive military victories.

Combined with the findings on conflict duration and termination in Chapter 5, the empirical results demonstrate that the escalating diffusion of battles across distant locations may help rebels' survival, while being less effective at achieving rebels' end political goals.[11]

1.3 Key Contributions

Taking the recent advances in civil war study as the point of departure, this dissertation sheds new light on the micro-level causes and macro-level consequences of civil war violence. This dissertation contributes to the civil war and broader literature in several ways. First, the first part of the empirical analysis in this dissertation classifies the previous literature on the micro-level determinants of violence into two broad schools —— endogenous and exogenous —— and examines the validity of each argument. By demonstrating how the determinants of violence vary depending on the forms of violence, this dissertation integrates previously divided schools into a unified framework. Previous micro-level studies that highlight either endogenous or exogenous determinants of violence can be considered as a special case of the proposed argument.

Second, the second part of the empirical analysis contributes to the emerging body of literature about the micro-level and dynamic determi-

[11] In the analysis on the effectiveness of terrorist strategies in civil conflicts, Fortna (2015) finds that terrorist rebel groups are generally less likely to achieve their political goals than are nonterrorist groups while civil conflicts where rebels employ terrorism last longer than other wars (see also, Abrahms, 2013, Thomas, 2014, and Wood and Kathman, 2014). The findings on the relationship between diffusion of combat activities and civil conflict termination in this dissertation somewhat mirror these earlier findings. See, for example, Valentino (2014) for an overview of the recent development of the literature on political violence against civilians including mass killing and terrorism. As Valentino (2014) summarizes, a near consensus within the recent research is that political violence against civilians, once assumed to be "irrational, random, or the result of ancient hatreds," is "primarily, if not exclusively, instrumental and coordinated by powerful actors seeking to achieve tangible political or military objectives" (91).

nants of civil war termination. Balcells and Justino (2014), Balcells and Kalyvas (2014), and Greig, Mason, and Hamner (2016) are correct in pointing out that much of the existing literature has relied on largely static determinants of conflict termination such as national characteristics. The links between the micro-level conflict process and macro-level variations in conflict duration and outcomes remain relatively under-explored in the previous literature. This gap within the previous literature is accurately articulated by Sambanis (2004a, 259):

> The already significant gap between the micro-level theories and their macro-level implications is magnified when the micro-macro relationships are studied solely through cross-national statistical analyses. Such studies often overlook the information on the causal pathways that link individual or group behavior with the outbreak of civil war.

Although Sambanis's quote focuses on conflict onset, the same can also be said regarding studies on conflict termination (see also, Cederman and Vogt, 2017). The micro-level dynamics of battle activities that occur during civil conflicts are the products of individual and group behavior and interaction. If micro-level conflict dynamics as well as structural conditions matter in altering the chances of conflict duration and outcome, any study on civil war termination remains incomplete without examining how and why fighting shapes the prospects of domestic peace (Balcells and Kalyvas, 2014; Greig, Mason, and Hamner, 2016; Kalyvas and Balcells, 2010). An empirical investigation of the likely impact of the spatio-temporal dynamics of battles in terms of conflict duration and outcome is a critical step towards understanding the determinants of civil war termination. Such an attempt also contributes to the recent call to bridge different phases of civil conflict by linking wartime dynamics and conflict termination (Cederman and Vogt, 2017, 2006–2007).[12]

[12] The major phases of civil conflict commonly investigated in the literature include outbreak, wartime dynamics, conflict termination, and postwar recovery (Cederman and Vogt, 2017). Chiba, Metternich, and Ward (2015) develop a copula-based, split-

Third and theoretically, the results also speak to the broader literature on the links between the conflict process and conflict termination in inter- and intra-national conflicts. A notable trend within the recent literature is the renewed call to investigate the question of conflict termination (e.g., Leventoglu and Slantchev, 2007; Powell, 2004a, 2012; Reiter, 2009; Slantchev, 2003a,b; Wagner, 2000). Since the seminal work of Fearon (1995), most previous studies have highlighted the question of why costly conflict occurs and treated war as an outcome to be explained. In contrast, the recent literature has increasingly moved its attention to the puzzle of how costly fighting itself resolves the bargaining problems that initially lead to inefficient war (Ramsay, 2008, 850–853). Building upon the insights from the intra-war bargaining literature, this dissertation offers systematic theoretical accounts and empirical tests of the likely impacts that spatio-temporal diffusion dynamics of violence have on civil war termination. In so doing, this study specifies the micro-foundations of the relevant theoretical accounts (Kertzer, 2017), and thereby contributes to this ongoing debate on conflict termination.

Forth and empirically, the findings underscore the advantage of incorporating dynamic information in explaining and predicting armed conflicts. Recent conflict literature underscores the utility of faster-moving or dynamic "process" variables such as civilian attitudes and battle activities, in addition to slow-moving or time-invariant "structural" variables (Blair, Blattman, and Hartman, 2017, 299, 309), in both micro- and macro-level studies (see also, Beger, Dorff, and Ward, 2016; Chadefaux, 2014, 2017; Chiba and Gleditsch, 2017; Hirose, Imai, and Lyall, 2017; Mueller and Rauh, 2017; Ward and Beger, 2017).[13]

population duration estimator and demonstrate the significant interdependencies between pre-conflict duration (time until conflict onset), conflict duration, and post-conflict duration (time until conflict recurrence; see also, Chiba, Martin, and Stevenson, 2015 and Fukumoto, 2015).

[13] See, for example, Chadefaux (2014); Gleditsch and Ward (2013); Gohdes and Carey (2017); Hegre, Karlsen, Nygård et al. (2013); Ward, Greenhill, and Bakke (2010); Ward, Metternich, Dorff et al. (2013); Witmer, Linke, O'Loughlin et al. (2017) for the recent development of prediction models in civil war study and related fields. See Cederman

For example, at the micro level, drawing on the original data from a survey experiment in 204 villages in Afghanistan, Hirose, Imai, and Lyall (2017) reveal how insurgents use civilian attitudes toward the counterinsurgent campaigns as "cues" to select their targets and tactics. The empirical results in Hirose, Imai, and Lyall (2017) show that incorporating civilian attitudes substantially improves predictive accuracy across multiple categories of insurgent targets and tactics, both in in-sample classification and out-of-sample forecast.[14] Similarly, at the macro level, Chiba and Gleditsch (2017) convincingly demonstrate how dynamic information of conflict and cooperation from the Integrated Conflict Early Warnings System (ICEWS) event data (Boschee, Lautenschlager, O'Brien et al., 2015) can improve forecasts of civil war onset and termination (see also, Mueller and Rauh, 2017). This dissertation demonstrates how dynamic information (i.e., spatio-temporal dynamics of battle activities) can help us explain and predict both the micro-level variations in conflict dynamics (Chapters 3 and 4) and macro-level variations in conflict duration and outcomes (Chapters 5 and 6) within a unified framework.

Finally and methodologically, the current study utilizes the recent innovation of the geographical information system (GIS), spatial data, and computational modeling in political science and related fields. The micro-level analysis presented in Chapters 3 and 4 demonstrate the methodological utility of data-driven, agent-based computational modeling. As discussed in detail in Chapters 2 and the following empirical chapters, this

and Weidmann (2017) for an overview.

[14]With the help of original survey experiment in Afghanistan, Lyall, Shiraito, and Imai (2015) find that coethnicity significantly shapes civilians' wartime attitudes about informing and beliefs about retaliation, or "coethnic bias" in wartime informing. Relatedly, utilizing a survey endorsement experiment, Lyall, Blair, and Imai (2013) demonstrate that ISAF-inflicted civilian damage is followed by reduced support for ISAF and increased support for the Taliban, while Taliban-inflicted damage does not produce greater support for ISAF. See Beath, Christa, and Enikolopov (2011), Berman, Shapiro, and Felter (2011), Blair, Christine Fair, Malhotra et al. (2013), Bullock, Imai, and Shapiro (2011), Condra and Shapiro (2012), and Fair, Malhotra, and Shapiro (2012) for related empirical findings. See Blair, Imai, and Lyall (2014) and Imai, Park, and Greene (2014) for a methodological discussion on the indirect survey techniques for sensitive questions.

empirically-explicit computational modeling approach enables us to formally represent the proposed mechanisms of disputant behavior and generate hypothetical spatial distributions of violence that are directly comparable with the observed records. Because the hypothetical distributions are solely derived from computational models and pseudo randomness, this approach serves as a valuable methodological tool to empirically validate the proposed mechanisms by examining whether theoretical propositions about insurgents' behavior can generate and explain the empirical realities.[15] This innovative computational approach allows us to tackle an otherwise challenging task to disentangle the validity of the theoretically distinct, but often observationally equivalent, mechanisms that govern the behavior of warring factions against empirical data.

The macro-level studies on conflict duration and outcome in Chapters 5 and 6 also utilize precisely geocoded data on civil war battles and the GIS technique to characterize the spatio-temporal dynamics of battle activities during civil conflicts. By revealing how the micro-level battle dynamics matter in determining when and how civil conflict ends, the empirical analysis demonstrates how the spatially-explicit approach helps with macro-level, as well as micro-level, studies of civil conflict.

1.4 Outline of the Dissertation

This dissertation is a scholarly endeavor to take a closer look into (1) how violent confrontation unfolds at the micro level after an initial bargaining failure, *and* (2) how the micro-level confrontation translates into conflict duration and outcome at the macro level. Chapter 2 lays out the research design, with a description of case selection criteria, empirical strategy, and scope conditions of the following analysis.

[15]The underlying rationale behind the agent-based computational modeling is the "if you didn't grow it, you didn't explain its emergence" slogan (Epstein, 2007, 8). The central purpose of the agent-based modeling, whether empirically-based or not, is to "provide computational demonstrations that a given microspecification is in fact *sufficient to generate* a macrostructure of interest" (8, emphasis in the original).

In Parts II and III, this dissertation highlights, first, the conditions that incentivize warring parties to resort to violence in particular locations and forms, and second, the causal pathways through which the seemingly brute battle activities alter when and how the conflict ends. These two parts each correspond to the two main research questions on the causes and consequences of civil war violence advanced above. The two chapters in Part II explore the causes of civil war violence, with particular interest in *where* and *how* insurgents conduct attacks in the challenge against the government's monopoly on violence. Utilizing precisely geocoded datasets and the approach of data-driven computational modeling, Chapters 3 and 4 investigate the determinants of the quantity and quality of insurgent violence in the ongoing war in Afghanistan. Chapter 3 develops a parsimonious but empirically-based computational model of insurgency to analyze the impacts that candidate determinants of violence have on the subnational risks of insurgent activities. Chapter 4 builds upon the proposed computational model and extends the analysis to decompose the determinants of selective and indiscriminate insurgent violence.

The empirical analysis in Part III examines how the micro-level conflict dynamics translate into macro-level conflict duration and outcomes. The seemingly brute use of force by warring parties on the ground is more than the confrontation of physical forces; it often has important implications for the future course of conflict and shapes when and how the civil conflict ends. Building upon the bargaining model of war, Chapters 5 and 6, with close attention to the diffusion dynamics of violence, explore the pathways through which the micro-level conflict process influences macro-level conflict termination.

Chapter 7 briefly summarizes the key findings and highlights the scholarly and policy implications. It then concludes by offering promising avenues for future research.

CHAPTER 2

Research Design

Data, Case Selection, and Method

This dissertation primarily focuses on the determinants and possible consequences of micro-level violence dynamics. To accomplish this task, the empirical analysis presented in the following chapters employs spatially and temporally disaggregated datasets as well as oft-employed aggregated data. Specifically, the in-depth micro-level analysis on the causes of violence in civil conflict relies on empirical records of violence in the ongoing war in Afghanistan. Similarly, the macro-level analysis of the possible impacts of the microdynamics of battles on the eventual duration and outcome of civil conflicts draws upon a series of datasets that cover broader cases of civil conflict in sub-Saharan Africa and other regions.

Methodologically, this dissertation utilizes a mixed empirical strategy of econometric analysis and agent-based computational modeling (ABM) technique incorporated with empirical data. The ABM technique is employed to formally model and empirically validate the hypothetical behavior of insurgents. As discussed in detail in the following sections and Chapter 3, the strength of this computational method lies in (1) its ability to represent spatially situated and locally interacting agents and (2) its flexibility in incorporating it with empirical data. These two advantages allow for the hypothesized mechanisms governing the micro-level behavior of warring parties to be formally represented *and* for their validity against empirical records to be examined.

This dissertation also presents a series of econometric analyses to characterize the spatio-temporal patterns of civil war battles and examine how such micro-level conflict dynamics influence when and how civil conflicts end. While the econometric approach remains standard in the field of civil war study, the methodological innovation here lies in the careful handling of the spatial dimension of the data. Specifically, we carefully examine the potential sensitivities of the estimation results to the selection of a spatial unit of analysis known as the modifiable areal unit problem (MAUP, Fotheringham and Wong, 1991; Jelinski and Wu, 1996; Openshaw and Taylor, 1979), a methodological issue widely noted in the theory but often neglected in practice in the literature.

The following sections lay out the methodological background of the case selection, followed by an overview of empirical datasets and methods. The scope of the empirical analysis is also discussed.

2.1 Empirical Data

Any scholarly endeavor to more closely examine micro-level conflict dynamics *and* macro-level conflict termination requires *both* disaggregated data of civil war battles and aggregated data of civil war duration and outcome. To accomplish this task, the empirical analysis in this dissertation draws on spatially and temporally disaggregated datasets of civil war battles and dyad-level conflict duration and outcome data.

2.1.1 Georeferenced Data

A noteworthy aspect of the advances in civil war study over the last decade is the so-called "micro-level" turn to disaggregate civil conflicts (Cederman and Vogt, 2017; Gleditsch, Metternich, and Ruggeri, 2014; Ito, 2015; Kalyvas, 2008, 2012; O'Loughlin and Raleigh, 2008; Weidmann, 2014).

Empirically, civil war research has increasingly explored subnational variations in civil war violence rather than the aggregated onset or termination of civil war at the national level. Theoretically, civil war study has moved toward specifying the microfoundations of civil war, reflecting a desire to improve the specification of the causal mechanisms underlying the statistical correlations (Kalyvas and Kocher, 2009, 335-336).[1] As Buhaug and Rød (2006, 316) put it, behind this turn is the common speculation in civil war study that

> the empirical study of civil war often suffers from a disturbing mismatch between theory and analysis. While standard statistical investigations are conducted exclusively at the country level, most hypotheses actually pertain to sub-national conditions. Consequently, quite a few commonly held notions about the correlates of civil war are still to be tested in an appropriate manner. . . . [Without a disaggregated approach,] we are likely to fall prey to the ecological fallacy by explaining local phenomena from aggregated data. Put generally, there is a tendency to neglect the spatial context of social phenomena.

Our core research questions, too, cannot be answered without taking a closer look at the local-level dynamics of violence in civil conflicts. Reflecting on this recent trend in civil war study, we opt to employ temporally and spatially disaggregated datasets to investigate the causes and consequences of violence in civil conflicts.

SIGACTs data of the war in Afghanistan In the micro-level empirical analysis on the causes of violence, we rely on the newly available military archive of civil war violence in the ongoing war in Afghanistan — the "Significant Activities" (SIGACTs) database, or the subset of the dataset leaked by WikiLeaks in 2010. The SIGACTs dataset is a collection of short summaries of events in relation to the actors involved, casualties, event types, locations, timing, and other related information that have been recorded

[1] See, for example, Donnay and Bhavnani (2016), Gleditsch and Weidmann (2012), Ito (2015), and Weidmann (2014) for an overview of available datasets.

by individual troops. The SIGACTs event data cover both violent (e.g., IED explosions) and nonviolent (e.g., information provision from civilians) incidents across the country between January 2004 and December 2009, and have been widely used in the civil war literature (e.g., Donnay and Filimonov, 2014; Hirose, Imai, and Lyall, 2017; O'Loughlin, Witmer, Linke et al., 2010; Schutte, 2016, 2017; Schutte and Donnay, 2014; Weidmann, 2013, 2015, 2016; Zammit-Mangion, Dewar, Kadirkamanathan et al., 2012).[2] Of the 76,910 entries, 52,196 are reports of violent incidents, while the remaining 24,714 are of nonviolent incidents.[3] The reports of violent incidents include 45,628 insurgent ($Violence^{\text{INS}}_{\text{Violence}}$) and 6,568 counterinsurgency (International Security Assistance Force, ISAF) attacks ($Violence^{\text{ISAF}}_{\text{Violence}}$). Figure 2.1 maps the spatial distribution of ISAF- and insurgent-initiated violence in Afghanistan during the study period.

The first part of the empirical analysis draws on the SIGACTs dataset to analyze the micro-level determinants of civil war violence. There are two reasons behind this case selection, practical and methodological. First and practically, the SIGACTs database offers a rare opportunity for researchers to explore the microdynamics of civil war. This dataset captures a more comprehensive, if not complete, picture of the events ongoing within the war in Afghanistan than other available datasets. Indeed, recent studies have reported that the SIGACTs database covers more events with few or no casualties while other available datasets, which are typically media-based, tend to under-report these small-scale events (Weidmann, 2016).

Although the Afghanistan's SIGACTs database offers a rare opportunity for civil war scholars to explore the microdynamics of civil war violence, it may also entail potential pitfalls (Donnay and Filimonov, 2014; Weidmann, 2013, 2015, 2016). First, there may be a tendency for mili-

[2]The Institutional Review Board of the University of Tokyo has carefully reviewed and approved my research proposal using the SIGACTs database (Approval Number: 15–199, January 12, 2016). Replication materials and codes in R statistical language for the empirical analysis in this dissertation are available upon request.

[3]The coding rule employed in the following analysis is described in detail in Chapters 3 and 4 and Appendix A. See also, Ito (2016).

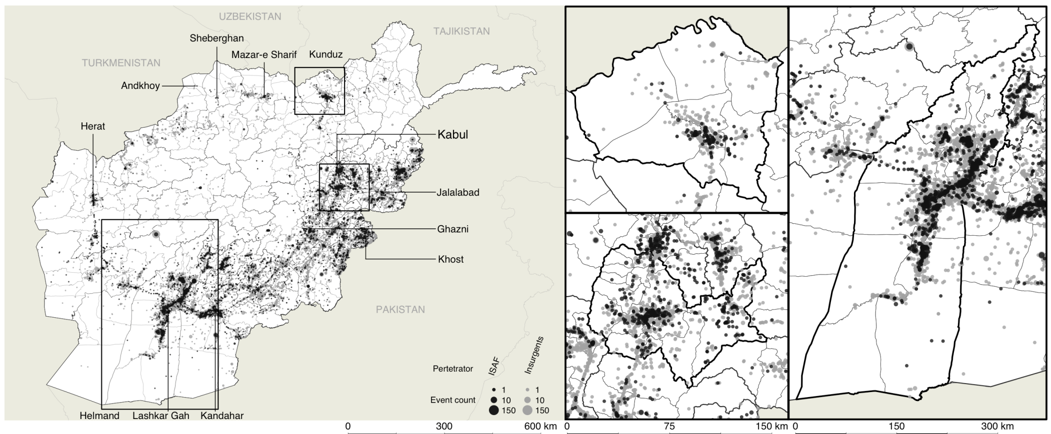

Figure 2.1: Distribution of ISAF and insurgent violence in Afghanistan, 2004–2009 ($Violence^{\text{ISAF}}_{\text{Violence}} = 6,568$, $Violence^{\text{INS}}_{\text{Violence}} = 45,628$)

Notes: Adopted from Ito (2016). Data are drawn from the SIGACTs database. Black and gray dots indicate unique reported locations of ISAF and insurgent violence, respectively. Size of each dot is proportional to the number of reported events. The coding rule to classify event types is described in Appendix A and Ito (2016).

tary troops to under-report the collateral damage caused by their operations. However, this possible bias is not likely to cause serious problems in the following analysis, since the main focus here is on the distribution of insurgent-initiated attacks. As Weidmann (2013) argues, this concern is further alleviated by the fact that the data were collected for internal use within the US military organization but not for public distribution (569). Second, the still classified reporting standards for the SIGACTs entries may vary across units and regions and/or have changed over time, possibly resulting in a significant measurement error. This concern is partly alleviated by focusing on the temporally aggregated spatial distribution of violence, as in the empirical analyses presented in Chapters 3 and 4.

Another concern regarding the reliance on the Afghanistan's SIGACTs database is the external validity of the empirical findings. One may reasonably wonder if the findings derived from the single case of Afghanistan can speak to broader cases of civil conflict. A possible strategy to address this concern in relation to external validity is to closely examine Afghanistan's structural characteristics that are known to substantially shape the likelihood of the onset and duration of civil conflicts (Hirose, Imai, and Lyall, 2017, 51). If Afghanistan is an outlier across the distributions, then the value of the focused analysis is reduced. Replicating the approach in Hirose, Imai, and Lyall (2017), Figure 2.2 plots the density estimates for the standard set of correlates of civil war, with vertical segments indicating the mean values for individual predictors of Afghanistan (blue) and sub-Saharan African states (gray) within the observation period (1945–2000). Afghanistan is located around the central value of each distribution in Figure 2.2, suggesting that focused analysis would yield relevant insights into the civil war dynamics in oft-employed cases.

GED data of civil war battles Although there is much promise in the Afghanistan's SIGACTs database, the scope of the database is limited to a single conflict. Nevertheless, any empirical analysis of the impacts of micro-level conflict dynamics on macro-level conflict termination requires a geocoded dataset with a broad temporal and spatial coverage that enables cross-case comparison.

The second part of the empirical analysis therefore utilizes another source of micro-level, georeferenced records of violence in civil conflicts the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED, Sundberg and Melander, 2013), to explore dynamics of broader cases of civil conflict. The GED version 4 covers incidents of organized violence within civil conflicts in Africa, the Middle East, Asia, and South America during the 1989–2014 period. It includes data on nearly 110,000 incidents of civil war battles between warring parties (state-based and non-state conflict) as well as their intentional and direct use of violence against civilians (one-sided violence).[4] Each record in the GED is coded relying on news sources, NGO reports, truth commission reports, histori-

[4]An event in the GED is defined as the "incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration" (Sundberg and Melander, 2013, 524).

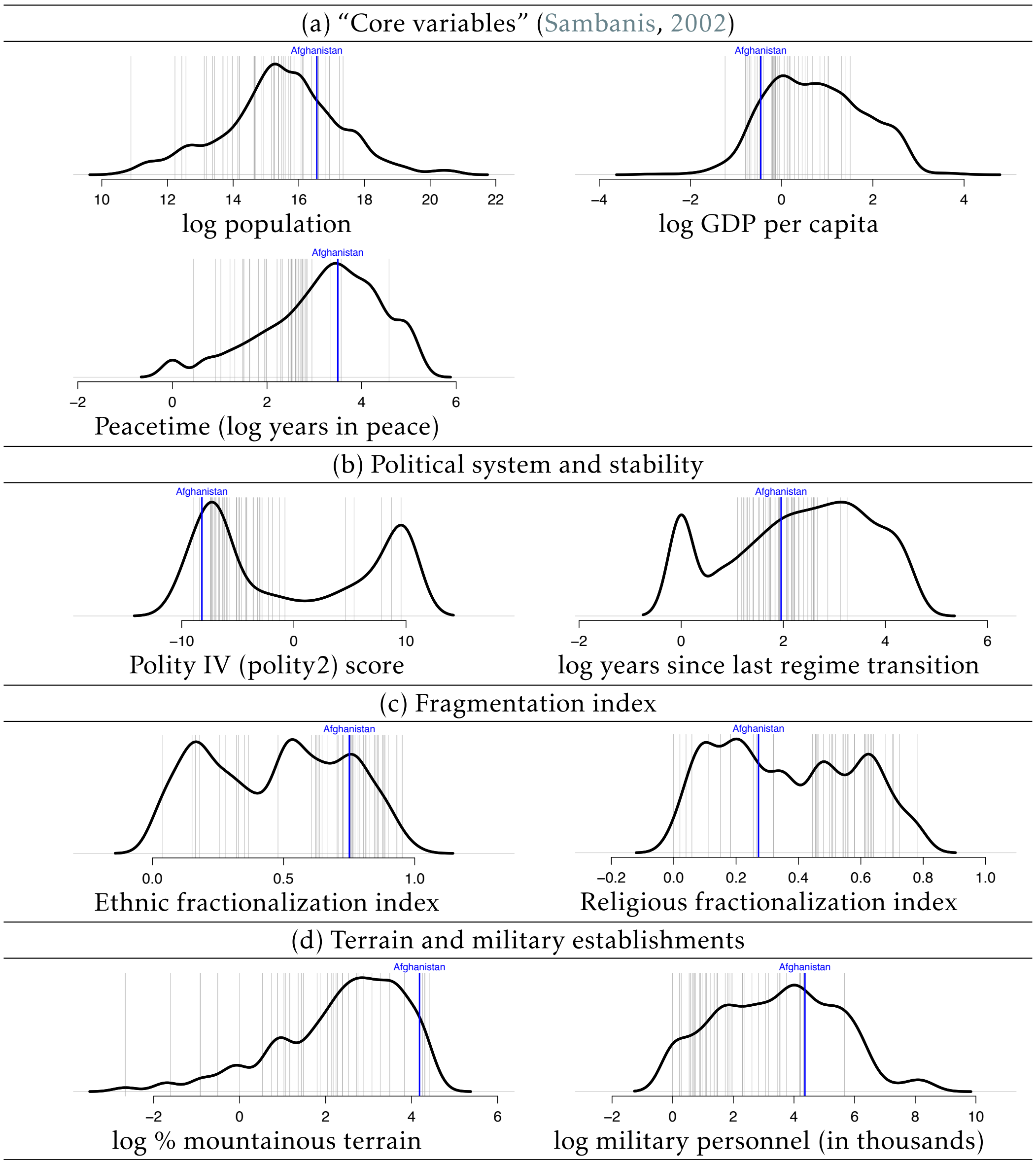

Figure 2.2: Correlates of civil war, 1945–2000

Note: Data drawn from Hegre and Sambanis (2006). Solid segments represent density estimates for the standard set of predictors of civil war onset. Vertical segments indicate the mean values for individual predictors of Afghanistan (blue) and sub-Saharan African states (gray) within the observation period (1945–2000).

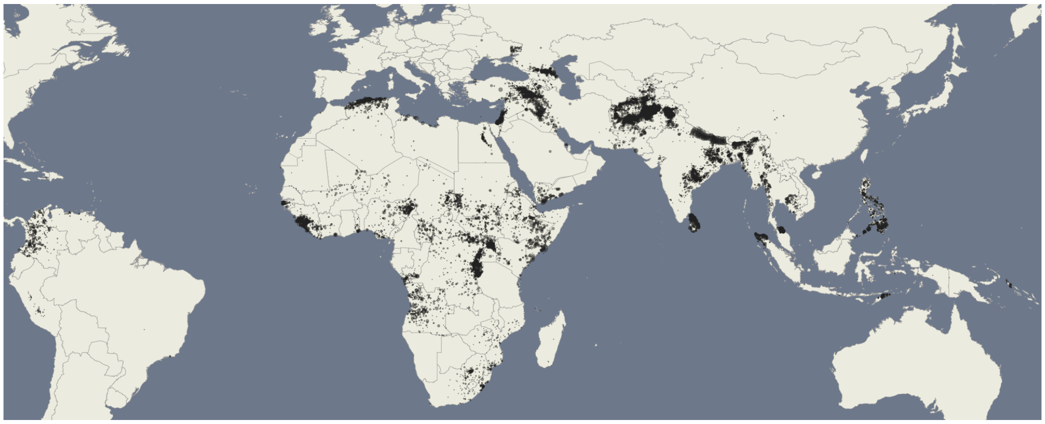

Figure 2.3: Distribution of battle events in civil conflicts

Notes: Data drawn from the UCDP Georeferenced Event Dataset (Sundberg and Melander, 2013). Each dot indicates a reported location of battle event between warring parties and violence against civilians during civil conflicts. Data on international borders are derived from Weidmann, Kuse, and Gleditsch (2010).

cal archives, and other sources of information, and comes with precise geographical locations, dates, and other information including battle deaths and civilian casualties. Figure 2.3 uses a map to visualize the global distribution of deadly incidents during civil conflicts covered by the GED. Utilizing this disaggregated dataset with a broad temporal and spatial coverage, the current study investigates the impacts that the micro-level dynamics of violence have on the duration and outcomes of civil conflicts.

Perhaps an important limitation of the GED data is that its coverage is restricted to fatal events, which could lead us to underestimate conflict intensity. In contrast to other georeferenced datasets such as the PRIO Armed Conflict Location and Event Dataset (ACLED, Raleigh, Linke, Hegre et al., 2010), non-fatal events are not recorded in the GED. Another but related concern is the flip side of the relative strength of the SIGACTs database: that is, primarily media-based datasets including the GED tend to under-report small-scale events. The sources of selective reporting are twofold: supply-side factors (e.g., some events are not reported due to the lack of information) and demand-side factors (e.g., some events are not sensational enough to be reported; Weidmann, 2015, 1130).[5] Although the GED does not rely only on media sources, media bias or selective reporting to under-report small-scale events may be present in the dataset (Weidmann, 2016). This limits the scope of the empirical analysis to the associations between deadly or relatively large-scale, rather than whole, battle events and macro-level variations in conflict termination.

Relatedly, selective reporting can also generate measurement error in our key independent variables (i.e., battle activities), thereby introducing related estimation issues such as the attenuation bias into our empirical analysis. As Weidmann (2016) argues, if event reporting is selective in the sense that it fails to identify certain types of events (e.g., non-deadly or small-scale events), the error in the dataset would be measurement error where some of our (violent) units are incorrectly coded as peaceful (207–208). This may not cause selection bias such that certain units are not observed at all while leading to incorrect coding and measurement error. As is widely acknowledged (e.g., Wooldridge, 2012, 320–323), measurement error in an independent variable, for example, can induce the attenuation bias that leads us to underestimate (but not overestimate) the magnitude of the corresponding regression coefficient.[6] Despite these important concerns, the GED remains among the best datasets currently available that cover diverse episodes of civil conflicts across different regions.[7]

[5] See also, Weidmann (2016, 207). Another key issue is the "Rashomon Effect" (or description bias) that "different newspapers, depending on their partisan orientation, can portray the same event in completely different ways" (Weidmann, 2016, 207; see also, Davenport, 2010; Earl, Martin, McCarthy et al., 2004; Weidmann, 2015). See, Croicu and Kreutz (2017), Donnay and Filimonov (2014), Gallop and Weschle (2017), Hollenbach and Pierskalla (2017), Weidmann (2013), and Woolley (2000) for a related discussion and findings. See, for example, Osorio and Reyes (2017) for a non-Anglocentrism event dataset drawing upon Spanish-language sources.

[6] See Carroll, Ruppert, Stefanski et al. (2006, 41–55) for the problem of measurement error-induced bias. Note also that Chapters 5 and 6 employ the GED to derive the key independent variables. The Monte Carlo experiments and diagnostic procedure in Weidmann (2016) focus on the cases in which reported events are used as dependent variable with measurement error correlated with one or more of the independent variables.

[7] The PRIO ACLED dataset is another possible choice to explore the micro-level dynamics of civil conflicts, yet its temporal coverage is limited to the post-1997 period (Raleigh, Linke, Hegre et al., 2010). The temporal coverage of the Integrated Conflict

2.1.2 Civil Conflict Data

The aggregated data on conflict duration and outcome draw on the Uppsala/PRIO Dyadic Armed Conflict Dataset (ACD), which includes rebel-government conflicts that generate at least 25 casualties in a given calendar year, over some incompatibility classified as control over the central government and/or territorial secession (Gleditsch, Wallensteen, Eriksson et al., 2002; Pettersson and Wallensteen, 2015). The coding of specific start and end dates of each conflict is provided by the dyadic version of the UCDP Conflict Termination Dataset, v.2-2015 (CTD, Kreutz, 2010). The empirical analysis in Chapters 5 and 6 chooses civil war (rebel-government) dyad-month as the unit of analysis to investigate the determinants of conflict duration and outcomes.

2.2 Empirical Strategy

Drawing upon the spatially, temporally, and conceptually disaggregated datasets, the first part of the empirical analysis utilizes a data-driven computational modeling to disentangle the determinants of violence in civil conflict (Chapters 3 and 4). The second part also relies on accurately disaggregated datasets and a series of econometric techniques to explore the causal links between the microdynamics of battles and eventual conflict duration and outcome (Chapters 5 and 6). This mixed method approach is necessary because answering different questions often requires different methods (Ito, 2013), and this dissertation explores the macro-level consequences as well as the micro-level causes of civil war violence.

2.2.1 Data-Driven Computational Modeling[8]

Agent-based modeling One of the critical methodological challenges in the micro-level analysis of civil war violence is to identify the mechanisms

Early Warnings System (ICEWS) event dataset is similarly limited to the post-1996 period (Boschee, Lautenschlager, O'Brien et al., 2015).

[8] Unless otherwise noted, what follows in this subsection is based on Ito (2013) and Ito and Yamakage (2015).

governing the behavior of warring actors. To accomplish this task, we employ the computational modeling approach to specify and validate the hypothetical behavioral mechanisms of insurgents. Specifically, the first part of the empirical analysis relies on the agent-based modeling (ABM) technique and incorporates the developed model with precisely geocoded data to examine the validity of theoretical expectations. The ABM technique has been used to simulate and investigate the relationship between the autonomous actions and interactions of individuals and the dynamics and behavior of the whole system. The widely-cited definition of this computational modeling is articulated by Cederman (2005, 873):

> Agent-based modeling is a computational methodology that allows scientists to create, analyze, and experiment with artificial worlds populated by agents that interact in nontrivial ways and that constitute their own environment.

Agent-based models are implemented as a set of computer codes that specify the rules of action and interaction between constituent elements of a system, commonly called agents. Researchers then examine what systemic or collective outcomes emerge from the accumulation of local-level actions and interactions between agents through computational simulations. As Epstein and Axtell (1996) describe, ABM is a methodology of "generative understanding" that enables us to explore how specific sets of micro-mechanisms generate a class of collective outcomes not reducible to properties of the constituent agents (Axelrod, 1997; Cederman, 2005; de Marchi and Page, 2014; Epstein and Axtell, 1996; Epstein, 2007; Helbing and Balietti, 2012; Macy and Willer, 2002). The rationale behind this modeling approach can be summarized by Epstein's (2007) slogan that "if you didn't grow it, you didn't explain its emergence" (8). The central purpose of agent-based modeling, whether empirically-based or not, is to "provide computational demonstrations that a given microspecification is in fact *sufficient to generate* a macrostructure of interest" (Epstein, 2007, 8, emphasis in the original).

One methodological utility of the agent-based simulation lies in its ability to represent spatially situated and locally interacting agents, which enables us to model the relationship between local conditions and insurgent behavior (de Marchi and Page, 2014). This flexibility is essential in the current context, as our propositions focus on how local-level conditions influence insurgents' incentives and opportunities to engage in violence (Buhaug and Rød, 2006; Zhukov, 2012).

The concepts, if not computational implementations, of the ABM approach in social science can be dated back to the early 1970s.[9] The pioneering contribution must be Schelling (1969, 1971, 1978), who developed a model of residential segregation by moving pennies and dimes representing residents of different races. Assuming that coins represent householders of different races seeking to reside amongst their own kind, his parsimonious model demonstrated that marked segregation within neighborhoods can emerge from seemingly mild, not strong, individual preferences (see Sakoda, 1971, for a similar game). Having yielded this counterintuitive insight, Schelling's parsimonious model is now regarded as a "theoretical basis" for the scholarly debate on the causes of urban residential segregation (Clark and Fossett, 2008, 4109).

The last few decades have witnessed an explosion of ABM applications. Political scientists have increasingly examined and extended existing theories via the simulations of agent-based models (e.g., Axelrod, 1997; Bhavnani, Findley, and Kuklinski, 2009; Bremer and Mihalka, 1977; Cederman, 1997; Cusack and Stoll, 1990; Findley and Rudloff, 2012; Johnson, Weidmann, and Cederman, 2011; Kustov, 2017; Laver and Sergenti, 2012; Lustick, Miodownik, and Eidelson, 2004; Schrodt, 1981; Siegel, 2009, 2011). Physicists have similarly developed agent-based models to investigate social phenomena (see Castellano, Fortunato, and Loreto, 2009; Helbing, Brockmann, Chadefaux et al., 2014 for an overview).

[9]The term agent-based modeling refers to the computational simulation methodology often contrasted with the equation-based modeling. "Multi-agent simulation" (MAS) and "agent-based computational modeling" (ABC-modeling) refer to the corresponding computational technique (Helbing and Balietti, 2012, 27).

Bridging models and empirical reality Another methodological utility of the agent-based models lies in its flexibility to be incorporated with empirical data, which allows for artificial models to be seeded and validated using observed records. While parsimony is vital in modeling attempts, models are required to have explicit connections with empirical observations to enrich our understanding of the generating processes underlying observed phenomena. Otherwise, it may be extremely difficult to test, evaluate, or validate agent-based models against empirical data.

This speculation leads us to the idea of incorporating computational models with empirical data to tighten the connections between artificial models and empirical phenomena by making models "time- and space-specified" (TASS, Ito and Yamakage, 2015). Rather than yielding purely theoretical insights, TASS-modeling essentially aims to identify the micro-mechanisms sufficient to generate the macro-outcomes consistent with observed phenomena. While no computational models can perfectly "re-run" history, such empirically-explicit computational experiments can serve as heuristic devices that enhance our understanding of the generating processes underlying time- and space-specified empirical phenomena (Weidmann and Salehyan, 2013, 61; see also, Bhavnani, Donnay, Miodownik et al., 2014; Lim, Metzler, and Bar-Yam, 2007; Lustick and Miodownik, 2009). For example, Lim, Metzler, and Bar-Yam (2007) and Weidmann and Salehyan (2013) develop empirically-explicit, agent-based models incorporated with spatial data from ethnic geography. Incorporating an artificial two-dimensional model space with the real geography, these studies examine the microfoundations underlying the observed associations between ethnic segregation and violence in India, Iraq, and former Yugoslavia, and demonstrate that a simple mechanism of ethnically- and/or security-motivated migration and violence accounts for the spatial distribution of violence in actual conflicts.

These empirically-explicit agent-based computational models can also serve as a heuristic device to explore the possible effects of proposed policy efforts. Having optimized model parameters such that the patterns of violence from the simulation closely fit the actual distributions, Bhavnani, Donnay, Miodownik et al. (2014) use a data-driven agent-based model to evaluate the relevance of proposed policy prescriptions by assessing how different levels and patterns of Israeli-Palestinian segregation may shape future violence in Jerusalem.[10]

As these studies demonstrate, the methodological advantage of data-driven computational modeling is twofold: first, this approach provides a formal representation of theoretically-derived assumptions on actors' behavior; and second, it allows us to test the validity of the model by searching the behavior algorithm or parameter combinations that minimize the discrepancies between the simulated and empirical data.[11]

The first part of the empirical analysis of this dissertation joins this emergent methodological move and establishes bridges between otherwise purely theoretical models and empirical data. In so doing, the computational modeling in this dissertation explicitly examines the validity of the hypothetical mechanisms governing the insurgent violence against empirical records.

2.2.2 Spatially-Explicit Econometric Analysis

The second part of the empirical analysis relies on the econometric approach. Unlike the data-driven computational modeling discussed above, this approach is standard, rather than an innovation in itself, within the field of international relations. Nevertheless, the twofold methodological innovation lies in the close attention paid to the spatial dimension of civil war battles. First, this dissertation utilizes spatially, temporally, and conceptually disaggregated data and characterizes the spatio-temporal dy-

[10] Applications of the data-driven computational modeling in the fields of social science include criminology (e.g., Johnson, 2008) and residential segregation (e.g., Benenson, Hatna, and Or, 2009; Bruch, 2014; Yin, 2009).

[11] See Ito (2013), Ito and Yamakage (2015), Lustick and Miodownik (2009), and Warren (2016) for a related discussion, and Berk (2008) and Helbing and Balietti (2012) for an overview of the validation criteria of computational models. Crooks, Castle, and Batty (2008) and Crooks and Wise (2013) each provide an overview of the promises and potential pitfalls of computational modeling incorporated with empirical data.

namics of civil war violence in the econometric analysis of conflict duration and outcome. By integrating the micro-level records of violence and the macro-level variations in conflict duration and outcome, the empirical analysis in Chapters 5 and 6 allows for the microdynamics of civil war to be connected with aggregated macro-level patterns.

Second, the current study pays careful attention to the methodological issue widely recognized in theory, but neglected in practice, inherent in the analysis of spatial data, or the sensitivity of estimation results to the selection of a spatial unit (modifiable areal unit problem, MAUP, Fotheringham and Wong, 1991; Jelinski and Wu, 1996; Openshaw, 1983; Openshaw and Taylor, 1979). This methodological issue generally refers to the potential effect the selection of the unit of observation has on the statistical results: the choice of the basic areal units can alter the inferential results of any statistical analysis that draws on discrete spatial units. The second part of the empirical analysis draws on an artificial spatial grid as the unit of observation when characterizing the spatio-temporal patterns of civil war battles. Consequently, one can reasonably question the robustness of the empirical findings to the spatial grid specification. To address this concern, Chapters 5 and 6 present a series of econometric analyses that vary the spatial grid specification, or the size and shape of the spatial grid, and carefully examine the robustness of the main findings.

2.3 Scope Conditions

The primary focus of this dissertation is on the dynamics of civil conflicts. Although civil conflict seems to be an intuitive concept at first glance, defining it is a conceptual minefield in itself (Cederman and Vogt, 2017; Kreutz, 2015; Sambanis, 2004b). As Sambanis (2004b) argues, "it is not possible to arrive at an operational definition of civil war without adopting some ad hoc way of distinguishing it from other forms of armed conflict" (815). His initial empirical investigation calls for a careful conceptualization of civil conflict (855):

> The quantitative literature on civil war reveals a remarkable degree of disagreement on how to code the onset and termination of wars, and the literature is fuzzy on how to distinguish among different forms of political violence. This implies the need for theorizing about civil war and then for a proper measurement of the concept.... The results from models of war prevalence suggest that predictions of civil war duration will be even less accurate than predictions of civil war onset. There was greater instability of empirical results in the prevalence model, so analyses of civil war duration will be much more affected by differences in the coding rules.

Deeply acknowledging this conceptual pitfall, this dissertation follows previous studies and proposes "broad" and "narrow" definitions of civil conflict. The broad conceptualization defines a civil conflict as an armed conflict between two or more organized actors fought primarily within a single state's borders. The narrow conceptualization defines a civil conflict as an armed conflict between two or more state and non-state actors primarily within a single state's borders. While these two conceptualizations define a civil conflict as an armed conflict primarily fought within a single country, the difference lies in the inclusion or exclusion of conflicts between non-state actors.

The broad conceptualization of civil conflicts essentially follows the definition in Kalyvas (2006, 5) that

> [c]ivil war is defined as armed combat within the boundaries of a recognized sovereign entity between parties subject to a common authority at the outset of the hostilities.

Conflicts fought between non-state actors that do not involve state actors, as well as those fought between state and non-state actors, are included in this definition. The narrow definition, on the other hand, excludes cases of armed conflict that do not involve state actors, which essentially corresponds to the definition in the widely used UCDP/PRIO Armed Conflict Dataset (ACD, Gleditsch, Wallensteen, Eriksson et al., 2002; Pettersson and Wallensteen, 2015). The ACD defines an armed conflict as a

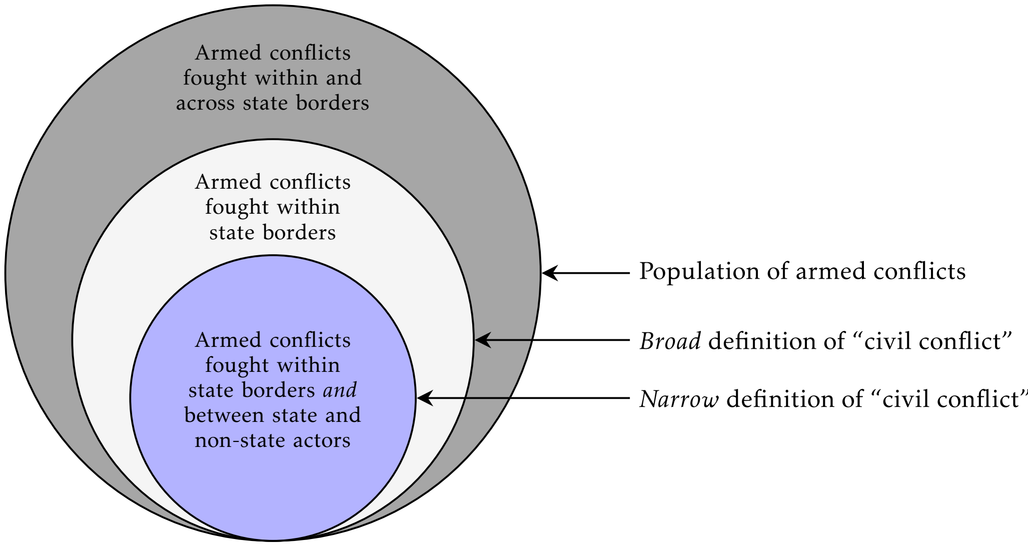

Figure 2.4: Tiered typology of armed conflicts and scope of analysis

Notes: Each circle represents a definition of armed conflict. The outer circle represents the set of armed conflicts within and across state borders, while the light-gray circle indicates the subset of intra-state armed conflicts, including those fought between non-state actors. The innermost circle indicates the subset of intra-state armed conflicts fought between state and non-state actors, which corresponds to the scope of the analysis in this dissertation. Note that intra-state armed conflicts that are fought between non-state actors as well as international conflicts have been omitted from the following analysis.

"contested incompatibility that concerns government or territory or both where the use of armed force between two parties results in at least 25 battle-related deaths," and civil or internal conflicts as a subset of the armed conflicts fought between the "government of a state and internal opposition groups" with or without intervention from other states (Gleditsch, Wallensteen, Eriksson et al., 2002, 618–619; see also, Small and Singer, 1982, 51–52).[12]

As depicted in Figure 2.4, this three-tiered typology of armed conflict

[12]In the ACD data, the total population of states is defined according to the systems membership definition in Gleditsch and Ward (1999). A sovereign government is considered to be an independent polity in Gleditsch and Ward (1999) dataset if it "a) has a relatively autonomous administration over some territory, b) is considered a distinct entity by local actors or the state it is dependent on, and c) has a population greater than 250,000" (398–399).

can be thought of as representing onion-like layers. The outermost layer in Figure 2.4 represents the population of intra- and inter-state armed conflicts fought within and across state borders. The second layer restricts its scope to those fought within a jurisdiction of single states and corresponds to the broad definition of civil conflict. The third layer (highlighted in blue) further restricts the scope to the armed conflicts between state *and* non-state actors, which are primarily, if not completely, limited to those fought within the jurisdiction of a single state.

Empirically, the scope of the following analysis is restricted to the narrow definition and thereby carefully drops from the analysis cases of intrastate conflict fought between non-state actors. The reason for this restriction is essentially practical rather than theoretical. On the one hand, disaggregated datasets increasingly cover battle events between non-state actors and the characteristics of non-state actors (Cunningham, Gleditsch, and Salehyan, 2013; Sundberg, Eck, and Kreutz, 2012). On the other hand, however, aggregated datasets on the duration and outcome of civil conflict, which are essential in the empirical analysis of conflict termination, have, to date, remained limited to the narrow definition of civil conflict (Kreutz, 2010; but see Sundberg, Eck, and Kreutz, 2012). Due to this limitation in the availability of datasets, the current study has carefully restricted the scope of the analysis to conflicts involving at least one state actor. This restriction also allows us to offer insights comparable to previous studies, drawing on similar typologies of civil conflict.

Theoretically, however, the scope of the proposed argument is not necessarily limited to the narrow definition of civil conflict. Rather, the elements of the theoretical argument themselves can logically be applied to the broad definition. The recent example of the Syrian Civil War is worth noting here. The Syrian Civil War can be characterized as multidimensional confrontations, involving third-party intervention (e.g., the United States and Russia) and confrontations between non-state actors (e.g., the Free Syrian Army, the Kurdish Syrian Democratic Forces, Tahrir al-Sham, and the Islamic State of Iraq and the Levant, ISIL) as well as confrontations between state (the Syrian government) and non-state actors. While this conflict episode does not necessarily fall within a single category of armed conflict in the ACD data, as discussed in detail in Chapters 5 and 6, the episode of intra-conflict bargaining between the Syrian government and rebel groups offers important insights into the bargaining model of war and the theoretical argument in this dissertation. Although the limitation of available datasets does not allow us to examine the external validity of the arguments, the core theoretical claims of this dissertation may travel to the microdynamics of violence and their impacts on the duration and outcomes of armed conflicts involving multiple confrontations.

Drawing on the research design illustrated in this chapter, the following four chapters present a series of empirical analyses on the causes and consequences of violence during civil conflict. The first two chapters report the empirical analysis on the microdynamics of civil war violence, and the following two chapters connect such micro-level dynamics of violence with macro-level variations in conflict duration and outcomes.

Part II

Conflict Process: Analyzing the Causes of Violence in Civil Conflicts

CHAPTER 3

Where Do You Strike Me?
Modeling the Determinants of Insurgent Violence in Civil Conflicts

> *[D]espite the obvious significance of the matter, there have been few attempts to move toward a systematic explanation of variation in violence — an oversight that has been puzzled more than one scholar.*
>
> Stathis N. Kalyvas (2006, 3)

Chapter Abstract *Why do insurgents strike some localities but not others? Two primary propositions have been proposed to explain spatial variations in insurgent violence: the first proposition stresses the role of the structural determinants of insurgent violence that are largely exogenous to conflict dynamics, while the second stresses the endogenous diffusion processes of insurgent activities. This chapter aims to examine the validity of each mechanism using an agent-based model incorporated with spatial (georeferenced) data from Afghanistan. The main findings are twofold. First, while ethnic geography is found to be a leading structural predictor of insurgent violence, a specific type of diffusion process, in which the occurrence of violence in a locality facilitates the geographic relocation of insurgents, substantially influences how insurgent violence unfolds. Second, the model yields a fairly good predictive performance when incorporated with diffusion dynamics, suggesting that the inclusion of diffusion dynamics yields a sizable improvement in our ability to explain insurgent activities in civil conflicts.*

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CHAPTER 4

How Do You Strike Me?
Decomposing the Determinants of Selective and Indiscriminate Violence in Civil Conflicts

Look at identical twins. When you get up closer, you start to see the small differences. . . . It all depends on how much you magnify it.

Brian Swanson[†]

Warring parties deliberately choose particular forms of violence with the aim of achieving their political objectives in civil conflicts (Bueno de Mesquita, 2013; Kalyvas, 2006). But why do warring parties employ violence selectively in some locations but indiscriminately in others? Significant variations are observed in the severity and types of violence within and across civil conflicts. Local distribution of the number and types of perpetrated violence is far from uniform even within a single conflict, as some localities experience severe civilian abuse while other localities are rarely exposed to such victimization during direct military confrontations between armed troops. What drives the spa-

[†]"No 2 snowflakes are the same, despite looking identical to naked eye." *McClatchy DC Bureau*, December 20, 2005. Available at: http://www.mcclatchydc.com/latest-news/article24452437.html, accessed May 31, 2017.

tial variation in the types of violence applied in civil conflicts? Why do the scale and forms of violence vary in civil conflicts?

Utilizing newly available micro-level, precisely-geocoded datasets of civil war battles, scholars have increasingly explored the determinants of insurgent violence in civil conflicts. Based on the difference in target selection, the existing literature regularly employs the conceptual distinction between selective and indiscriminate violence (Kalyvas, 2006, Chap. 6; see also, Ellsberg, 1970; Hechter, 1987; Leites and Wolf, 1970). Selective violence, or the punishment according to individual criteria, refers to violence applied conditional on the past behavior of the targets and is typically observed as violence targeted at collaborators of the opponent. In indiscriminate violence or "reprisals," on the other hand, personalized targeting in selective violence is replaced by collective criteria, typically based on ethnic group affiliation and settled localities, and such instances of violence are often observed as intentional civilian abuse by warring parties during civil conflicts.[1]

As reviewed in detail below, the civil war literature in recent years has increasingly explored the impacts that levels of territorial control (e.g., Kalyvas, 2006), battlefield dynamics (e.g., Hultman, 2007; Wood, 2014a), competition among rebel groups (e.g., Wood and Kathman, 2015), organizational configurations of warring actors (e.g., Humphreys and Weinstein,

[1]The types and forms of violence mainly refer to the selectivity of targets independent of the scale of targeting (Kalyvas, 2006). The distinction between selective and indiscriminate violence is analogous to the distinction between selective incentives and collective goods. Selective violence and incentives are provided conditional on the past behavior of individuals, while indiscriminate violence, or collective "bads," and collective goods are distributed on the basis of membership in a group (Hechter, 1987; Kalyvas and Kocher, 2007; Olson, 1965). Rebel groups can employ various tactics to gain civilian support and extract local resources, from the provision of economic incentives and local public goods to coercion and predation (Azam, 2006; Herbst, 2000; Lichbach, 1995). Because indiscriminate violence is often targeted at members of, for example, a specific ethnic group rather than applied completely at random, Steele (2009) proposes the concept of "collective violence" to describe this type of violence. Souleimanov and Siroky (2016) distinguish between "random" and "redistributive" violence, or sub-types of indiscriminate violence. Empirical records of civil war violence in the Chechen wars demonstrate that the instances of these two types of violence have differing impacts on subsequent violent activities of the opponent.

2006), relative reliance on local and external sources of support (e.g., Salehyan, Siroky, and Wood, 2014; Zhukov, 2017), and ethnic and physical geography (e.g., Fjelde and Hultman, 2014; Schutte, 2017) each have on the types, frequency, locations, and severity of violence in civil conflicts. Previous empirical studies have demonstrated that these factors, either exogenous or endogenous to conflict dynamics, substantially shape how violence unfolds in the context of civil conflict.

What remains relatively under-investigated in the literature is the relative importance of each class of factors. Perhaps a noteworthy aspect of existing studies is their division of labor, reflecting the prediction targets. Those studies that explore the determinants of selective violence tend to stress the role of factors that are largely endogenous to the conflict dynamics (e.g., territorial control), while those focusing on the determinants of indiscriminate violence typically highlight the role of largely preexisting factors that are often exogenous to the conflict processes (e.g., physical geography). Although these studies offer valuable insights into the possible determinants and mechanisms of civil war violence, we know relatively little about how and why the determinants of selective and indiscriminate violence may differ from each other.

This chapter argues that the relative importance of endogenous and exogenous determinants of violence depends on the types of violence applied. Exogenous factors play an important role in predicting indiscriminate violence, because (1) this type of violence is primarily motivated by damage-maximizing incentives, and (2) the locations where warring parties can maximize their opponents' pain are largely determined by exogenous factors. By contrast, endogenous factors matter in determining the locations of selective violence, because (1) the availability of the information required to apply violence selectively is largely a function of levels of territorial control (Kalyvas, 2006), and (2) the use of violence itself contributes to changes in levels of territorial control.

In order to disentangle the determinants of selective and indiscriminate violence, this chapter employs the empirically-grounded agent-based model developed in the previous chapter. This computational approach enables us to clearly specify the hypothesized mechanisms and generate hypothetical spatial distributions of violence that are directly comparable with the observed records. Because the hypothetical distributions are computationally derived from the computational model, this approach serves as a valuable test of whether theoretical propositions about insurgents' behavior can generate and explain the empirical reality.

The simulation exercise yields two major findings and provides strong empirical support for our theoretical expectations: indiscriminate violence can be predicted well solely by exogenous factors, while endogenous factors, or the recent history of violence that captures the battlefield dynamics and changing balance of territorial control, are vital in predicting where selective violence is applied.

The remainder of this chapter is organized as follows. In Section 4.1, we examine the recent expansion of the literature on civil war violence, followed by theoretical propositions. The case and empirical data are explained in Section 4.3, and we propose a parsimonious but empirically-grounded computational model in Section 4.4. We highlight the empirical results in Sections 4.5 and 4.6, and briefly report the results of sensitivity tests in Section 4.7. We then conclude by offering the scholarly and policy implications of our findings.

4.1 State of the Debate

The last decade has witnessed a tremendous growth in scholarly understanding of the determinants of violence in civil conflicts. The existing literature demonstrates that levels of territorial control (e.g., Kalyvas, 2006), battlefield dynamics (e.g., Hultman, 2007, 2012; Lyall, 2009; Souleimanov and Siroky, 2016; Wood, 2014a), competition among rebel groups (e.g., Metelits, 2010; Raleigh, 2012; Wood and Kathman, 2015), organizational configurations of warring actors (e.g., Azam, 2006; De la Calle, 2017; Eck, 2014; Humphreys and Weinstein, 2006; Johnston, 2008; Stanton, 2013;

Weinstein, 2005, 2007), relative reliance on local and external sources of support (e.g., Ottmann, 2017; Salehyan, Siroky, and Wood, 2014; Toft and Zhukov, 2015; Wood, 2014b; Zhukov, 2017), and ethnic and physical geography (e.g., Balcells, 2011; Di Salvatore, 2016; Fjelde and Hultman, 2014; Schutte, 2017) each invariably influence how violence unfolds in civil conflicts. This section briefly reviews these recent advances in the literature and elaborates the state of the scholarly debate.

4.1.1 Candidate Determinants of Civil War Violence

Territorial control and conflict dynamics Kalyvas (1999, 2006) brought back into the literature the conceptual distinction between selective and indiscriminate violence proposed by Leites and Wolf (1970). Selective violence involves individual targeting, whereas violence is indiscriminate when targeting is based on collective criteria (Kalyvas and Kocher, 2007, 187–188). The primary predictor of civil war violence in Kalyvas (2006) is the distribution of territorial control. Warring parties employ selective violence in zones of dominant but incomplete territorial control to foster civilian collaboration while deterring support for their opponents. In contrast, the frequency of indiscriminate violence is expected to be inversely related to the level of territorial control. This type of violence, due to the lack of intelligence to discriminate between collaborators of the opponents and innocent civilians, tends to be perpetrated where armed groups have very limited levels of territorial control.

Yet, indiscriminate violence is counterproductive in altering civilian behavior, because the "'innocent' can do little or nothing to escape punishment and the 'guilty' are no more (and sometimes less) threatened" (Kalyvas, 2006, 171). "In a regime of indiscriminate terror," as Kalyvas (1999) argues, "compliance [with the perpetrator] guarantees no security" (251). Due to its counterproductive nature, therefore, indiscriminate violence is expected to be the "product of a lag" and to decline as conflict persists. As warring actors learn the counterproductive nature of the indiscriminate use of violence, they eventually switch to selective violence (Kalyvas, 2006, 172). Utilizing the recently declassified, precisely geocoded records of combat activities from the Hamlet Evaluation System (HES), Kalyvas and Kocher (2009) have examined these theoretical predictions against the observed associations between territorial control and violence in the Vietnam War (see also, Dell and Querubin, 2017; Kalyvas and Kocher, 2007; Kocher, Pepinsky, and Kalyvas, 2011). Consistent with the theoretical claims in Kalyvas (2006), the empirical records show that the locations of selective and indiscriminate violence tend to be separated in space, and highlight the role of territorial control in determining the locations and types of violence perpetrated by warring actors.[2]

Rising battlefield losses and attrition would incentivize warring parties to employ violence indiscriminately, thereby shaping the frequency and manner of violence applied during civil conflicts (Downes, 2007; Hultman, 2007, 2012; Lyall, 2009; Souleimanov and Siroky, 2016; Wood, 2014a). Building upon the bargaining model of war, Hultman (2007) proposes that recent losses in the battlefield incentivize rebels to target civilians in order to impose political and military costs on the incumbent. The instrumental use of violence against civilians demonstrates rebels' "power to hurt" (Schelling, 1966) and thereby improves their bargaining position against the incumbent (see also, Acosta, 2016; Hultman, 2009, 2012; Stanton, 2013). Wood (2014a) further highlights the conditioning effects of largely static characteristics of rebel groups, such as effective territorial control and sources of rebel financing, on the relationship between rebels' battlefield losses and incentives for civilian victimization.

A related determinant of civil war violence is rebels' inter-group com-

[2]A related issue in the literature is the effectiveness of selective and indiscriminate violence in mobilizing civilian support and containing the opponents' activities. Kalyvas's theoretical prediction can be summarized as "[t]o be efficient, terror needs to be selective; indiscriminate terror tends to be counterproductive" (Kalyvas, 1999, 251). The empirical results in Dell and Querubin (2017), Kalyvas and Kocher (2007), and Kocher, Pepinsky, and Kalyvas (2011) provide support for the theoretical claim, whereas Downes (2007), Lyall (2009), and Merom (2003) highlight the violence-reducing effect of indiscriminate counterinsurgency campaigns. Toft and Zhukov (2015) stress the conditioning effect of rebels' relative reliance on local and external sources of support.

petition over local resources and bargaining power relative to the incumbent (Metelits, 2010; Raleigh, 2012; Wood and Kathman, 2015). Wood and Kathman (2015) contrast dynamic changes in the severity of competition among rebel groups during conflicts with the mere existence of multiple groups. Existing rebel groups are more likely to intentionally target civilians upon the entrance of new groups into the conflict because existing groups may perceive the arrival of new groups as a threat to their control of resources and the expected payoff of winning the conflict. Targeting civilians selectively offers a means to foster civilian collaboration and deter defection, thereby securing their material capability and bargaining power against the incumbent.

Group characteristics and geographic conditions Perhaps a common aspect of these arguments is their focus on dynamic factors that are essentially endogenous to the conflict process, such as the changing balance of territorial control (Schutte, 2017, 381–382). Nevertheless, several empirical studies have examined the role of relatively static factors that are largely, if not completely, predetermined and exogenous to conflict dynamics in altering the frequency and type of violence in civil conflicts.

The internal characteristics of rebel groups are one of these static determinants of civil war violence (Azam, 2006; Beardsley and McQuinn, 2009; De la Calle, 2017; Eck, 2014; Humphreys and Weinstein, 2006; Johnston, 2008; Stanton, 2013; Toft and Zhukov, 2015; Weinstein, 2005, 2007; Wood, 2010, 2014b). For example, Humphreys and Weinstein (2006) posit that high levels of civilian abuse tend to be conducted by warring actors that lack the capabilities to coordinate and police the actions of their members. Armed groups that are ethnically fragmented, tend to rely on material incentives or economic endowments to mobilize participants, and lack credible internal mechanisms for punishing indiscipline, tend to suffer from an inability to monitor their members' actions. Armed groups with such characteristics are therefore expected to be more likely to abuse civilians. The micro-level empirical records of civilian abuse conducted by multiple rebel groups in Sierra Leone confirm these theoretical expectations (see also, Weinstein, 2005, 2007).[3]

Another camp of the literature stresses the role of human and physical geography. Fjelde and Hultman (2014) highlight the role of local ethnic configuration and argue that warring actors often use ethnic affiliation to identify groups with suspected loyalty to the opponents when individual wartime affiliations remain private information. Warring actors, who often depend on civilian support to sustain combat activities, target the suspected enemy collaborators using local ethnic configurations as cues to guide their target selection in order weaken the enemy's capacity. The empirical patterns of civilian abuse in civil conflicts in Sub-Saharan Africa between 1989 and 2009 are consistent with their theoretical claims. In a similar vein, Balcells (2011) argues that indirect violence (violence perpetrated with heavy weaponry) tends to be applied to localities associated with levels of prewar support for the opponent, while direct violence (violence perpetrated with light weaponry) tends to increase with the level of political parity between factions in a locality. The empirical records of violence in the Spanish Civil War (1936–1939) provide support for the posited relationships. Utilizing a novel estimating methodology and survey data in Afghanistan, Hirose, Imai, and Lyall (2017) convincingly demonstrate that village-level pro-government attitudes are followed by an increased risk of insurgent attacks.

While local support for warring parties and, to a lesser extent, local ethnic configurations, can increase over time, geographical conditions such as elevation and distance from national capitals rarely change during the course of conflict. Schutte (2015, 2017) focuses on the role of physical geography, which is almost purely, if not completely, exogenous to conflict

[3] This logic can be applied to explain the impact of external sources of support on insurgent behavior. Heavy reliance on external, rather than local, sources of support reduces warring actors' need to win the "hearts and minds" of the local civilian population in order to sustain their campaigns and increases the risk of civilian abuse (Salehyan, Siroky, and Wood, 2014; Zhukov, 2017). In a similar vein, Stanton (2013) demonstrates how the size of rebels' civilian constituency influences types of rebel violence. Ottmann (2017) highlight the role of constituency overlap between rebels and the incumbent as well as the monadic civilian constituency in shaping the severity of violence against civilians.

processes. Schutte (2017) extends Boulding's (1962) notion of the "loss of strength gradient" (LSG) to explain the quality of targeting and proposes the notion of "loss of accuracy gradient" (LAG). The stylized model predicts that the selectiveness of applied projected violence decays as a function of distance from the warring actors' power centers (e.g., national capitals and rebel bases in periphery) due to the growing inability of the actors to distinguish between collaborators of the opponents and "innocent" locals, or due to the warring parties' "information problem" (Kalyvas, 2006). Empirical analyses using the geocoded event datasets of the ongoing war in Afghanistan and 10 cases of African insurgencies provide support for the notion of LAG.

4.1.2 Endogenous and Exogenous Determinants of Civil War Violence

The candidate determinants of violence in civil conflicts illustrated above can be thought of as representing a continuum with purely exogenous or static factors at one extreme and purely endogenous or dynamic factors at the other, as depicted in Figure 4.1. Geographic conditions such as distance to national capitals and elevation are most exogenous to conflict and lie at the left end, while territorial control and battlefield dynamics are largely determined by conflict processes and thus lie at the opposite end of the continuum. Other classes of determinants of violence are located between both ends, as the degree to which these factors are endogenous or exogenous to conflict dynamics initially depends on preexisting conditions, but the degree may vary across conflicts and time.

Admittedly, the relative location of each class of factors can vary and change in different conflicts. For example, ethnic geography can change through security-motivated migration and forced resettlement of the local population during conflicts (Steele, 2009; Weidmann and Salehyan, 2013; Zhukov, 2015). Nonetheless, it is highly unlikely that these factors change drastically over short time periods. Indeed, previous studies typically treat them as static or determined *ex ante*, rather than dynamic or *ex post*, determinants of civil war violence (e.g, Humphreys and Weinstein, 2006; Toft

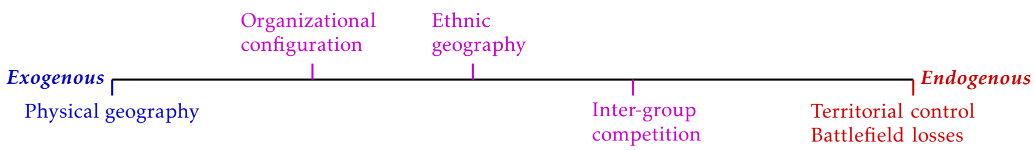


Figure 4.1: Continuum of determinants of civil war violence

Note: Each class of determinants of civil war violence is ordered according to the extent to which it can be assumed to be exogenous to the conflict process from the left end. The leftmost class of factors includes geographic conditions such as elevation and distance from national capitals, whereas the most dynamic factors, including balance of territorial control and battlefield dynamics, are located at the right end. The exact locations of intermediate factors can vary across conflicts and time.

and Zhukov, 2015; Weinstein, 2005, 2007; Wood, 2014a). Reflecting on these insights, it is reasonable to assume that organizational configurations, external support, ethnic geography, and inter-group competition lie somewhere between the two ends. These factors are likely to be less exogenous to conflict processes than physical geography but less endogenous than the balance of territorial control and battlefield dynamics.

4.2 Determinants of Violence Depend on the Types of Violence

A noteworthy aspect of existing studies lies in their different formulations of independent and dependent variables. Studies on the determinants of selective violence tend to focus on the effects of endogenous factors, while those on indiscriminate violence highlight the role of exogenous factors. For example, Kalyvas's (2006) theory highlights the impact of territorial control, which is largely endogenous to conflict dynamics, on locations of selective violence. By contrast, Fjelde and Hultman (2014) and Schutte (2017)each demonstrate the vital role of exogenous factors in determining the frequency of indiscriminate violence. Although indiscriminate violence is no more than a product of lag for Kalyvas (2006), these studies suggest that largely static characteristics such as physical geography substantially shape the frequency and locations of this type of violence.

What remains relatively unclear in the literature, however, is the relative importance of exogenous and exogenous factors in shaping the risk of violence in civil conflicts. Building upon the contributions of previous studies, this chapter proposes a nuanced and unified theoretical framework that specifies the likely impacts that the two classes of factors each have on the likelihood of selective and indiscriminate violence.

4.2.1 Determinants of Indiscriminate Violence

We argue that the relative importance of each class of factors varies depending on the types of violence perpetrated by the warring actors. Specifically, we posit that exogenous factors substantially shape the risk of both selective and indiscriminate violence. We also expect endogenous factors to be less important in determining the locations of indiscriminate violence. Rather, this class of factors plays an important role in altering the locations of selective violence.

Underlying these expectations is the speculation that different types of violence are motivated by different sets of warring parties' incentives. For example, Balcells (2011) and Fjelde and Hultman (2014) demonstrate how a preexisting geographic configuration of suspected supporters of the opponents, which is largely determined by pre-war affiliations, shapes how indiscriminate violence unfolds during civil conflicts.

If indiscriminate violence tends to "backlash" and undermine popular support for the perpetrator (Ellsberg, 1970; Kalyvas, 2006), instances of this type of violence would be either a product of error or reflect incentives that differ from the facilitating popular support of local civilians. As clearly formulated in Azam and Hoeffler (2002) and Fjelde and Hultman (2014), an important strategic consideration that motivates this type of violence is to maximize the damage and costs imposed on the opponents and their collaborators. Collective targeting against the suspected supporters of the opponent is often employed in order to undermine the productive capacity of the opponents' constituency, rather than to expand constituent support for the perpetrator or loot local resources (Azam and Hoeffler, 2002; Downes, 2007; Fjelde and Hultman, 2014; Stanton, 2013; Zhukov, 2015; see also, Acosta, 2016; Downes, 2006, 2008). The use of indiscriminate violence may also be efficient at pressuring the opponent into entering negotiations (Hultman, 2009).

Hultman (2007, 2012) and Wood (2014a) demonstrate how warring parties' incentives to employ indiscriminate tactics vary over time, reflecting battlefield dynamics within single conflicts. These arguments suggest that the *frequency* of indiscriminate use of violence at specific localities may vary over time. Nonetheless, the *locations* that are susceptible to this type of violence, or the locations where warring parties would expect to be able to maximize the damage to the opponent, are largely a function of preexisting or exogenous factors such as physical and ethnic geography. We therefore hypothesize:

Hypothesis 4.1 (Determinants of indiscriminate violence)
Subnational risks of indiscriminate insurgent violence are determined by exogenous factors.

4.2.2 Determinants of Selective Violence

Another key insight from previous studies is that the locations of selective violence reflect the dynamic elements of conflict such as levels of territorial control and recent history of battles. While Kalyvas (2006, 132–140) highlights the role of preexisting geographic factors in determining the initial spatial distribution of territorial control, the theory predicts that the balance of territorial control exercised by warring parties is the primary predictor of selective violence. In contrast to collective targeting, the likely motivation underlying the selective use of violence is to maximize popular support and deter defection, thereby strengthening the perpetrator's territorial control within the targeted regions (Eck, 2014; Herbst, 2000; Kalyvas, 2006). Successful use of selective violence may eventually shift local civilians' support for warring parties and thereby cause subsequent changes in territorial control (Kalyvas, 2006, Chap.7). The changes in territorial control in turn alter the locations that are susceptible to selective violence or where warring parties have incentives and opportunities to employ violence selectively in the subsequent periods.

These dynamics suggest that a recent history of violence as well as preexisting conditions should play an important role in predicting the location of insurgent violence, as they reflect the changing levels of territorial control. Although the underlying causal mechanism remains unspecified, empirical assessments of violence patterns in several civil conflicts have highlighted the role of the records of past violence in shaping future violence (Braithwaite and Johnson, 2012, 2015; Hirose, Imai, and Lyall, 2017; Linke, Witmer, and O'Loughlin, 2012; Zammit-Mangion, Dewar, Kadirkamanathan et al., 2012). We therefore expect insurgents' selective targeting to be a function of not only exogenous factors but also the endogenous dynamics of conflict.

Hypothesis 4.2 (Determinants of selective violence)
Subnational risks of selective insurgent violence are determined by both exogenous and endogenous factors.

To evaluate the validity of these hypotheses, we rely upon the precise and micro-level records of violent incidents in the ongoing war in Afghanistan and a computational model. The following section provides a brief overview of the empirical data.

4.3 Data and Empirical Context

This chapter uses the ongoing irregular warfare in Afghanistan as a case to disentangle the determinants of selective and indiscriminate violence in civil conflicts. Following the former Taliban leader Mullah Muhammad Omar's vow to "retake control of Afghanistan" in 2004 (Gall, 2004), the Taliban remnants had regrouped and launched large-scale insurgency by late 2005 (Johnson, 2013, 10–11). Despite the losses and attrition that the Taliban have suffered and the U.S.-led troop "surge," or a massive increase of coalition troops, the counterinsurgency campaign is not yet completed

(Farrell and Giustozzi, 2013; Johnson and DuPee, 2012; Johnson and Mason, 2008).

The following empirical analysis relies on the U.S. military internal database called "Significant Activities" (SIGACTs).[4] The SIGACTs are a collection of short summaries of events in relation to the actors involved, casualties, event type, locations, timing, and other related information that have been recorded by individual troops. The SIGACTs event data cover both violent (e.g., IED explosions) and nonviolent (e.g., information provision from civilians) incidents across the country between January 2004 and December 2009, and have been widely used in the civil war literature (e.g., Donnay and Filimonov, 2014; Schutte, 2017; Weidmann, 2015, 2016; Zammit-Mangion, Dewar, Kadirkamanathan et al., 2012).

Because the activities of ISAF and Afghan national forces are likely to be affected by factors other than the local-level determinants of violence illustrated above, the following analysis employs insurgent violence as the primary dependent variable. Of the 76,910 entries, 52,196 comprise reports on violent incidents and the remaining 24,714 are on nonviolent incidents.[5] We aggregated 45,628 incidents of insurgent-initiated violence to the settlement level using their geo-coordinates ($N_{\text{stl}} = 37,484$).[6] During the period covered by the dataset, 7,644 (20.4%) settlements experienced one or more insurgent attacks.

[4]As in the previous Chapter, the following empirical analysis employs the "Afghan War Diary" (AWD), a subset of the SIGACTs that has been released by WikiLeaks.org.

[5]Although the SIGACTs database offers a rare opportunity for researchers to explore the microdynamics of civil war, it may suffer from potential bias (Donnay and Filimonov, 2014; Weidmann, 2015, 2016). First, there may be a tendency for military troops to underreport the collateral damage caused by their operations. However, this bias is unlikely to cause a serious problem in the following analysis, since the main focus here is on the distribution of insurgent-initiated attacks. Second, the reporting standards for SIGACTs may vary across units and/or have changed over time, possibly resulting in a significant measurement error. This concern is partly alleviated by focusing on the temporally aggregated spatial distribution of violence.

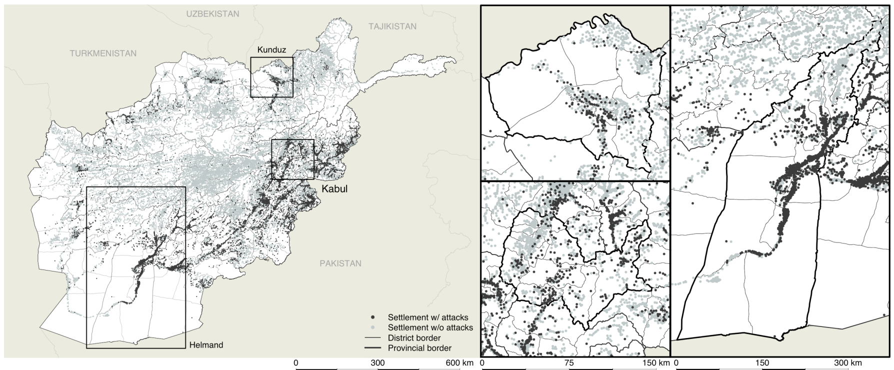
[6]Individual incidents are tagged with the geographically closest settlements. Geocoded settlement dataset is obtained from the USAID "Afghanistan: Settlements." Available at: https://www.humanitarianresponse.info/operations/afghanistan/dataset/afghanistan-settlements-villages-towns-cities-0, accessed July 25, 2014

Table 4.1: Distribution of insurgent violence across population settlements, by event types

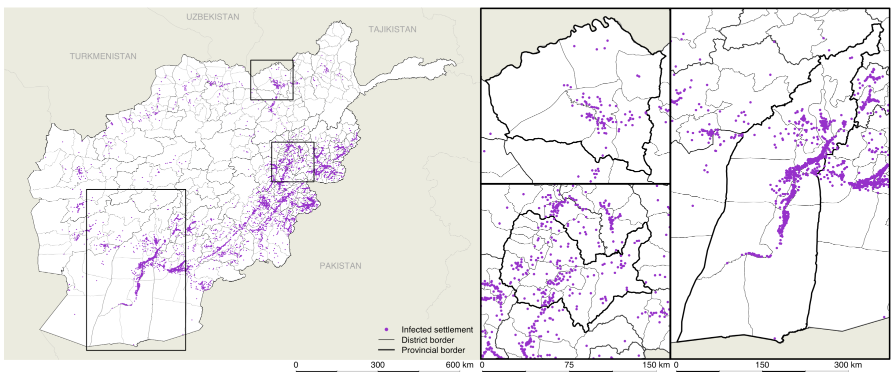
	w/o IED incidents	w/ IED incidents
w/o non-IED incidents	29,840	2,131
w/ non-IED incidents	2,765	2,748

The operationalization of selective and indiscriminate violence is the key to the following empirical analysis. We operationalized indiscriminate insurgent violence by attacks using IED (improvised explosive device) and selective violence by non-IED attacks. Underlying this operationalization is the idea that IED attacks, as exemplified by roadside bombs, are rarely selectively targeted, which generally fits with the operational definition of indiscriminate violence. Specifically, the selection criteria employed the "Affiliation," "Category," and "Type" columns (short event description and perpetrator) in the SIGACTs database to filter the records of IED and non-IED insurgent attacks. Specifically, "Explosive Hazard," "IED Ambush," "IED Explosion," "IED Found/Cleared," "IED Threat," "IED Hoax," "IED False," "IED Suspected," "Interdiction," "Premature Detonation" (premature IED detonation), "Mine Found/Cleared," "Mine Strike," "Unknown Explosion," and "Vehicle Interdiction" categories were coded as IED events, while the remaining events affiliated with insurgents were coded as non-IED events. We further matched the subsets of the data against the "Affiliation" variable, which contains information about the perpetrator ("FRIEND," "ENEMY," "NEUTRAL," "UNKNOWN"), and coded those records with "Affiliation"="ENEMY" as insurgent-initiated events. This coding procedure yielded 19,567 records of indiscriminate IED attacks and 26,061 selective non-IED attacks.

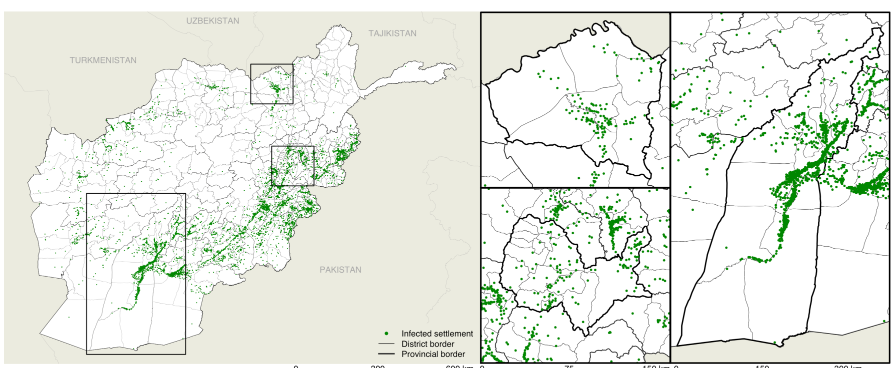
Table 4.1 summarizes the resultant distribution of IED and non-IED insurgent attacks across villages, and Figure 4.2 uses maps to visualize the spatial distribution of population settlements with and without insurgent violence. While an initial look at Figure 4.2 suggests that IED and



(a) Spatial distribution of insurgent violence



(b) Spatial distribution of indiscriminate insurgent violence (IED attacks)



(c) Spatial distribution of selective insurgent violence (non-IED attacks)

Figure 4.2: Spatial distribution of insurgent violence in Afghanistan, 2004–2009, by event types

Note: (a) Black (•) and gray dots (•) indicate settlements with and without insurgent attacks, respectively. (b) Purple dots (•) represent settlements with indiscriminate (IED) insurgent attacks. (c) Green dots (•) represent the location of settlements with selective (non-IED) insurgent attacks.

non-IED attacks tend to cluster in similar regions (panels (b) and (c)), the cross-tabulation reported in Table 4.1 depicts otherwise. Although 2,748 villages had experienced both types of insurgent attacks, the remaining $2,131 + 2,765 = 4,896$ out of 7,644 settlements with one or more insurgent attacks had been exposed to *either* IED or non-IED but not another type of attack during the study period. Similarly, the village-level correlation between the number of IED and non-IED attacks remains modest, with Pearson's $r = 0.418$.[7] The variations in the spatial distributions of insurgent violence offer a suitable foundation for testing the validity of the two propositions advanced in the previous section.

4.4 Computational Model

The following computational experiments employ the empirically-explicit agent-based model developed in the previous chapter, with the dependent variables differently specified. See Section 3.3 for details.

4.5 Results I: Determinants of Insurgent Violence

The following two sections report the main findings derived from the computational model. Because the model is not analytically tractable, the analysis derives its results via computational simulation. The validation strategy is twofold: first, we specify empirically plausible parameter sets and thereby examine the likely determinants of insurgent activities. We then evaluate the predictive power of the calibrated model. The analysis in this section aims to optimize the model's parameter combinations such that the simulation outcomes closely fit the empirical records along the specified dimensions of agreement, thereby identifying the likely determinants of insurgent violence. In the following subsections, we first present the validation strategy and then examine the individual parameters estimates.

[7] The absence of the lack of spatial overlap between selective and indiscriminate insurgent violence is consistent with the earlier finding of Kalyvas (2006).

4.5.1 Parametrization strategy

Our parametrization strategy broadly follows that of Weidmann and Salehyan (2013, 58). First, $N_{\text{run}} = 50,000$ simulations are conducted with parameter combinations drawn from uniform distributions (parameter space $\mathbf{\Theta}_0$). We then select a subset of parameter combinations $\mathbf{\Theta}_1 \subset \mathbf{\Theta}_0$ that generates spatial distributions of insurgent violence similar to the observed distribution. This parametrization strategy allows for the parameter values to be specified that are necessary to generate realistic patterns of violence and their impacts on simulation outcomes.[8]

Define "good-fit" runs The generated distributions of violence are compared with the empirical records along two target classes: *location* and *number* of insurgent violence. The agreement between the predicted and observed locations of violence is quantified by true positive rate (TPR = $\frac{\#\,\text{true positives}}{\#\,\text{total positives}}$), false positive rate (FPR = $\frac{\#\,\text{false positives}}{\#\,\text{total negatives}}$), and accuracy (ACC = $\frac{\#\,\text{true positives}+\#\,\text{true negatives}}{\#\,\text{total cases}}$). Similarly, the degree of agreement for the number of attacks is quantified by the Root Mean Squared Error (RMSE) = $\sqrt{\sum_{i=1}^{N}(\hat{Y}_i - Y_i)^2/N}$.

We define "good-fit" runs as those that minimize the deviation of the model outcome from the empirical records that fulfill the following conditions: (1) ACC > 0.67, (2) TPR $>$ FPR, and (3) (weighted) RMSE $< \text{RMSE}^{\text{rnd}}_{0.05}$. In order to filter the runs that fulfill these conditions, we first discard the noninformative runs that generated no insurgent attacks and then select those that fulfill these three conditions to obtain the optimized parameter space $\mathbf{\Theta}_1$. A random coin toss produced an ACC score of 0.5, and thus a > 0.67 ACC ensures that the corresponding run correctly classifies more than two-thirds of the observations (condition 1). Similarly, as a general rule, a model with high binary predictive capability has a TPR that is consistently higher than the corresponding FPR (condition 2).

[8]This parametrization approach allows for a large parameter space to be examined at a relatively low computational cost compared to the oft-employed sequential parameter sweeping that is known to be the equivalent of comparative statics in game-theoretic models (Holland, Holyoak, Nisbett et al., 1989).

A "good-fit" run should also minimize the deviation of predicted numbers of violence from the observed data series (condition 3). $\text{RMSE}^{\text{rnd}}_{0.05}$ denotes the 5th percentile value of the RMSE distribution obtained by N_{run} random null predictions. A null prediction is generated by assigning the observed number of IED and non-IED attacks to randomly selected population settlements. This procedure is repeated N_{run} times to generate a hypothetical sample of "random conflicts." If the RMSE obtained from a run is smaller than $\text{RMSE}^{\text{rnd}}_{0.05}$, the prediction is considered to outperform random guesses.

One concern regarding the reliance on RMSE is that this metric may potentially be ill-suited for the validation here, given that the occurrence of violence is relatively rare in our dataset (13% for IED attacks and 14.7% for non-IED attacks, respectively). A noninformative prediction, which simply assigns $\hat{Y}_i = 0$, would produce a small RMSE indicating a "good-fit." To address this concern, we employ the *Weighted* RMSE (WRMSE) $= \sqrt{\sum_{i=1}^{N} w_i(\hat{Y}_i - Y_i)^2 / \sum_{i=1}^{N} w_i}$, with weight $w_i = 1 - p(Y_i \geq 1) = 0.870$ for the settlements with IED attacks and $w_i = 0.130$ for those without IED attacks (0.853 and 0.147, for non-IED attacks) instead of standard RMSE in the following analysis. As the adjusted Brier score employed in Chadefaux (2014, 15), WRMSE penalizes prediction errors for rare observations (i.e., $Y_i \geq 1$) more severely than those for abundant ones (i.e., $Y_i = 0$).

Detect "significant" parameters The difference between uniform distribution (Θ_0) and the optimized parameter distribution (Θ_1) provides an intuitive indicator of the effects of individual parameters on the model's predictive performance. A significant difference between the parameter values in Θ_0 and Θ_1 indicates a systematic impact of the corresponding parameter on the model's fits, while an insignificant difference indicates otherwise (Weidmann and Salehyan, 2013, 58–60).

A formal statistical test is informative to quantify the resultant difference between the "prior" (Θ_0) and "posterior" (Θ_1) distributions. Nonetheless, because we are interested not only in *whether* there is a statistically significant difference between the two distributions, but also in *how* the distributions differ, standard statistical tests comparing central tendencies, such as the Student's t-test, do not suffice for the purpose here. Indeed, a pair of distributions can significantly differ from each other in their lower or upper tails even when the difference in their central tendencies remains statistically indistinguishable from zero.

To accomplish this task, we employ the Harrell–Davis quantile estimator in conjunction with a percentile bootstrap (Harrell and Davis, 1982; Wilcox, Erceg-Hurn, Clark et al., 2014). This newly proposed estimator quantifies the difference between two given distributions using the differences in paired decile values, and then computes the confidence intervals of the decile differences via a bootstrap estimation while controlling over the Type I (α) error probability. By comparing the paired decile values, this estimator allows us to evaluate whether and in which part (decile) there are statistically significant differences between the two distributions.

Recall that our central theoretical claim expects the determinants of selective and indiscriminate violence to be distinct from each other. If this theoretical expectation is consistent with the empirical records of insurgent violence in Afghanistan, different sets of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ parameters should exhibit significant shifts in optimized parameter space Θ_1 from the population of random distributions.

4.5.2 Estimation Results

For the following exercise, two sets of N_{run} simulation runs were conducted using parameter combinations $(\alpha, \boldsymbol{\beta}, \boldsymbol{\gamma})$ randomly drawn from uniform distributions $U(-10, 10)$ and different random seeds for two prediction targets (i.e., IED and non-IED attacks). $M = 20,000$ agents are allocated to randomly selected population settlements at the beginning of a run. Each run continues until either (1) t reaches $t_{\max} = 300$, or (2) the cumulative number of simulated insurgent attacks reached the observed number of attacks ($N^{\text{IED}}_{\text{attack}} = 19,567$ for IED attacks and $N^{\text{NonIED}}_{\text{attack}} = 26,061$

for non-IED attacks).[9] Of 50,000 randomized trials, 4,685 runs (9.37%, IED attacks) and 1,707 runs (3.41%, non-IED attacks) fulfilled the criteria above, respectively.

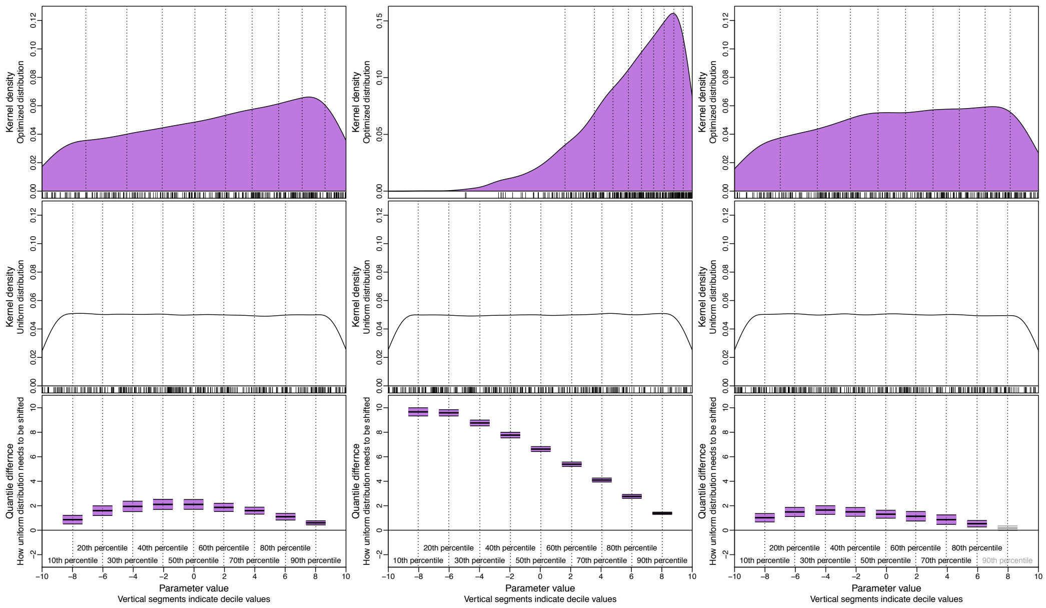
Determinants of IED (indiscriminate) attacks Each panel in Figure 4.3 represents a layer of information. The first comprises the distributions of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ parameters in $\boldsymbol{\Theta}_1$ that successfully generate realistic spatial patterns of insurgent violence (top density plot). The second comprises the density estimate of the baseline of uniform parameter distribution $\boldsymbol{\Theta}_0$ for comparative purposes (middle density plot). The third comprises quantile difference estimates accompanied by bootstrapped confidence intervals plotted at the bottom of each panel. Using the Harrell–Davis quantile estimator, the third part of each panel quantifies how much the decile values of one distribution (parameter values in $\boldsymbol{\Theta}_0$) need to be arranged to match the other distribution ($\boldsymbol{\Theta}_1$).[10] In other words, the quantile estimator indicates the decile differences between the parameter values in the optimized distribution and those in the uniform distribution. A statistically significant shift at the conventional 5% level in each decile is marked by black horizontal segments, while an insignificant shift is shown in light gray.

Hypothesis 4.1 expects insurgents' decision to employ violence indiscriminately as a function of static factors. The simulation results reported in Figures 4.3 provide strong support for this theoretical expectation. The effects of this class of predictor of violence are captured by $\boldsymbol{\beta}$ parameters in our computational model. As shown in panels (a) to (g) of Figure 4.3, almost all $\boldsymbol{\beta}$ parameters are significantly shifted from the population of uniform distribution in the optimized parameter space.

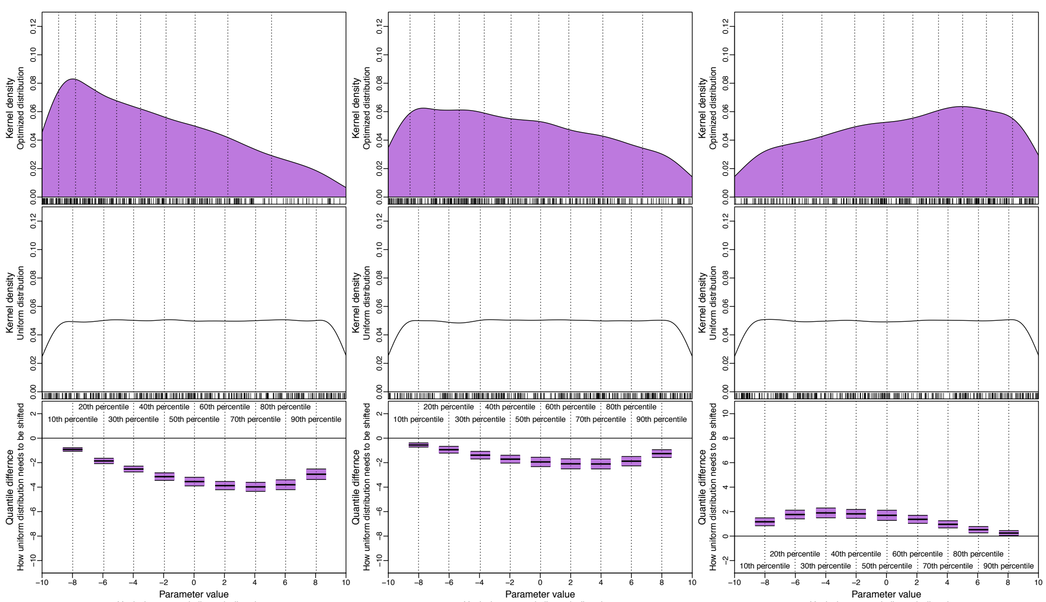
The most apparent impact is found for *PashtunPop* (β_2), which measures the impact of the local Pashtun population on the risk of indiscriminate violence. The 10th to 40th quantiles of the distribution of β_2 in $\boldsymbol{\Theta}_1$

[9] The second condition is an arbitrary one to speed up simulation runs. Removing this condition does not markedly alter the results reported below.

[10] The 95% confidence intervals were obtained via 200 bootstraps. WRS package in R (https://github.com/nicebread/WRS) was used to obtain the reported statistics.

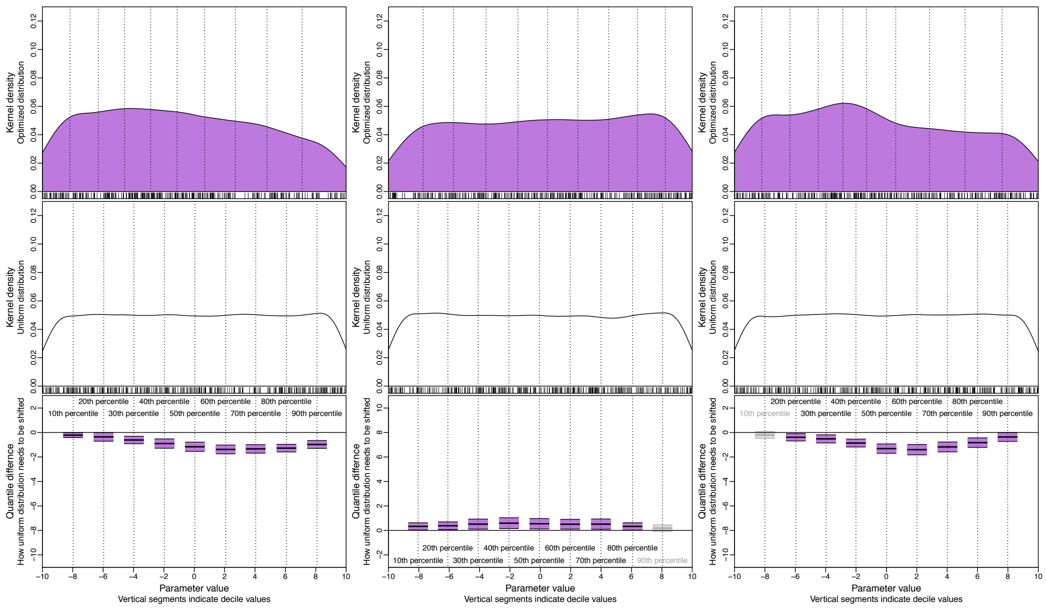


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

Figure 4.3: Optimized parameter distribution, IED attacks



(g) (cont.) *APborder* (h) (cont.) *Spread* (i) (cont.) *History*

Figure 4.3 (cont.): Optimized parameter distribution, IED attacks

Note: The topmost raw in each panel represents the density estimate for a given parameter in Θ_1, while the middle raw shows the corresponding density in Θ_0. Vertical dashed segments indicate the decile values of each parameter in Θ_0 and Θ_1. The bottom raw plots the decile shift estimates. The decile-difference estimates (thick horizontal segments) between the optimized and uniform distributions are plotted along the vertical axis for each decile of uniform distribution. Thin horizontal segments and gray shades indicate the corresponding 95% bootstrap confidence intervals. Significant differences at the 5% level are marked by black segments, while insignificant differences are marked by gray segments.

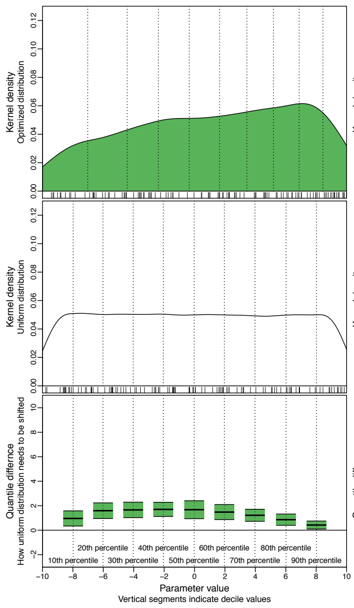
are shifted by more than 8 from uniform distribution, indicating a strong positive impact of *PashtunPop* on the probability of indiscriminate violence. Put another way, this result demonstrates that insurgent agents tend to conduct indiscriminate attacks in settlements with a large Pashtun population in good-fit simulation runs that generate a realistic spatial distribution of indiscriminate violence. Although a simple statistical test comparing the central tendency can also demonstrate a statistically significant difference between the two distributions, it can tell us little about how and how much the distributions differ.

Although similar statistically significant decile shifts are also found for other $\boldsymbol{\beta}$ parameters, the estimated shift sizes remain relatively smaller. Perhaps an exception is *Ruggedness*, or the local elevation differences. The parameter values are negatively skewed in optimized parameter space $\boldsymbol{\Theta}_1$, indicating that insurgent agents are more likely to conduct attacks in easily accessible, rather than inaccessible, settlements (Figure 4.4(d)). Again, the estimated shift function suggests a statistically significant difference with a relatively large effect size across the parameter range.

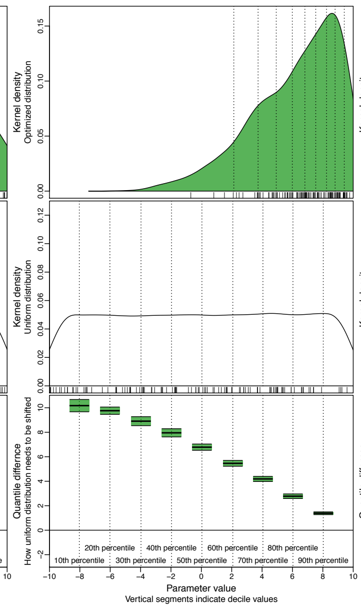
In sharp contrast, the estimated shifts in $\boldsymbol{\gamma}$ parameters, or endogenous factors, remain indeterminate compared with $\boldsymbol{\beta}$ parameters. As illustrated in Figures 4.3(h) and (i), although many of the estimated shifts of *Spread* and *History* retain statistical significance at the conventional 5% level, the effect sizes remain smaller than the shifts in $\boldsymbol{\beta}$ parameters and substantially insignificant. Combined, these simulation results suggest that insurgent agents' decisions to employ indiscriminate IED attacks are largely a function of exogenous factors, while endogenous factors or a recent history of violence have little impact on the risk of this type of insurgent attack.

Determinants of non-IED (selective) attacks Figure 4.4 represents the decile-shift plots for the determinants of non-IED attacks. Two significant results emerge from Figure 4.4. First, the two exogenous factors, *PashutunPop* and *Ruggedness*, that are found to be strong predictors of IED attacks exhibit clear decile shifts in Figure 4.4. As the shift signs indicate, *PashutunPop* positively impact the risks of indiscriminate (IED) and selective (non-IED) insurgent attacks while *Ruggedness* negatively impacts the likelihood of both types of insurgent violence.

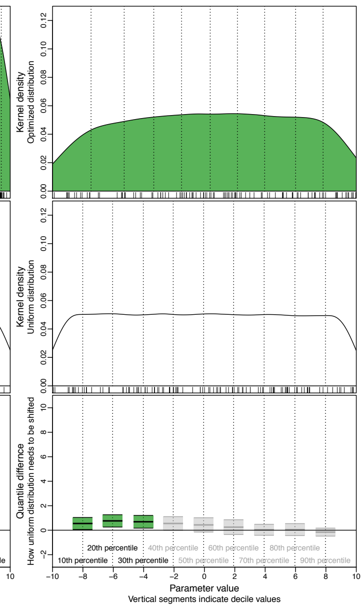
Second and more importantly, one of the modeled endogenous factors, namely *History*, is found to have a substantial negative impact on the agents' decision to conduct non-IED attacks. The large and consistently negative shifts of γ_2 suggest that a marked history of violence facilitates agents' migration to nearby settlements rather than further violence in the originating settlements. The corresponding quantile estimates further indicate the sizable differences in deciles between parameter values



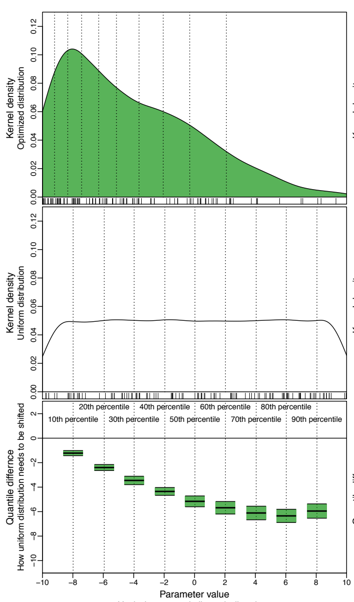
(a) *PopSize*



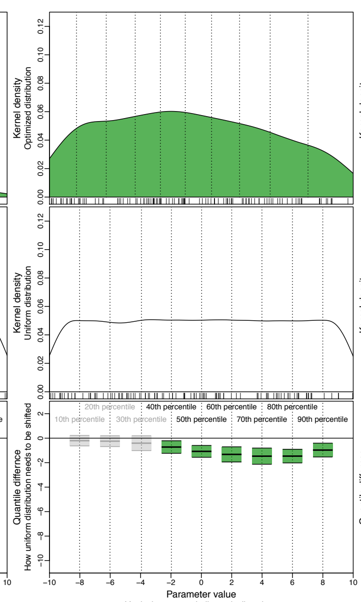
(b) *PashtunPop*



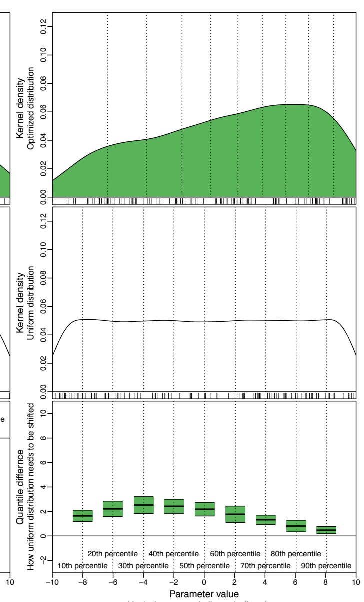
(c) *Development*



(d) *Ruggedness*

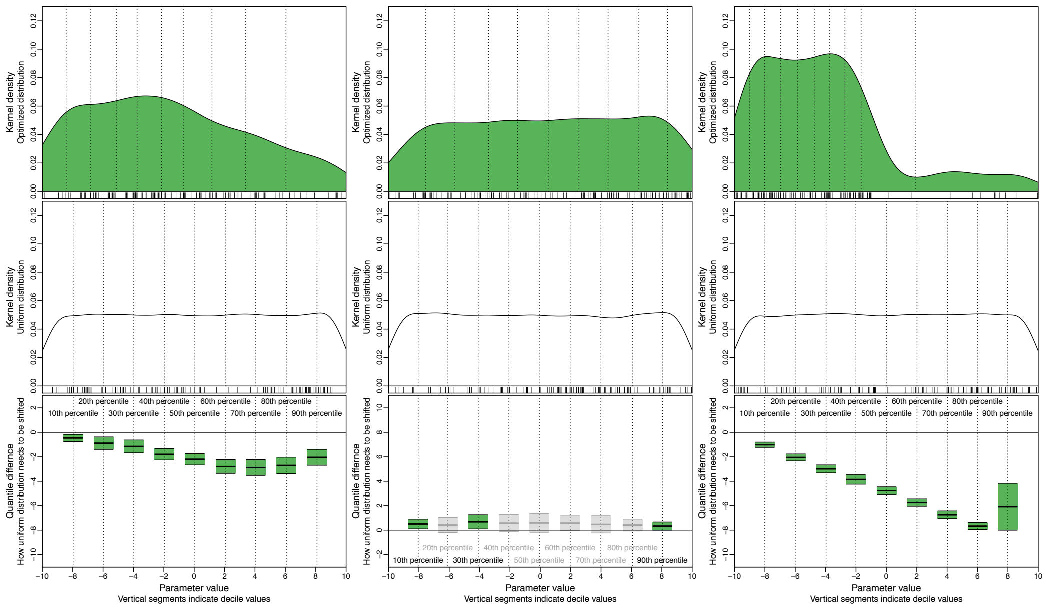


(e) *RoadDist*



(f) *CapDist*

Figure 4.4: Optimized parameter distribution, non-IED attacks



(g) (cont.) *APborder* (h) (cont.) *Spread* (i) (cont.) *History*

FIGURE 4.4 (cont.): OPTIMIZED PARAMETER DISTRIBUTION, NON-IED ATTACKS
Note: See notes in Figure 4.3.

in $\mathbf{\Theta}_0$ and $\mathbf{\Theta}_1$. In contrast, the estimate for γ_1 (*Spread*) remains weaker or statistically indistinguishable from the uniform distribution across the sampling range, suggesting that γ_1 is unlikely to have a systematic impact on the model's fit with the empirical records. In other words, the results suggest that while a history of violent activities systematically shapes the future prospects of the violence in a given settlement, spatial context may not matter in determining the probability of insurgent violence.

Generally, the simulation results provide strong empirical support for our central theoretical claim that the determinants of violence vary across types of violence. Recall that Hypothesis 4.2 posits that insurgents' decisions to employ selective violence is a function of endogenous as well as exogenous factors. Combined with the simulation results for β parameters, these results in Figure 4.4 are consistent with this theoretical expectation.

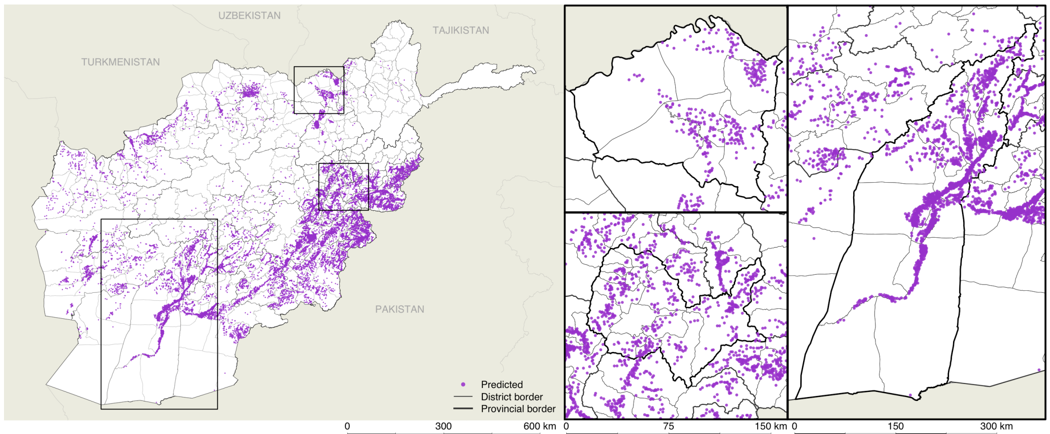
4.6 Results II: Prediction Performance

Does the model correctly predict the location and number of insurgent attacks across settlements, and to what extent? What are the determinants of the model's predictive performance? The analysis in the previous section provided valuable insights into the determinants of insurgent violence, yet on its own it provides little information on the veracity of the model. Indeed, the validity of the simulation experiment relies on a potentially unwarranted assumption that the model's explanatory power is at least reasonable. An assessment of predictive performance should be a valuable heuristic in this context (Ward, Greenhill, and Bakke, 2010).

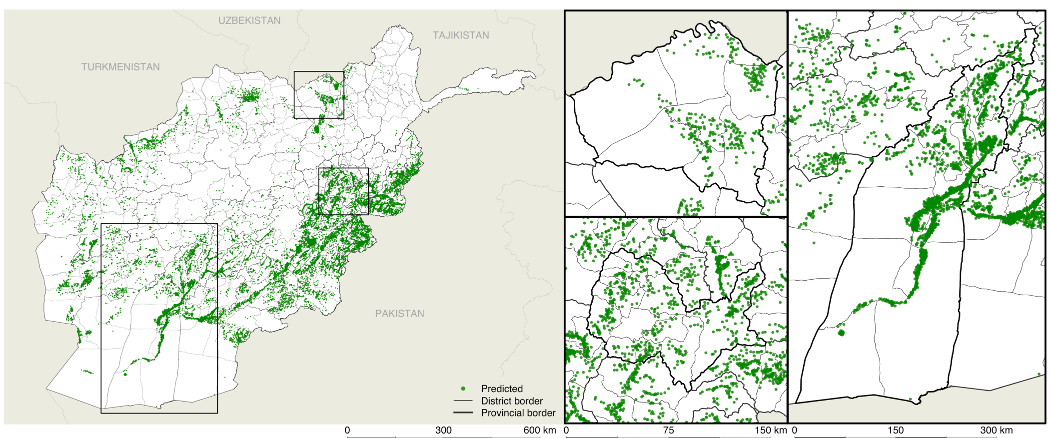
A model's capability to correctly classify binary outcomes (e.g., presence or absence of insurgent violence) can be quantified using the Receiver Operating Characteristic (ROC) curve and the area under the ROC curve (AUC) score. An ROC curve plots TPR and FPR as the output of each possible probability threshold for positive prediction. The resultant plot displays the balance between TPR and FPR, where a highly predictive model (with high TPR and low FPR) produces the curve up in the top left corner. An AUC score, which is defined as the area covered by the corresponding ROC curve, ranges between 0 and 1, and provides a single number summary of the model's classification performance. A random coin toss produces an AUC score of 0.5, whereas a model with higher classification performance should yield an AUC score of greater than 0.5.

Figure 4.5 maps the (a) predicted locations of IED and (b) non-IED insurgent attacks to visualize the model's predictive performance. The ROC analysis yields AUC scores of 0.794 (95% CI: 0.793, 0.806, IED attacks) and 0.789 (95% CI: 0.785, 0.797, non-IED attacks), indicating that the model's classification performance far exceeds randomness.[11]

[11] The predicted probability of violence assigned to each settlement reflects the fraction of simulation runs in $\boldsymbol{\Theta}_1$ in which one or more attacks have occurred in the corresponding settlement. The 95% CIs were obtained by bootstrap using R's pROC package (Robin, Turck, Hainard et al., 2011).



(a) Predicted locations of IED attacks



(b) Predicted locations of non-IED attacks

Figure 4.5: Predictive performance: Locations of IED and non-IED attacks
Note: (a) spatial distribution of predicted locations (settlements) of IED attacks. (b) predicted locations of non-IED attacks. These figures are generated using the best threshold values obtained by the ROC analysis.

4.7 Robustness Checks

The main results do not on their own preclude the potential sensitivities of the simulation experiments. Consequently, one may reasonably wonder how the "moving parts" or parameter settings of the computational model change the results. Four parameters and assumptions warrant investigation to examine the robustness of the main results: (1) neighborhood size k, (2) number of agents M, (3) the attack-or-relocate dichotomy in the behavior algorithm, and (4) exponential weight ϕ for $Spread$ and $History$.

To examine the robustness of the main results, 700,000 additional simulations were conducted, varying these parameter settings and assumption. Reassuringly, none of these sensitivity tests reported in Appendix A.5 yielded results that deviate markedly from the main results reported above. These results provide confidence that the specific parameter settings and assumption are not driving the main findings.

4.8 Conclusion

Civil war studies have increasingly explored the determinants of violence during civil conflicts. Theoretically, the distinction between selective and indiscriminate violence lies at the center of the debate. Empirically, previous studies have demonstrated how a variety of factors can alter the frequency, locations, and types of violence in civil conflicts. Building upon these insights, this chapter has proposed that the determinants of civil-war violence vary across types of perpetrated violence: the decision by warring parties to employ indiscriminate violence is largely a function of exogenous factors, whereas selective violence is a function of endogenous as well as exogenous factors. Drawing on the SIGACTs event data and spatial data of local geography in Afghanistan, the results from the empirically-grounded, agent-based model have yielded two main findings. First, exogenous factors substantially shape agents' decisions to attack indiscriminately. Second, endogenous factors, or a recent history of violence within the same localities, have a sizable impact on agents' decisions to employ selective violence. These results of empirically-based, agent-based simulations provide compelling support for our theoretical argument.

This chapter has significant implications for scholarly and policy debates. First, these findings underscore the importance of disaggregating the types of violence used in civil conflicts. The simulation results demonstrate that while several exogenous or static factors have substantial impacts on the risk of indiscriminate violence, the relative importance of endogenous factors may vary across types of violence. Although no single case study can provide a definitive answer, closer attention, both theoretically and empirically, should be paid to this difference in future research.

Second and methodologically, this chapter demonstrates the methodological utility of data-driven computational modeling. While it is often difficult to disentangle the endogenous and exogenous explanations of the conflict process using observational data alone, the computational approach allows researchers to tackle this challenging task. Indeed, this chapter demonstrates how the empirically-based computational approach helps us to isolate the impact of each factor and supplements the standard observational approaches.

Finally, this chapter should also inform policymakers and practitioners of counterinsurgency. Counterinsurgency campaigns primarily aim at minimizing insurgent activities and restoring the state's monopoly on violence within its borders. If the determinants of insurgent violence vary across types of violence, effective counterinsurgency campaigns should also vary across targeted types of violence. Thus, rather than adopting a blanket approach, counterinsurgency efforts to contain different types of insurgent violence also need to address different factors if they are to be successful.

Part III

Conflict Termination and Outcome: Analyzing the Consequences of Violence in Civil Conflicts

CHAPTER 5

Violence Diffusion Shapes When Civil Conflict Ends

A Spatially-Explicit Empirical Analysis of Conflict Termination

> *Military strategy can no longer be thought of, as it could for some countries in some eras, as the science of military victory. . . . Military strategy, whether we like it or not, has become the diplomacy of violence.*
>
> Thomas C. Schelling (1966, 34)

Recent advances in the micro-level civil war literature have found a wide cross-national variation in the conflict geographies (Beardsley, Gleditsch, and Lo, 2015; Buhaug and Gates, 2002; O'Loughlin and Witmer, 2012; O'Loughlin, Witmer, and Linke, 2010; Schutte and Weidmann, 2011; Townsley, Johnson, and Ratcliffe, 2008; Zhukov, 2012). Battle activities in some conflicts gradually diffuse from the originating locations toward geographically contiguous locations, just like a forest fire, while the battle locations in other civil wars spread toward wider areas that have not previously been exposed to violence. In still other conflicts, the conflict-affected areas remain relatively contained and stable.

How do such micro-level conflict processes, then, "scale up" to the macro-level? How and why do different patterns of battles at the micro level have differing impacts on the eventual conflict duration and termination? Traditionally, much of the literature on conflict termination has focused on structural or static factors, such as state capacity and the existence of natural resources (e.g., Collier, Hoeffler, and Söderbom, 2004; DeRouen and Sobek, 2004; Fearon, 2004). Consequently, the micro-level, dynamic determinants of civil war termination have been left relatively under-studied in the current literature, which would lead us to biased conclusions (Balcells and Kalyvas, 2014, 1391–1392).

In contrast, a small but growing body of literature in recent years has increasingly demonstrated that battle intensity (Ruhe, 2015), battle locations (Greig, 2015; Greig, Mason, and Hamner, 2016; Ruhe, 2015), civilian victimization (Wood and Kathman, 2014), and acts of terrorism (Fortna, 2015; Thomas, 2014) each influence civil war termination and outcome. For example, Greig (2015) argues that the relative locations and movements of battles toward strategic locations such as capital cities reveal previously unavailable information to warring parties and thereby influence their willingness to participate in war-ending diplomacy. Empirical records show that the locations, movement, and dispersion of battles influence the onset and outcomes of peace talks. Ruhe (2015) also emphasizes the role of battle locations in altering the chances of mediation onset. Intense battle activities are viewed as costly by warring parties only when they occur at locations at intermediate distances from national capitals and thereby alter the chances of mediation success. This is because such geographical locations of battles indicate that the situation is in stalemate rather than that either side is taking the upper hand. Empirical records follow the theoretical expectation: increasing conflict intensity lowers the probability of mediation acceptance when battles occur in locations close to or very far from the capital, whilst the same increasing conflict intensity is followed by a substantial increase in the probability of mediation acceptance when it occurs at intermediate distances from the capital.

Related studies have demonstrated that civilian casualties and rebel strategies also invariably affect when and how a conflict ends. Rather than direct confrontations between troops, Wood and Kathman (2014) highlight the role of direct and intentional violence against civilians. An intermediate level of civilian victimization improves the bargaining position of the rebels, primarily because continuous civilian victimization imposes costs on the regime and reveals information about the likely costs of the conflict. In contrast, an extremely high level of civilian abuse may hinge the prospects of negotiated settlements as it contributes to a shift in the underlying power balance and thereby exacerbates the credible commitment problem. Consistent with their theoretical claims, Wood and Kathman (2014) report an inverted U-shaped relationship between the level of civilian abuse and the chances of negotiated settlement of conflict. Fortna (2015) and Thomas (2014) explore how the use of terrorism rewards rebel groups in achieving their political goals. While these studies disagree on the direction of the causal effect, they generally agree on the correlation between the acts of terrorism and the eventual outcomes of civil conflicts.

These studies are suggestive in considering how and why battlefield outcomes shape when and how civil conflicts end. What remains relatively under-investigated in the literature is the possible impact of spatio-temporal violence diffusion on conflict termination, which is the primary interest of this chapter. Theoretically, this chapter builds upon the bargaining model of war and argues that battle diffusion matters in altering conflict duration because it influences the incentives of belligerents to continue inefficient fighting. The diffusion of battle activities, a largely non-manipulable product of the underlying capability and resolve of warring parties, reveals previously unavailable information while contributing to fluctuations in the underlying balance of power. These diffusion dynamics in turn alter conflict duration since these information-revealing and power-shifting effects ease or exacerbate the two primary bargaining problems — informational asymmetry and the credible commitment problem — that cause the pre-war bargaining breakdown and therefore need to be resolved to stop inefficient fighting.

Empirically, drawing on fine-grained and geocoded event data of civil war battles, this chapter examines how different diffusion dynamics of combat activities impact the chances of conflict termination differently. The empirical findings suggest that *distant* diffusion (diffusion of battles across non-adjacent locations) has a substantial negative impact on the likelihood of conflict termination, while the effect of *proximate* diffusion dynamics (diffusion of battles across geographically contiguous areas) remains relatively indeterminate. Additionally, the expansion or shrinkage of conflict-affected zones is itself found to have little impact on the chances of conflict termination. Put differently, the empirical analysis indicates that it is not *whether* battles diffuse or not, but *how* battles diffuse that matters in influencing the opportunity for peace.

This chapter makes several contributions to the emerging body of literature about micro-level and dynamic determinants of civil war termination. Balcells and Kalyvas (2014) and Greig, Mason, and Hamner (2016) are correct in pointing out that much of the existing literature has relied on largely static determinants of conflict termination. Yet, if conflict dynamics as well as static conditions matter in altering the chances of conflict termination and outcome, any study on civil war termination remains incomplete without examining how fighting alters the prospects for domestic peace. An empirical investigation on the likely impact of the spatio-temporal dynamics of battles on conflict duration and outcome is a critical step toward understanding the determinants of civil war termination.

Our results also speak to the broader literature on the relationship between the conflict process and conflict termination in inter- and intranational conflicts. A notable trend within the recent literature is the renewed call to investigate the question of conflict termination (e.g., Leventoglu and Slantchev, 2007; Powell, 2004a, 2012; Reiter, 2009; Slantchev, 2003a,b; Wagner, 2000). Since Fearon (1995), most previous studies have highlighted the question of why costly conflict occurs and have treated war as an outcome to be explained. In contrast, recent literature has increasingly shifted the attention to the puzzle of how and why fighting resolves the bargaining problem that leads to war (Ramsay, 2008, 850–853). Building upon the bargaining theory of war, this chapter offers theoretical accounts and empirical tests of the likely impacts of violence diffusion on civil war termination. In so doing, this chapter specifies the micro-foundations of the relevant theoretical accounts (Kertzer, 2017), and thereby contributes to this ongoing debate on conflict termination.

The remainder of this chapter is divided into four sections. In Section 5.1, we examine the recent expansion of the literature on the spatio-temporal dynamics of violence, followed by theoretical propositions and testable implications that relate violence diffusion and conflict termination. The research design is explained in Section 5.2, and we highlight the empirical results in Section 5.3. We then conclude by offering some further avenues for research and potential policy implications.

5.1 Violence Diffusion and Conflict Bargaining

How and why do battle activities spread across space and time in civil conflicts? What impacts do the micro-level diffusion dynamics of violence have on the chances of conflict termination? Civil war studies have in recent years focused on the spatial and temporal dynamics of violence in civil conflicts, and have identified likely determinants and specific types of patterns in the diffusion of civil war violence. This section first briefly reviews the recent advance in the civil war literature in relation to micro-level violence diffusion. We then advance several competing hypotheses related to such diffusion dynamics and conflict termination.

5.1.1 Conceptualizing the Diffusion Patterns of Violence

Recent advances in civil war studies have yielded valuable insights into how and why violent activities diffuse in civil conflicts. Schutte and Weidmann (2011) propose a typology of violence diffusion and demonstrate that the patterns of diffusion in civil war are expansive in scope (expan-

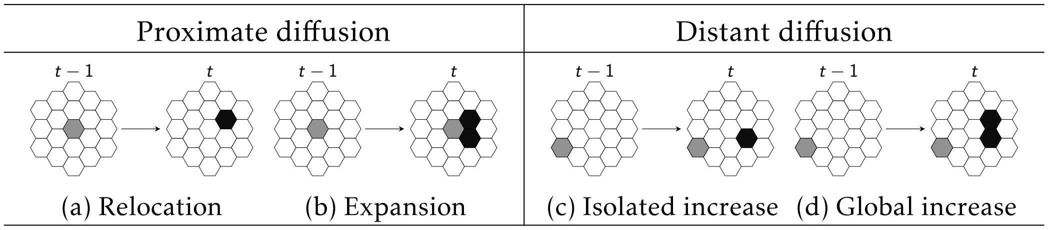


Figure 5.1: Grid representation of proximate diffusion and distant diffusion

Note: (a), (b) examples of proximate diffusion. (c), (d) examples of distant diffusion. Note that the definition of distant diffusion does not require the originating locations to continue to experience violence at t. Solid cells represent cells with 1+ events at $t-1$ (gray) and t (black), while cells without events are left blank.

sion diffusion) rather than changing from one location of violence to another (relocation diffusion). Beardsley, Gleditsch, and Lo (2015) find that conflict-affected zones relocate when civil wars are fought by rebel groups that lack strong ethnic ties with the local population and sufficient military strength. Such rebel groups stay mobile as a means of survival in the face of relatively well-equipped government forces. Beardsley and Gleditsch (2015) highlight the role of peacekeeping operations in shaping the diffusion of battles in civil conflicts. Peacekeeping operations, especially when robust forces are deployed and when rebel groups have strong ethnic ties with the local population, contain movement of conflict-affected zones.

We rely on a similar typology to investigate how violence diffusion influences conflict termination. Specifically, following the typology developed by previous studies, we distinguish two broad categories of diffusion patterns in micro-level battle dynamics: *proximate* diffusion and *distant* diffusion (Cohen and Tita, 1999; Gould, 1969; see also, Baudains, Johnson, and Braithwaite, 2013; Schutte and Weidmann, 2011; Zhukov, 2012).

The distinction between these two diffusion patterns is based on the geographical contiguity between the originating locations of violence and previously peaceful locations. Proximate diffusion refers to the process in which the status among neighboring spatial units affects the future status of their neighboring units. In the case of civil war violence, this type of diffusion process corresponds to instances where violence spreads to areas contiguous to previously affected areas. Depending on whether or not the originating locations continue to experience violent activities, the cases are characterized either as relocation diffusion, in which the originating location stops experiencing violence, or expansion diffusion, in which the originating location continues to be exposed to violence.

In contrast, distant diffusion reflects the spread of phenomena that do not depend on physical contact between spatial units. The instances of distant diffusion refer to the increase of events in physically or geographically non-adjacent locations. Processes of distant diffusion are further divided into two subcategories of isolated and global increase, depending on whether or not the phenomena of interest spread to single or multiple spatial units. Since Gould (1969), this proximate-and-distant typology of diffusion processes has been widely adopted by spatial analysis in micro-level criminal and civil war studies (Baudains, Johnson, and Braithwaite, 2013; Cohen and Tita, 1999; LaFree, Dugan, Xie et al., 2012; Schutte and Weidmann, 2011; Zhukov, 2012).[1]

Figure 5.1 uses grid-cell representation to illustrate these two distinct diffusion patterns and four subcategories. In the current context, the proximate diffusion process is exemplified by the movement of front lines (Figure 5.1(a)) or gradual expansion of conflict zones (Figure 5.1(b)), while the distant diffusion process is typified by the spread of battles across geographically distant locations within the country (Figures 5.1(c) and 5.1(d)). Although it is possible to further divide diffusion patterns into four subcategories, for simplicity, we opt to rely on the dichotomous categorization.

5.1.2 Diffusion, Information, and Credible Commitment

This chapter posits that the diffusion dynamics that occur during the process of conflict substantially influence conflict termination by, first, revealing previously unavailable information, and second, contributing to the

[1]Following previous studies (e.g., Beardsley, Gleditsch, and Lo, 2015; LaFree, Dugan, Xie et al., 2012), we regard the dynamics of violence diffusion as the product of military strategies and interactions of disputants that can reveal previously unavailable information and contribute to the fluctuations of underlying power balance between disputants.

shifts in underlying power balance between disputants. Behind this speculation is the bargaining model of war. Given that war is *ex post* inefficient as it imposes otherwise unnecessary costs on the warring parties, there always exists a bargaining range that can make both sides better off than dividing the disputed good through fighting (Powell, 2006, 177). Disputants in some situations, however, fail to reach efficient pre-war agreements due to asymmetric information about, for example, the distribution of power and likely outcome of war, combined with incentives to misrepresent private information (information problem, Fearon, 1995). Bargaining may also fail when disputants cannot credibly commit not to renege on a pre-war agreement in the absence of a central enforcement mechanism due to, for example, a rapid shift in the underlying power balance and the resultant temptations to renege on war-avoiding concessions (commitment problem, Powell, 2006).

Even after bargaining breaks down, presumably none of the rational warring parties have an incentive to continue with inefficient fighting once the original bargaining problem has been resolved. In this sense, if conflict onset is a bargaining *failure* caused by a commitment problem or information problem (Fearon, 1995), then conflict continuation is a bargaining *process* that ends when the original bargaining problem is resolved through the costly use of force (Blainey, 1988; Schelling, 1966). The bargaining model of war initiation asks why pre-war bargaining breaks down into inefficient fighting, while the bargaining model of war termination asks how fighting itself resolves (or exacerbates) the underlying bargaining problem.

Violence diffusion as an information flow In situations where the information problem caused the original bargaining failure (Fearon, 1995), the flows of public information from the battlefield, such as casualties and location of battles, update the belligerents' beliefs and expectations about the likely outcome of the conflict (Blainey, 1988; Filson and Werner, 2002; Powell, 2004a; Slantchev, 2003b; Wagner, 2000). The information flows in turn shape the prospects of conflict termination, or the feasibility of a war-ending agreement. Put another way, fighting itself contributes to conflict termination because it reveals previously unavailable information and narrows the informational asymmetry.

What makes the battlefield outcome a distinguishable source of information is its non-manipulability (Blainey, 1988; Ramsay, 2008; Reiter, 2009). On the battlefield, as Ramsay (2008) argues, "one cannot pretend to be stronger, to have better leadership, or to be better equipped than one actually is" (854). The same cannot be said for diplomacy or negotiation.[2] While disputants inherently have incentives to manipulate their own image and to misrepresent private information to obtain a better deal, battlefield outcomes reduce uncertainty about the underlying balance of power and their willingness to bear the costs of fighting. Turning to advances in empirical investigation, Weisiger (2016) carefully distinguishes several branches of the information account of war and empirically examines the information-revealing role of battle activities. The empirical results demonstrate that cumulative conflict intensity, or the "sum of past information," is a good predictor of war termination, while short-term intensity or recent "spikes" in battle intensity are unlikely to have a substantial impact on war duration due to their poor informational value.

While many of the rationalist explanations of civil war onset and termination focus on the credible commitment problem (e.g., Fearon, 2004; Walter, 1997), informational asymmetry matters in the context of civil war (Findley, 2013; Mattes and Savun, 2010, 512–516). Thomas, Wood, and Wolford (2016) develop a formal model of rebel-government bargaining that emphasizes the role of the informational problem. In the situation of war-avoiding or war-ending bargaining, the government's willingness to take the demands of rebels invariably depends on the credibility of the rebels' threat to fight when their demands are rejected. To make their threats credible, militarily weak rebels make unrealistically large political demands on government, which in turn can result in inefficient fighting

[2] Yet, the negotiation table can serve as another important channel of learning (Slantchev, 2003b). Offers, counteroffers, and rejections during negotiation are the products of rational decisions and reveal private information (628).

(see also, Lindsey, 2015; Park, 2015).[3] Governments are likely to have difficulty in distinguishing weak rebels, pretending to be stronger than they actually are, from the militarily stronger opponents due to the rebels' incentive to misrepresent their strength. Empirically, utilizing precisely geocoded event datasets, recent studies have highlighted the information-revealing role of intensity and locations of battle activities in civil conflicts (Greig, 2015; Ruhe, 2015; Wood and Kathman, 2014).

Just as with the intensity and locations of battles, spatio-temporal diffusion dynamics are non-manipulable products of the underlying power balance and belligerents' resolve to bear the costs of warfare. The observed battle activities in civil conflicts are the product of coercive interactions between government and rebel forces with contrasting aims. A government facing active uprisings would seek to minimize the geographic scope and temporal persistence of insurgent violence through coercive means and thereby restore the monopoly of violence within its borders (Toft and Zhukov, 2012). Rebels, on the other hand, have incentives to continue and expand their violent campaigns to coerce the government into making policy concessions and compromises. Because the diffusion of conflict activities is never favorable to the government, such dynamics are likely to be observed when the government fails to contain violence in space and time; or, equivalently, when the rebels are being relatively successful in their military campaigns in relation to the government forces.

The spatio-temporal diffusion of battles is thus a unique source of information, especially concerning rebels' battlefield performance and their military strategy to confront government forces. In such circumstances, where battle activities diffuse across space and time, the exact nature of the diffusion depends on rebels' military strategies. For example, building

[3] Related to this argument, Park (2015) argues and finds that the weaker bargaining disputant often feels insecure and demands more political power at the negotiation table to end costly conflict than its power share would predict, while the stronger disputant in such a situation may be willing to overcompensate the weaker to assuage her concerns. The rebels' fear may strengthen their incentive to make larger political demands than expected from the underlying balance of bargaining power.

upon the proximate-and-distant diffusion typology and previous works on terrorist decision-making (McCormick, 2003), LaFree, Dugan, Xie et al. (2012) relate the observed diffusion patterns of violence to the military strategy employed by rebel forces. LaFree, Dugan, Xie et al. (2012) first distinguish two rebel strategies: control strategy, which is intended to generate popular support for the rebel group and consolidate territorial control, and attrition strategy, which aims to inflict pain on the government and its supporters. They then attribute control strategy to proximate diffusion and attrition strategy to distant diffusion.

Control attacks are more likely to follow proximate diffusion patterns, because these attacks should concentrate around rebel bases and areas where they wish to eventually govern. On the other hand, attrition-based attacks would exhibit patterns of distant diffusion such that attacks in a location are followed by subsequent attacks in geographically non-adjacent locations. This is because attrition attacks tend to target broad areas such as national capitals and major cities far beyond rebel bases that are often located in the periphery, in order to maximize the damage of the incumbent. The records of violent activities of Basque Homeland and Freedom (ETA) during the period between 1970 and 2007 provide empirical support for such claims: the diffusion patterns of ETA attacks changed from mainly proximate to distant after the group's public announcement in 1978 that it was shifting from a control-based to attrition-based strategy.[4]

Therefore, the diffusion patterns of battles reveal information about rebels' strategies and how well they are being implemented, or the information that cannot be revealed from the intensity or locations of battles alone. For example, even if the number of casualties remains identical, the instances of distant diffusion may signal the rebels' success in implementing attrition strategies. In contrast, the absence of diffusion may indicate that government forces are gaining the upper hand over rebels and suc-

[4]Control strategy is exemplified by the Maoist doctrine of communist insurgency. An oft-cited example of rebel groups that heavily rely on attrition strategy is RENAMO in the Mozambican civil war (Hultman, 2009). The more recent case of the strategy adopted by Taliban insurgents in Afghanistan provides another example (Johnson, 2013).

ceeding in containing the battles within limited areas, while not conveying meaningful information about rebels' strategies. In these hypothetical cases, conflict dynamics can send different information about rebels' strategies and their success in battlefields, depending on the diffusion patterns of combat activities. All else being equal, these additional flows of information narrow the informational asymmetry and thereby lead warring parties to agree to stop inefficient fighting.

Consistent with this informational perspective, our first class of hypotheses expects battle diffusion to be positively associated with the likelihood of conflict termination:

Hypothesis 5.1a (Information problem and proximate diffusion)
Increasing the instances of proximate diffusion increases the probability that a civil conflict will end.

Hypothesis 5.1b (Information problem and distant diffusion)
Increasing the instances of distant diffusion increases the probability that a civil conflict will end.

Violence diffusion and (in)credible commitment In addition to its information revealing role, the diffusion of battle activities can shape the prospects of conflict termination by affecting the severity of the credible commitment problem that needs to be resolved for a civil conflict to end. The credible-commitment account of war suggests that although there generally exists a bargaining range that both disputants prefer to costly fighting, war-avoiding or war-ending bargaining may fail if such agreements are not enforceable due to the temptations of one or more disputants to renege on prior agreements (Fearon, 1995, 2004; Powell, 2004b, 2006; Walter, 1997, 1999, 2002).

For example, when a rapid and large shift in the underlying balance of power in its favor is expected, a disputant is likely to find itself unable to credibly commit not to renege on the agreement that reflects the current balance of bargaining power.[5] This is primarily because the disputant

[5]Generally speaking, it follows that if a large and rapid shift in the underlying power

would face a strategic incentive to exploit its enhanced bargaining position once the shift occurs. Anticipating the opponent's future temptations to renege on the prior compromises, the other disputant is likely to be unwilling at best to accept a negotiated settlement over the disputed goods today. This combination of disputants' strategic incentives in turn causes mutually-beneficial bargaining to break down into inefficient fighting.

A logically equivalent story applies to situations where the current balance of capability and bargaining power favors the rebels due to disturbances in the government's capability, caused by a temporary shock (Fearon, 2004). Such temporary fluctuations in government capability can result from both exogenous factors such as a sharp economic downturn and endogenous processes such as battlefield dynamics. Regardless of the exact causes, the temporarily weakened government would commit to giving concessions to the rebels, reflecting on its deteriorating bargaining position in these instances. The same government, however, cannot credibly commit to the agreement because, once fighting stops (or is avoided), it will likely regain its capability. The government in the post-conflict period would then have a strong incentive to exploit its regained bargaining position and renege on the prior policy concessions. Given that "nothing stops it from overturning or undermining the arrangements" in the absence of enforcement mechanisms, the common knowledge that the shock is temporary renders the government's commitments not to renege incredible (Fearon, 2004, 290, 294).

Attrition and control strategies, when successfully implemented, induce a negative shock on the government's capability and bargaining po-

balance causes pre-war negotiations to fail, then inefficient fighting persists until the rate of shift slows (Fearon, 1998; Powell, 2006, 2012; see also, Leventoglu and Slantchev, 2007). Another oft-noted pathway through which a war under commitment problem ends is that third-parties step in to enforce the war-ending agreements, if they are able to commit to implementation of the agreement and provide a credible guarantee on the settlement (Walter, 1997, 1999, 2002). Nonetheless, the same credible-commitment logic tells us that external intervention can, in some situations, prolong conflicts. For example, Metternich (2011) argues that when militarily strong groups with low public support expect external interventions with democratization mandates, they have an incentive to continue fighting due to their fear of the post-conflict power-shift induced by elections.

sition.[6] The successful use of control strategy would consolidate rebel's territorial control while eroding state reach within the area, which in turn helps boost local civilian support and mobilization (Kalyvas, 2006). Successful attrition campaigns effectively inflict damage on the government and its supporters, thereby undermining popular confidence in the state's capacity (Hultman, 2009; Kydd and Walter, 2006; Thomas, 2014). In both cases, the critical implication of the battlefield outcomes is that the state's monopoly on violence within its borders is being eroded, and the underlying balance of capability and bargaining power currently favors the rebels.

The proximate and distant diffusion of battle activities, or the rebels' success on the battlefield, indicate fluctuations in the government's capabilities. Yet, because such shocks are likely to be temporary, the government is likely to regain its capability once the fighting stops. As illustrated above, common knowledge about the government's incentives to renege on prior agreements due to the recovery of its capability, even in the absence of incomplete information, would impede war-ending agreements.

Another but related source of the commitment problem in the context of civil war is that rebels are often enforced to disarm, demobilize, and disengage their military forces and prepare for peace during or after peace negotiations, which inevitably shifts the underlying power balance in the government's favor (Walter, 1997, 2002). The rebels with arms, however, would, at best, have little incentive to accept such conditions for negotiations. This is primarily because both sides know that in the post-conflict environment where it no longer faces opposition groups with arms, the government would soon have strong incentives to renege on the war-ending agreements (Walter, 1997; see also, Fearon, 2004; Powell, 2004b, 2006). At the same time, once the rebels "lay down their weapons and begin to integrate their separate assets into a new united state," as Walter (1997) argues, "it becomes almost impossible to either enforce future

[6] Other sources of conflict-induced power shifts include external intervention, the depletion of resources, successful recruitment, decisive battles, decline of the state's economic and military capability resulting from combat, and civilian victimization (Wood and Kathman, 2014, 694).

cooperation or survive attack" in the absence of enforcement mechanisms (335–336). The fear of being left tomorrow without effective means to enforce the government to respect the war-ending bargain, disincentivizes the rebels from stopping fighting today.

Indeed, the disarmament of rebel forces is often cited by incumbents as the necessary condition for negotiations. For example, Syrian President Bashar Assad noted (quoted in Mcdonnell, 2013, emphasis added):

> We are willing to negotiate with anyone, including militants, who *surrender their arms*.... We can engage in dialogue with the opposition, but we cannot engage in dialogue with terrorists.... we will not negotiate with terrorists.

In a similar vein, former Yemeni Foreign Minister Riad Yassin expressed in 2015, although Shiite Houthi rebels were now in control of the capital and much of the north, that the rebels "must implement the UN resolution and *surrender their weapons*, and *only then* the dialogue and political process can begin, with the participation of all Yemeni parties" (quoted in Stuster, 2015, emphasis added).

Expecting these probable future pathways, the rebels are likely to be reluctant to negotiate with the government and stop fighting, despite the existence of the mutually-beneficial bargaining range and their improving bargaining position as a result of military confrontations. What exacerbates the underlying bargaining problem is the expectation that the more the government needs to compromise, the stronger its incentives become to renege when it finds itself once more in a superior position in the post-conflict environment (Fearon, 2004, 295–296). Consequently, and somewhat paradoxically, the more temporarily powerful the rebels are, the larger the expected size of the post-conflict power shift and the rebels' fear in relation to the shift becomes. This combination of warring parties' incentives in the face of an expected power shift leads to the continuation of inefficient conflict.

The paradoxically growing rebels' fear in the face of their battlefield success may well be summarized by Thucydides's phrase that "to lose what one has got is more disgrace than to be baulked in getting" (Thucydides, 1910, 94). In extreme cases, this fear may make rebels *more*, rather than *less*, reluctant to accept offers of negotiation when their temporary bargaining position seems to be improving due to success on the battlefield, and thus the division of the disputed good currently acceptable to both sides favors them. Just as the fear of the weak, in relation to future power shifts in favor of the strong, causes the initial bargaining breakdown (Fearon, 1998), the exacerbated fear of rebels, even with an enhanced bargaining position, impedes conflict termination.

Empirically, following the findings in LaFree, Dugan, Xie et al. (2012), one may reasonably assume that successful implementations of control and attrition strategies can be observed as instances of proximate and distant diffusion patterns, respectively. In contrast to Hypotheses 5.1a and 5.1b, this credible-commitment story predicts negative, rather than positive, associations between escalating diffusion dynamics and the chances of conflict termination. Therefore, we hypothesize:

Hypothesis 5.2a (Commitment problem and proximate diffusion)
Increasing instances of proximate diffusion decrease the probability of a civil conflict ending.

Hypothesis 5.2b (Commitment problem and distant diffusion)
Increasing instances of distant diffusion decrease the probability of a civil conflict ending.

In essence, the two classes of proposition illustrated above draw on the two major camps of rationalist explanation of war termination and posit contrasting theoretical predictions.[7] Drawing on the informational account of war, Hypotheses 5.1a and 5.1b predict positive associations between the increasing diffusion of battles and the likelihood of conflict termination. On the other hand, Hypotheses 5.2a and 5.2b refer to the credi-

[7] Another possible pathway through which a civil conflict can occur between rational disputants is reputation building (Walter, 2006, 2009). Governments may be less likely to accommodate one challenge in order to deter possible future challengers by building a reputation for toughness.

ble commitment account of war and posit negative relationships between increasing instances of battle diffusion and conflict termination.

5.2 Data and Empirical Strategy

Our empirical analysis largely relies on micro- and macro-level datasets for intra-state armed conflicts provided by the Uppsala Conflict Data Program (UCDP). Specifically, the following analysis draws on the UCDP's Dyadic Armed Conflict Dataset (ACD), which records rebel-government conflicts that generate at least 25 battle-related casualties in a given calendar year, over some incompatibility classified as control over the central government and/or territorial secession (Gleditsch, Wallensteen, Eriksson et al., 2002; Pettersson and Wallensteen, 2015). The coding of specific start and end dates for each conflict is provided by the dyadic version of the UCDP Conflict Termination Dataset, v.2-2015 (CTD, Kreutz, 2010).

While conflict termination can take a variety of forms, such as military victory and negotiated settlements, the following analysis does not differentiate how civil conflict ends. This is because our core arguments primarily concern when warring actors have stronger or weaker incentives to continue fighting, regardless of the types of conflict outcomes. We choose the civil war (rebel-government) dyad-month as our unit of analysis. Our dependent variable, *Termination*, or the dyad-level conflict termination is coded using a binary indicator, which takes the value of 1 if a conflict no longer satisfies the 25-casualty threshold and 0 otherwise.

Fine-grained event data are required for specifying and comparing different types of diffusion patterns of violence. We use the UCDP Georeferenced Events Dataset (GED), version 4.0, which covers incidents of organized violence within civil conflicts in Africa, the Middle East, Asia, and South America during the 1989–2014 period (Sundberg and Melander, 2013). The GED includes data on nearly 110,000 incidents of civil war battles between warring parties (state-based and non-state conflict) as well as their intentional and direct use of violence against civilians (one-sided violence). Each record in the GED is coded relying upon news sources, NGO reports, truth commission reports, historical archives, and other sources of information, and comes with precise geographical locations, dates, and other information, including battle deaths and civilian casualties.[8]

We restrict the temporal scope of the empirical analysis to the 1989–2011 period, which is covered by the CTD, GED, and other sources of control variables. Following Ruhe (2015, 249), the GED records are aggregated into dyad-month level, based on the end date variable to ensure that all battle activities have occurred within a month, when an event is attributed to more than two months. Because we are primarily interested in the dynamics of rebel-government dyads, approximately 10,000 records of non-state violence (battles between non-state actors) were carefully dropped from the following analysis.[9] Also note that those records with relatively high spatial and temporal precision are used in the following analysis.[10]

5.2.1 Characterize Diffusion Dynamics

Following the typology of diffusion patterns discussed above, we distinguished two broad types of diffusion pattern — proximate diffusion and distant diffusion. In order to detect the instances of these diffusion dynamics within empirical records of civil war violence, we employed the two-step procedure described in detail below.

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[8] An event in the GED is defined as the "incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death in either the best, low or high estimate categories at a specific location and for a specific temporal duration" (Sundberg and Melander, 2013, 524). Perhaps the most important limitation of the GED is that its coverage is limited to fatal events, which could lead researchers to underestimate conflict intensity. Nonetheless, the GED remains among the best datasets currently available.

[9] In the following, by "battle" or "violent events" we refer to instances of direct confrontation between government and rebel troops ("armed conflict events" in the GED), but not the intentional use of violence against civilians ("one-sided violence") or confrontations between non-state actors ("non-state conflict").

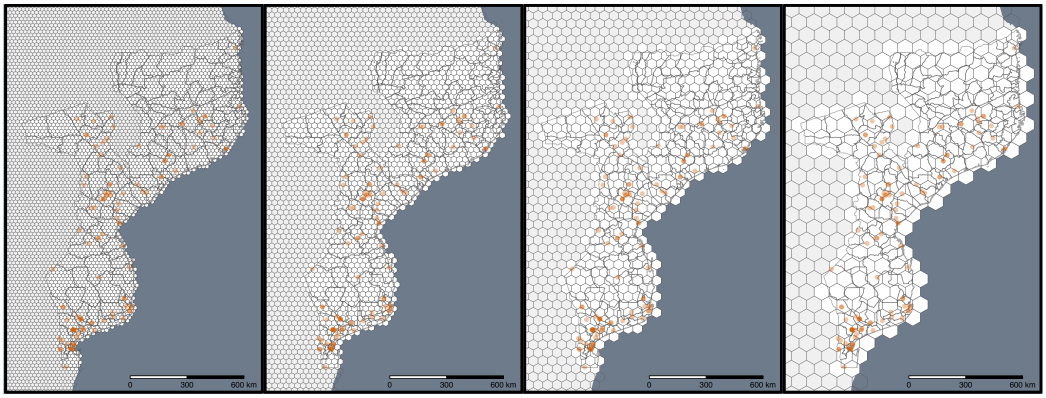
[10] The GED entries with spatial precision scores ("where_prec" variable) of 1 to 3 (event locations can be located at the second order administrative division or lower level) and temporal precision scores ("date_prec" variable) of 1 to 4 (event dates can be specified at the month or lower level) are used.

Step 1: Generate spatial grids We first constructed a spatial grid with an arbitrary spatial resolution r. The common approach in existing studies is to divide the study region into an artificial spatial grid and then allocate the observed records of violence to each unit at a given time step t (e.g., Baudains, Johnson, and Braithwaite, 2013; Schutte and Weidmann, 2011). To illustrate this procedure, Figure 5.2 represents several differently-sized spatial grids overlaid onto the boundary of Mozambique and the reported geo-coordinates of violent incidents. This geographical aggregation allows for the diffusion patterns of battle events to be interpreted, simply by considering how the presence of violent incidents within individual grid cells change or remain unchanged over subsequent time periods, or more precisely, counting the number of cases that fulfill the definition of diffusion patterns outlined above.

While existing studies often employ rectangular grids in this procedure, we opted to employ *hexagonal* grids to measure diffusion patterns. The primary reason for the use of hexagonal rather than rectangular grids is that the nearest neighborhood in a hexagonal grid is less ambiguous than in a rectangular grid (Birch, Oom, and Beecham, 2007). This clarity in neighborhood definition is critical in the current context because our typology of diffusion primarily distinguishes the two diffusion patterns using information about the presence or absence of battle events within its boundary *and* neighborhood.[11] Using a hexagonal grid minimizes the possibility that our results are driven by an arbitrary choice of neighborhood.

Another issue is the grid-size selection. Theoretically, we had no prior reasons to select a given grid size over others (Schutte and Weidmann, 2011, 147). Empirically, insights from previous studies suggest that the use of a relatively high resolution is likely to be suitable to capture local-level conflict dynamics. For example, O'Loughlin and Witmer (2012) em-

[11] Moore neighborhood (eight cells surrounding a given cell are defined as neighbors) and von Neumann neighborhood (four orthogonal cells are defined as neighbors) are often used to define neighbors in a rectangular grid. In both definitions, the difference between the inter-cell Euclidean distance and the corresponding grid distance increases as the neighborhood order increases (Birch, Oom, and Beecham, 2007).



(a) $r = 20$ km (b) $r = 30$ km (c) $r = 50$ km (d) $r = 80$ km

Figure 5.2: Hexagonal grid generation over Mozambique

Note: (a)–(d) grid cells with $r = 20$, 30, 50, and 80 km resolution, respectively. White cells represent the cells that fall within the borders of Mozambique, whereas dots indicate the reported locations of battle activities. Segments represent the boundaries of second-order administrative divisions.

ploy fine-grained spatial grids to explore the diffusion dynamics of insurgent violence in Russia's North Caucasus and highlight that few significant spatio-temporal patterns are detected when using grid sizes that exceed 50 km. Methodologically and most fundamentally, the selection of grid size, or the choice of basic areal units, can have a substantial impact on the results of any statistical analysis that draws on discrete spatial units (modifiable areal unit problem, MAUP, Fotheringham and Wong, 1991; Jelinski and Wu, 1996; Openshaw, 1983; Openshaw and Taylor, 1979).[12]

In order to prevent the MAUP from plaguing the estimates and ensure that our empirical findings were not a result of an arbitrary selection of spatial grid size, we performed the empirical analysis varying the spatial grid specification. Specifically, the following analysis comprises replicated with varying grid size r, ranging from a highest resolution of 10 km to a lowest resolution of 100 km, and a neighborhood order k, ranging from 1 to

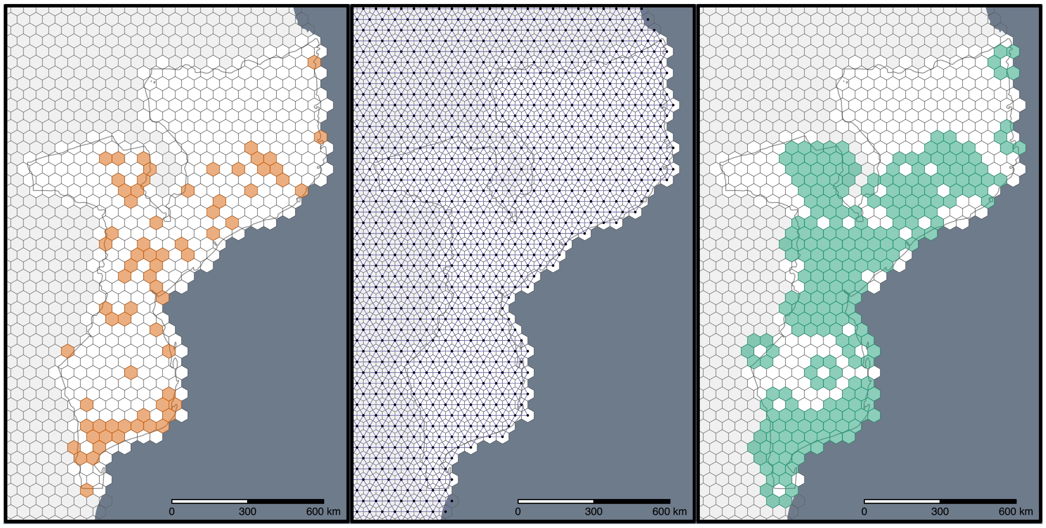
[12] More precisely, the effect of the grid-resolution selection on the estimation results is known as the "scale problem," or a special case of the MAUP in which the variation in results when the same spatial data are aggregated in differently sized spatial units (Jelinski and Wu, 1996).

3. As previous studies have demonstrated (Baudains, Johnson, and Braithwaite, 2013; O'Loughlin and Witmer, 2012; Schutte and Weidmann, 2011; Townsley, Johnson, and Ratcliffe, 2008), varying the grid-cell size allows us to address this problem and to investigate whether and how empirical patterns vary over different spatial scales. Similarly, because the definition of two diffusion types essentially depends on the neighborhood structure, an empirical test in which neighborhood order is varied is also critical to examine the robustness of the results in the current context.

Step 2: Identify diffusion patterns Relying on the artificial spatial grids, we interpreted the two diffusion processes of interest in three sub-steps. First, we overlaid the GED points onto the hexagonal grid and specified whether at least one battle event had occurred within each cell in month t. Figure 5.3(a) represents the spatial distribution of cells at "conflict" (orange) and cells remaining at "peace" (white) in the 50-km resolution grid-cell space over Mozambique for the purpose of illustration.

Second, we constructed the neighborhood network, or an $N \times N$ spatial weight matrix $\boldsymbol{W}$ to define the adjacency between grid cells, where N denotes the number of grid cells within the topological space. The diagonal elements $w_{ii} = 0$ and non-diagonal elements $w_{ij} \geq 0$ capture the relative connectivity between cells, where $w_{ij} = 1$ if cells i and j are adjacent, and $w_{ij} = 0$ otherwise. Figure 5.3(b) represents the resultant neighborhood network, with dots denoting the coordinates of individual cells and segments denoting the connectivity. Note that the size of the neighborhood network increases as neighborhood order k increases.

Last, following existing studies (Baudains, Johnson, and Braithwaite, 2013; Cohen and Tita, 1999; LaFree, Dugan, Xie et al., 2012), we interpreted the diffusion patterns of violence by considering how the presence (or absence) of violent incidents in a given cell relates to the occurrence of violence in neighbor cells. This procedure was implemented by computing the spatial lag $\sum_{j=1}^{n} w_{ij} v_{jt}$ for each cell i in a given month t, where n denotes the number of neighboring cells of i, and the binary indicator $v_{it} \in \{0,1\}$ determines whether at least one battle event has been recorded



(a) Cells with $v_{it} = 1$ (b) Contiguity-based SWM (c) Cells with $s_{it} = 1$

Figure 5.3: Measuring the spatial distribution of violence

Note: (a) distribution of cells with 1+ battle events or $v_{it} = 1$ (cells in orange). (b) contiguity-based spatial weight matrix, with segments denoting the connectivity between cells. (c) distribution of cells with binary spatial lag $s_{it} = 1$ (cells in green).

in cell i at t, with $v_{it} = 1$ denoting the presence of events and $v_{it} = 0$ otherwise. For simplicity, we collapsed the spatial lag into a binary indicator s_{it}, with $s_{it} = 1$ denoting one or more battle events occurring within the neighbors of cell i at t, or $\sum_{j=1}^{n} w_{ij} v_{jt} \geq 1$, and $s_{it} = 0$ otherwise. Figure 5.3(c) highlights the distribution of grid cells where one or more battle incidents occurred within their neighbor cells, or $s_{it} = 1$ in green.

Recall that proximate diffusion refers to the spread of phenomena toward adjacent locations, while distant diffusion refers to the diffusion process between non-adjacent locations. Typically, proximate diffusion corresponds to instances in which one or more battle events have occurred in neighboring cells of i at $t-1$ (i.e., $s_{it-1} = 1$), and one or more events have occurred in i at t (i.e., $v_{it} = 1$). Another instance of proximate diffusion is a transition where battle events have occurred in i at $t-1$ (i.e., $v_{it-1} = 1$), and one or more events have occurred in i at t (i.e., $s_{it} = 1$). Similarly, an instance of distant diffusion is defined as the transition where no battle events have been observed in cell i and its neighboring cells of i at $t-1$ (i.e., $v_{it-1} = 0$ and $s_{it-1} = 0$), while one or more events have occurred in i and/or its neighboring cells at t (i.e., $v_{it} = 1$ and/or $s_{it} = 1$).

Formally, let $(v_i, s_i)_t$ denote the combination of the status of cell i and its neighboring cells at time period t. The instances of proximate diffusion are defined as the transitions between $(v_i, s_i)_{t-1}$, and $(v_i, s_i)_t$, such that $(1,0)_{t-1} \rightarrow (0,1)_t$, $(0,1)_{t-1} \rightarrow (1,0)_t$, $(0,1)_{t-1} \rightarrow (1,1)_t$, or $(1,0)_{t-1} \rightarrow (1,1)_t$. As illustrated in Figures 5.1(a) and (b), violent activities spread toward geographically contiguous areas in these cases. Similarly, an instance of distant diffusion is defined as a process $(0,0)_{t-1} \rightarrow (0,1)_t$, $(0,0)_{t-1} \rightarrow (1,0)_t$, or $(0,0)_{t-1} \rightarrow (1,1)_t$, in which violence diffuses to a wider area that had not experienced violence at $t-1$ (Figures 5.1(c) and (d)).[13]

Diffusion variable The resultant terms *Proximate Diffusion* and *Distant Diffusion* count the instances that satisfy the definitions of proximate diffusion and distant diffusion patterns per dyad month, respectively. Note that this three-step procedure was repeated using different grid-cell settings to prevent the MAUP from plaguing the estimation results. Note also that conflicts with multiple rebel groups were separated into separate dyads, and instances of diffusion were detected using individual dyads as the unit of analysis. These two diffusion terms were log-transformed due to the notable positive skewness.

Importantly, it is possible that simple changes in the scope of conflict zones, rather than the nature of diffusion, influence the opportunity for peace (Greig, 2015; Greig, Mason, and Hamner, 2016). To control for this possibility, we also measured the month-to-month change in the number of grid cells with 1 or more battle events (*Naive Diffusion*). A positive value in this variable indicates the geographic expansion of conflict-affected zones over subsequent months, while a negative value indicates otherwise.

Following previous studies (Greig, 2015; Greig, Mason, and Hamner,

[13]Note that many other transition patterns are possible, such as $(0,0)_{t-1} \rightarrow (0,0)_t$ (absence of battles) and $(1,1)_{t-1} \rightarrow (1,1)_t$ (persistent battles), which are not of particular interest to us.

2016; Ruhe, 2015; Wood and Kathman, 2014), we coded these diffusion terms as a moving average over previous Δt months with $\Delta t = 6$ in the baseline setting.[14] This reflects the idea that warring actors will update their beliefs about the course of conflict using the recent history of conflict, but a single monthly record that largely deviates from the recent history is not, on its own, likely to change their overall expectations.[15]

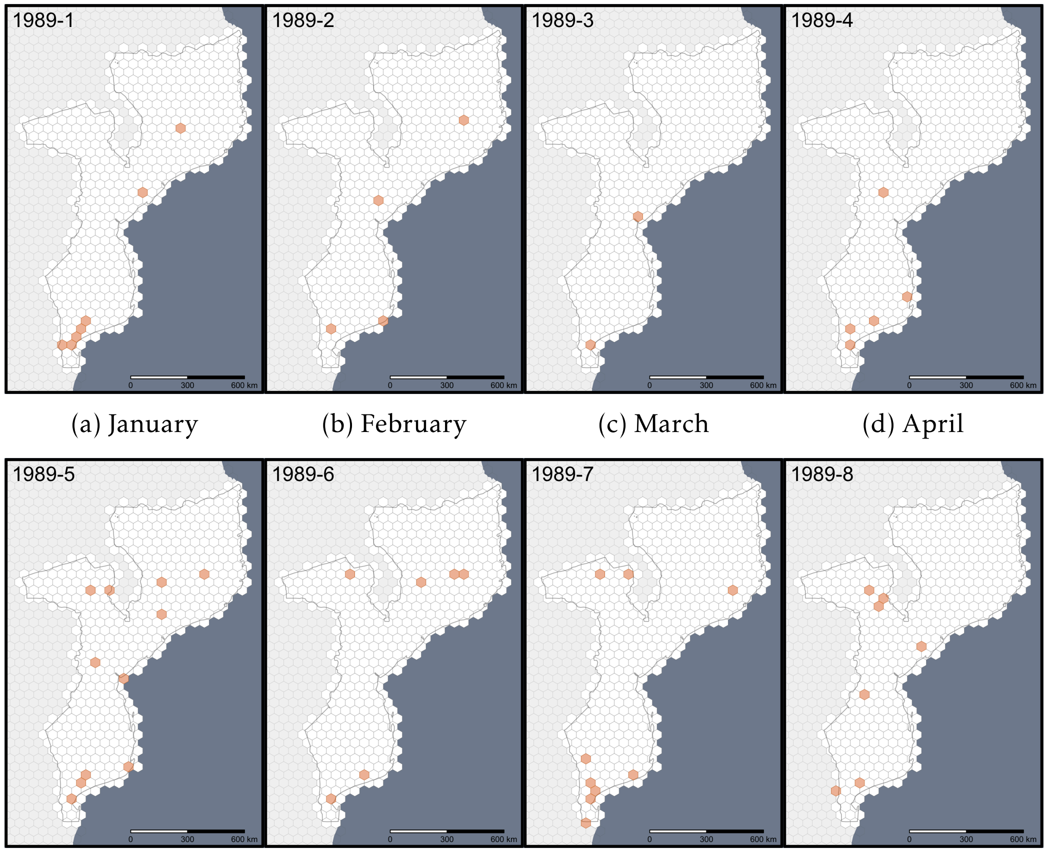
Illustrative episode To facilitate a better feel for what these diffusion terms indicate, Figure 5.4 illustrates the observed cases of violence diffusion in the Mozambican civil war. This conflict episode is characterized by a combination of proximate and distant diffusion patterns. Several instances of proximate diffusion are observed in the southern part of the country, while the conflict geography in the central and northern parts is better characterized by distant diffusion over the selected period.

5.2.2 Control Variables

Structural factors and rebel attributes We included a number of confounding variables that are known to be associated with conflict termination and violence dynamics in our regression estimates. State-level controls include logged *per capita GDP* as the proxy of state capacity and wealth (Gleditsch, 2002) and *Democracy* (a dummy variable indicating 6+ Polity score) as the proxy of regime type (Marshall, Gurr, and Jaggers, 2014). Our models also incorporated *Country Size*, or the geographical area of the country in logged square kilometers (Weidmann, Kuse, and Gleditsch, 2010). A large country size may hinge the government's power projection and help militarily weak insurgents to survive. It may also constrain the potential of battle activities to spread geographically.

[14] We report the robustness check using an alternative temporal window size $\Delta t = 12$ in Appendix B.3.

[15] For dyad-month observations where no violent incidents are recorded at $t-1$, these diffusion terms were computed using location information from the previous month with events, as in Greig (2015) and Ruhe (2015). Underlying this imputation rule is the expectation that it is highly unlikely that belligerents will update their belief about the course of conflict in the absence of new information.



(a) January (b) February (c) March (d) April

(e) May (f) June (g) July (h) August

Figure 5.4: Evolution of conflict geography in the Mozambican civil war, 1989

Note: (a)–(h) distribution of grid cells with 1+ battle events in the Mozambican civil war, 1989 (cells in orange). Spatial grids with $r = 50$ were employed for the visibility purpose.

Recent studies suggest that the characteristics of rebel groups shape both battle dynamics (Beardsley and Gleditsch, 2015; Beardsley, Gleditsch, and Lo, 2015) and the chances of conflict termination (Akcinaroglu, 2012; Buhaug, Gates, and Lujala, 2009; Cunningham, Gleditsch, and Salehyan, 2013). Drawing on the Non-State Actor dataset (Cunningham, Gleditsch, and Salehyan, 2013) and the Ethnic Power Relations dataset (Wucherpfennig, Metternich, Cederman et al., 2012), we included a series of binary variables to capture the characteristics of rebel groups. *Territorial Con-*

trol takes the value of 1 if rebels exercise a moderate or high level of control over territory. *Rebel Much Weaker* is a dummy variable representing whether rebel forces are extremely disadvantaged relative to government forces.[16] *Ethnic Claim* takes the value of 1 if a rebel group makes an exclusive claim to fight on behalf of a particular ethnic group. Finally, our models incorporated *Multi Dyads*, which takes the value of 1 if the government fights two or more conflicts in a given month, and 0 otherwise.

Conflict dynamics Our regression models incorporated a set of control variables that capture different dimensions of the micro-dynamics of conflicts. First, we included conflict intensity (Greig, 2015; Mason and Fett, 1996; Ramsay, 2008; Ruhe, 2015) and civilian casualties to influence the chances of conflict termination (Wood and Kathman, 2014). We relied on the total number of battle deaths per dyad-month (*Conflict Intensity*) and total troop deaths until month $t-1$ (*Cumulative Casualty*) to capture the short- and long-term impacts of the losses and attrition that warring parties have suffered. *Rebel OSV* and *Govt OSV* are monthly counts of civilian deaths caused by the intentional and direct use of violence against civilians (one-sided violence) by rebel and government violence, respectively. *Collateral Damage* measures the number of civilian deaths caused indirectly by confrontations between rebel and government troops per dyad month.

Conflict geography Second, we controlled for a series of variables that represent the local geography. Specifically, the logged mean geodesic distance from reported battle locations to capital cities (*Capital Distance*, Weidmann, Kuse, and Gleditsch, 2010), average population density in conflict-affected zones (*Local Population*), and shortest geodesic distance between event locations and resource rich areas (*Natural Resource Distance*) were included. The underlying expectation is that the occurrence of battles in territories with strategic, subjective, or objective values may provide

[16] The multichotomous variable in Cunningham, Gleditsch, and Salehyan (2013) includes "much weaker," "weaker," "parity," "stronger," and "much stronger." The latter four categories are coded 0 in our dataset.

belligerents with the incentive to continue fighting (Fearon, 2004; Greig, 2015; Lujala, 2010; Lujala, Rød, and Thieme, 2007).

In addition, we controlled for accessibility of conflict zones, as difficult terrain may constrain the potential of battle activities to expand and relocate to nearby locations (Beardsley and Gleditsch, 2015; Beardsley, Gleditsch, and Lo, 2015). *Ruggedness* measures mean elevation variance, while *Road Density* indicates kilometers of primary and secondary roads per square kilometer within battle-affected cells (Defense Mapping Agency, 1992). Inaccessible terrain hinges government's power projection while allowing rebels to inflict disproportionate damage on government forces (Fearon and Laitin, 2003; Tollefsen and Buhaug, 2015). Similarly, because logistical constraints shape the costs of sustaining and expanding combat activities (Zhukov, 2012), road networks influence both the diffusion of violence and the duration of conflicts.[17] We took the moving average with a temporal window Δt and log-transformed the variables, controlling for conflict intensity and geography. Table 5.1 reports the summary statistics of the variables.

5.2.3 Spatial-Grid Setups

A spatial grid with $r = 30$ and $k = 1$ was employed in the baseline setting for two reasons. First, this grid setting roughly corresponds to the geocoding accuracy of the event dataset. Recall that our dataset contains the battle events that can be located at the second or lower level admin-

[17] These georeferenced variables are constructed by, first, overlaying the dyad-month observations of battle events on the Population Count Grid dataset (Balk, Deichmann, Yetman et al., 2011), georeferenced natural resource datasets (Buhaug and Lujala, 2005; Gilmore, Gleditsch, Lujala et al., 2005; Lujala, Rød, and Thieme, 2007), and grid-based elevation variance data generated by SpatialGridBuilder (Pickering, 2016), and then taking the mean values. *Natural Resource Distance* measures the average shortest geodesic distance between reported battle locations and locations of lootable diamonds and gemstone deposits, drug cultivation, and hydrocarbon production. *Ruggedness* is measured by computing the elevation variance of each cell from its immediate neighbors in a 0.05° ($\sim$ 5.56 km) resolution grid-cell space. *Road Density* is computed by overlaying the road network data provided by the Digital Chart of the World (Defense Mapping Agency, 1992) on the originally developed spatial grids described above.

Table 5.1: Summary statistics

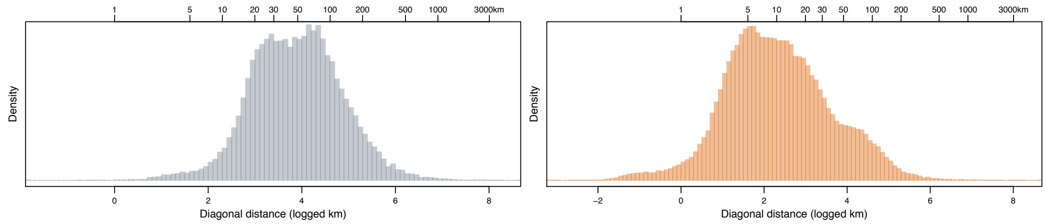
	Mean	St. Dev.	Min	Median	Max
Violence diffusion					
Proximate Diffusion	0.260	0.380	0.000	0.000	2.485
Distant Diffusion	1.645	1.024	0.000	1.638	4.570
Naive Diffusion	0.012	0.968	−20.667	0.048	10.333
Government attributes					
per capita GDP	7.601	1.054	5.217	7.520	10.163
Democracy	0.374	0.484	0	0	1
Country Size	13.242	1.494	9.234	13.416	16.639
Rebel attributes					
Territorial Control	0.382	0.486	0	0	1
Ethnic Claim	0.667	0.471	0	1	1
Rebel Much Weaker	0.428	0.495	0	0	1
Multi Party	0.626	0.484	0	1	1
Conflict dynamics					
Conflict Intensity	2.098	1.583	0.000	1.939	8.355
Cumulative Casualty	5.496	2.175	0.000	5.695	10.404
Collateral Damage	0.614	0.927	0.000	0.174	6.798
Govt OSV	0.682	1.142	0.000	0.000	10.370
Rebel OSV	0.830	1.206	0.000	0.000	8.786
Conflict geography					
Capital Distance	5.802	1.264	0.0003	5.959	7.689
Local Population	1.728	1.222	0.0003	1.639	6.300
Natural Resource Distance	5.936	0.964	2.211	6.006	7.782
Ruggedness	1.472	0.586	0.321	1.516	3.042
Road Density	0.013	0.008	0.000	0.012	0.063

Note: Diffusion terms are constructed using a spatial grid with $r = 30$ and $k = 1$.

istrative divisions (note 10). As the logged mean (median) diagonal distances of second- (city/municipality) and third-level administrative units (town/village) are located at 3.91 or $e^{3.91} \sim 49.89$ km ($e^{3.89} \sim 49.30$ km) and 12.05 km (10.4 km; Figure 5.5), respectively, individual battle events, roughly speaking, can be accurately located within 30 km grids. Second, the clear correspondence between administrative divisions and artificial grids allows for an intuitive interpretation of the diffusion terms. Typically, with $r = 30$ and $k = 1$, *Proximate Diffusion* indicates battle diffusion within single municipalities and their neighbors, whereas *Distant Diffusion* captures diffusion beyond such geographical distances.

5.2.4 Model

The coding and aggregation procedure left us with 7,341 dyad-month observations with 199 unique dyadic conflict episodes (spells). Of the 199



(a) Second-level administrative divisions (b) Third-level administrative divisions

Figure 5.5: Distribution of diagonal distance of administrative divisions
Note: Data derived from the GADM database of Global Administrative Areas (http://www.gadm.org/).

episodes, 149 conflicts were coded as terminated within the observation period, while the remaining dyadic episodes were coded as ongoing as of December 2011. The average duration of dyadic conflict episodes is 59.34 months (4.95 years), and the median duration is 30 months (2.5 years). Since our dependent variable *Termination* is coded as a binary indicator and the main independent variables varied over time, we employed a discrete-time event history model with a logit link function (Beck, Katz, and Tucker, 1998; Box-Steffensmeier and Jones, 2004). Following the recommendation of Carter and Signorino (2010), we incorporated a cubic function of time to control for duration dependence and modelled the baseline hazard in the sample dyads.[18] Because observations within the same rebel-government dyads may share unobserved characteristics and thus their standard errors may correlate, we report standard errors that are robust to dyad-level clustering.

5.3 Empirical Findings

Our primary independent variables include diffusion patterns of violence in civil conflicts. Table 5.2 reports the estimation results of discrete-time duration models of conflict termination. We first estimated a model with

[18]We included $t/100$ and its square and cube in our regression models, with t denoting the number of months since the onset of the dyadic conflict episode.

TABLE 5.2: DISCRETE-TIME DURATION MODELS OF CONFLICT TERMINATION

	Dependent variable: Conflict Termination		
	Model 1	Model 2	Model 3
Violence diffusion			
Proximate Diffusion	−0.139 (0.394)	−0.080 (0.404)	−0.020 (0.421)
Distant Diffusion	−0.662** (0.115)	−0.678** (0.118)	−0.683** (0.136)
Naive Diffusion	−0.073 (0.086)	−0.073 (0.086)	−0.058 (0.099)
Government attributes			
per capita GDP		−0.092 (0.091)	−0.127 (0.101)
Democracy		0.173 (0.217)	0.091 (0.303)
Country Size		0.004 (0.058)	−0.002 (0.081)
Rebel attributes			
Territorial Control		−0.067 (0.200)	−0.137 (0.213)
Ethnic Claim		−0.118 (0.182)	−0.073 (0.194)
Rebel Much Weaker		−0.191 (0.188)	−0.128 (0.201)
Multi Party		0.065 (0.204)	0.048 (0.217)
Conflict dynamics			
Conflict Intensity			0.022 (0.092)
Cumulative Casualty			0.144* (0.057)
Collateral Damage			−0.191 (0.170)
Govt OSV			−0.102 (0.095)
Rebel OSV			−0.197 (0.126)
Conflict geography			
Capital Distance			−0.005 (0.106)
Local Population			−0.028 (0.101)
Natural Resource Distance			−0.070 (0.087)
Ruggedness			−0.060 (0.175)
Road Density			3.011 (9.302)
Duration dependence			
t^1	−2.597** (0.691)	−2.490** (0.686)	−3.050** (0.757)
t^2	1.642** (0.505)	1.547** (0.494)	1.696** (0.528)
t^3	−0.280** (0.095)	−0.261** (0.091)	−0.263** (0.100)
Observations	7,341	7,341	7,341
Log Likelihood	−683.619	−682.007	−675.171
Akaike Inf. Crit.	1,381.238	1,392.015	1,398.342

Note: $^{*}p < 0.05$; $^{**}p < 0.01$
Unit of analysis: conflict dyad–month. Robust standard errors clustered on dyad in parentheses.
Intercepts are omitted for brevity.

the diffusion terms with a cubic function of time. Model 2 incorporates the control variables for government and rebel attributes. Model 3 further incorporates the control variables that capture the possible impacts of conflict dynamics on conflict termination.[19]

The coefficient estimates for *Distant Diffusion* are negatively signed and

[19] To avoid omitted variable bias and reverse causality, we replicated the following regression models with dyad- and year-random effects to minimize bias induced by year- and dyad-specific unobserved factors and independent variables lagged by one month. The results remained qualitatively unchanged.

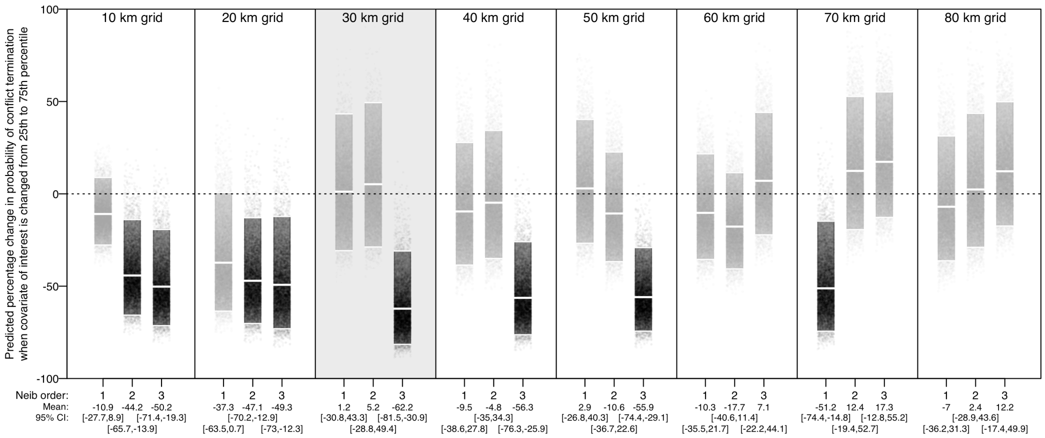
statistically significant across the model specifications, while *Proximate Diffusion* fails to retain statistical significance at the conventional 5% level. The estimates for these diffusion terms already provide tentative support for our argument that micro-level diffusion patterns of violence, as well as the intensity or locations of battles, systematically shape the probability of civil conflicts ending. Specifically, the coefficient signs across model specifications are consistent with Hypothesis 5.2b, which predicts a negative association between distant diffusion and the likelihood of conflict termination. The initial results suggest that *Distant Diffusion*, or the spread of battles across non-adjacent locations, is associated with lower chances of conflict termination, while *Proximate Diffusion*, or the diffusion of battle activities across adjacent localities, may not have a discernible impact on conflict termination. Importantly, the coefficient on *Naive Diffusion* fails to retain substantial and statistical significance across model specifications. Combined, these results indicate that it is *how* battles diffuse, rather than *whether* battles diffuse, that is vital in altering the opportunity for peace.[20]

5.3.1 Does Violence Diffusion Matter?

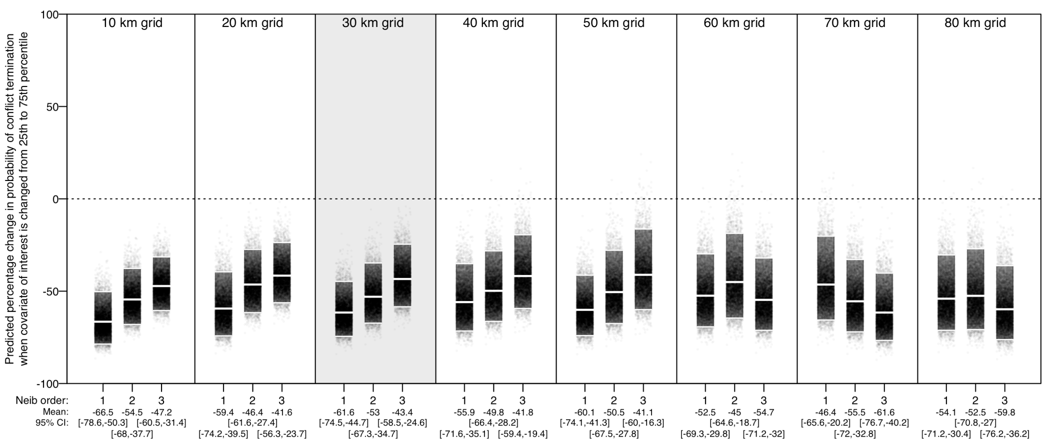
Nonetheless, unlike in linear models, in non-linear models, raw coefficients alone do not allow for meaningful interpretation of the substantial impacts of the corresponding covariates on the dependent variable. Another methodological issue that requires explicit investigation here is the potential sensitivity of the results to the selection of a basic spatial unit, or grid resolution r and neighborhood order k. As the MAUP suggests, examining the robustness of the estimation results to the spatial unit selection is critical to avoid reporting spurious relationships in any empirical analysis that employs discrete spatial units.

In order to account for these two estimation issues, Figure 5.6 utilizes simulations to assess the impact of diffusion dynamics on the probability of conflict termination across differently-specified spatial grids. Specifi-

[20]As reported in Appendix B.1, the statistically insignificant estimates for *Naive Diffusion* hold across different spatial grid settings.



(a) First difference estimates for *Proximate Diffusion*



(b) First difference estimates for *Distant Diffusion*

Figure 5.6: Effect of violence diffusion as percentage change in the probability of conflict termination across different spatial grid settings

Notes: Each dot indicates a predicted change in the probability of conflict termination, drawn from a single simulation when *Proximate Diffusion* (*Distant Diffusion*) is changed from the 25th to 75th percentile (first difference estimate), holding all other variables constant at their median (continuous) or mode (binary). Estimates that are statistically significant at the 5% level are plotted in black. White segments indicate the corresponding mean (thick) and 95% confidence intervals (thin) of predicted values. Labels of the horizontal axis also report the mean estimates and 95% confidence intervals. A black horizontal segment running through each panel indicates the zero-reference line. Gray shades indicate the estimation results using the baseline grid size of 30. The uncertainty estimates are obtained from 10,000 simulations, which are based on Model 3 in Table 5.2.

cally, it plots how the interquartile (25th to 75th percentile) increase in *Proximate Diffusion* and *Distant Diffusion* changes the probability of conflict termination against different grid resolutions and neighborhood orders, holding all other continuous variables constant at their median and binary variables at their mode. The left-most row within the gray-shaded area corresponds to the baseline result of Model 3 reported in Table 5.2, with the spatial grid setting of $r = 30$ and $k = 1$.. Statistically significant estimates at the conventional 5% level are plotted in black, whilst insignificant estimates are represented in gray. White segments represent the mean and 95% confidence intervals of predicted values. We obtained uncertainty estimates for the predicted values via 10,000 simulations, following the recommendation of King, Tomz, and Wittenberg (2000).

The predicted impacts of diffusion dynamics provide strong empirical support to the theoretical expectation of Hypothesis 1b: increasing instances of *Distant Diffusion* substantially lower the chances of conflict termination, and the association remains qualitatively unchanged across different spatial grid resolutions (Figure 6.1(b)). Specifically, an increase in *Distant Diffusion* from the 25th to 75th percentile is followed by a statistically and substantially significant decrease in the likelihood of conflict termination, with a 61.3% drop in the predicted probability that the conflict will end (95% Confidence Interval: $-74.2, -44.6$). This association is consistently held across different geographic scales, while the predicted impact gradually decreases as grid resolution r and neighborhood order k increase. Indeed, the impact followed by the same amount of chance in *Distant Diffusion* decreases to -53.6% (95% CI: $-70.7, -30.2$), with $r = 80$ and $k = 1$, and -43.5% (95% CI: $-58.4, -24.9$) with $r = 30$ and $k = 3$.

In contrast, Figure 6.1(a) indicates that the association between *Proximate Diffusion* and conflict termination remains sensitive at best to grid settings. Hypotheses 5.1a and 5.2a receive little empirical support from these simulations, both of which expect *Proximate Diffusion* to have a substantial impact on the likelihood of conflict termination. The relatively large ranges of confidence intervals for the interquartile increase in *Proximate*

Diffusion do not allow us to reject the null hypothesis of non-difference from zero in 16 out of 24 grid settings.

5.3.2 Alternative Spatial Grid Definition

A clear, methodological implication of the results in Figure 5.6 is the presence of the MAUP discussed in Section 5.2, or its special case "scale problem," in which estimation results vary when spatial data are aggregated using differently sized areal units. The analysis above, however, does not, on its own, preclude all potential sensitivities to spatial unit specification. Because the selection of grid *shape* as well as resolution and neighborhood order could influence when instances of proximate and distant diffusion are detected, another explicit examination is required to examine the robustness of the main results to arbitrary spatial grid definitions.

To further explore the effect of the spatial unit selection, Figure B.2 in Appendix B replicates the estimations and simulations reported in Figure 5.6 using differently specified rectangular grids and the Moore neighborhood. Reassuringly, the results in Figures B.2(a) and B.2(b) do not deviate markedly from the main results: *Distant Diffusion* consistently has a substantial and negative impact on the probability of conflict termination across different grid settings, while the effect of *Proximate Diffusion* remains indeterminate or sensitive to the grid specifications. These results provide additional confidence that the specific parameter settings are not driving the main findings.

One may reasonably wonder why we see somewhat inconsistent estimates for the impact of proximate-type diffusion on conflict termination. A possible interpretation of the absence of consistent estimates for *Proximate Diffusion* is that such estimates are purely driven by the MAUP. They are no more than a product of arbitrary spatial grid specification. Another and more nuanced interpretation is that the distinction between proximate and distant diffusion patterns blur in some grid settings. The statistically significant estimate for *Proximate Diffusion*, for example, with resolution $r = 30$ and neighborhood order $k = 3$ may capture the effect measured by

Distant Diffusion in the estimates employing lower neighborhood orders (Figure 5.6). Due to the relatively large areas covered by the neighborhoods, *Proximate Diffusion* in this grid setting is likely to be influenced by instances of violence diffusion across distant geographical areas that are conceptually defined as *Distant Diffusion*. Consistent with this interpretation, the effect size of *Distant Diffusion* tends to decrease as the effect size of *Proximate Diffusion* increases. These interpretations lead us to the conclusion that it is not battle diffusion across geographically close and contiguous areas, but the diffusion across geographically distant areas that matters in determining the prospects for peace.

Overall, these results provide strong empirical support for our core theoretical expectation that the micro-level diffusion dynamics of violence shape conflict termination at the macro level. Although not all dimensions of conflict dynamics are equally important, the diffusion of battle activities and spread of battles across geographically distant, non-adjacent areas in particular, considerably shape the duration and termination of civil conflicts. The empirical results are consistent with Hypothesis 5.2b, which predicts a negative association between instances of distant diffusion and the probability that a civil conflict will end due to conflict-induced fear and the credible commitment problem. By contrast, Hypotheses 5.1a, 5.1b, and 5.2a receive little support from the empirical analysis.

5.3.3 Additional Results

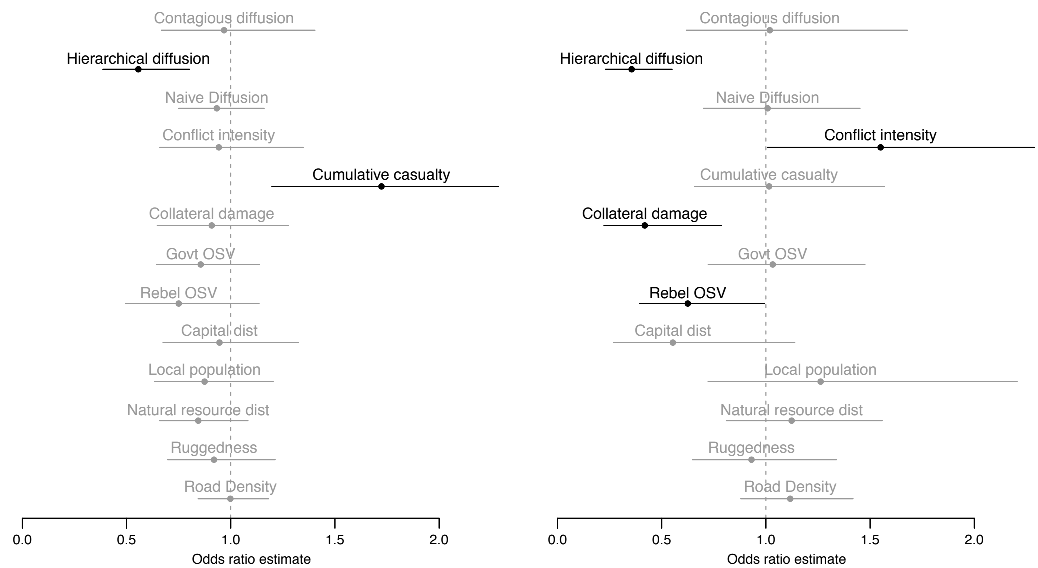
Informational account of war and battle intensity In addition to the relationships of central theoretical interest, some of the control variables yield results that are also worth mentioning. Among these, the estimation for conflict severity yields valuable insights. A positive and significant association between long-term conflict severity (*Cumulative Casualty*) and the likelihood of conflict termination is present across all model specifications. On the other hand, coefficient estimates for short or intermediate conflict severity (*Conflict Intensity*) remain indeterminate across model specifications. These results underscore the differing effects of short- and long-term conflict severity (Table 5.2). While short- or intermediate-term conflict severity may not have substantial impacts on the chances of conflict termination, the long-term or cumulative costs of fighting may lead warring parties to stop inefficient fighting.

This finding essentially mirrors the informational argument and findings on the association between long-term conflict intensity and conflict duration in Weisiger (2016): cumulative conflict intensity, or "sum of past information," is a plausible predictor of war termination, while short-term intensity or recent "spikes" in battle intensity are unlikely to have a substantial impact. While Weisiger (2016) focuses on the variation in duration of interstate conflicts, our results suggest that the diverging effects of conflict intensity may also travel to civil conflicts. The generalizability of the role that short- and long-term conflict intensity plays in determining conflict duration warrants a focused analysis.

What matters may depend on the disputed issue One may reasonably question whether the impacts of battle diffusion vary depending on the disputed issue. For example, rebels who aim to achieve independence for their "homeland" may not have incentives to diffuse battle activities beyond the areas they wish to eventually govern. In contrast, rebel groups competing with the incumbent to replace the central government may have stronger incentives to diffuse combat activities across the country, in order to destabilize areas suspected of loyalty to the incumbent (Beardsley, Gleditsch, and Lo, 2015).[21] Related studies suggest that rebel characteristics also shape their objective and thereby alter the contested incompatibility within each conflict (Buhaug, 2006; Sobek and Payne, 2010).

To provide an initial look, an additional estimation with separated samples of governmental and territorial conflicts would be informative. Figure 5.7 and Table 5.3 report and compare the estimation results of sep-

[21] We are grateful to Han Dorussen (University of Essex) for making this observation. See Beardsley, Gleditsch, and Lo (2015) and Buhaug and Rød (2006) for a related discussion on the determinants of battle locations and diffusion in conflicts over different issues, and Buhaug (2006) for the possible difference in the mechanisms underlying territorial and governmental civil conflicts.



(a) Odds ratio estimates: Governmental conflict (# obs = 4,138)

(b) Odds ratio estimates: Territorial conflict (# obs = 3,203)

Figure 5.7: Odds ratio estimates, governmental and territorial conflicts
Note: odds ratio estimates for (a) governmental and (b) territorial conflicts. Estimates are based on standardized independent variables for comparative purposes. Statistically significant estimates at the 5% level are shown in black, whilst insignificant estimates are plotted in gray. Models are specified as Model 3 in Table 5.2. Estimates for government and rebel attributes, duration dependence, and intercepts are omitted for brevity. A spatial grid with $r = 30$ and $k = 1$ is employed.

arate models for the two subsamples.[22] As the coefficient signs and statistical significance indicate, the determinants of conflict termination may vary depending on the disputed issue. For example, *Cumulative Casualty*, or long-term conflict intensity, has a conflict-shortening effect in the governmental conflict subsample (Figure 5.7(a)), but fails to attain statistical significance in the territorial conflict subsample (Figure 5.7(b)). In sharp

[22]"Incomp" $\in$ {Governmental, Territorial} in the ACD data, which indicates issue incompatibility in each conflict, is used to separate samples. A comprehensive test on the difference between the determinants of governmental and territorial conflicts requires a pooled model with interaction terms between covariates of interest and an incompatibility variable such as *Distant Diffusion* $\times$ *Incompatibility* (Kam and Franzese, 2007, Chap.5). Although no strong empirical claim can be made from the estimation results, a separate-sample estimation would still be informative to detect potential differences.

contrast, *Conflict Intensity*, or short-term conflict intensity, increases the chances of conflict termination in the territorial conflict subsample (Figure 5.7(b)) while the coefficient remains substantially and statistically indistinguishable from 0 in the governmental conflict subsample estimate (Figure 5.7(a)). Similarly, *Collateral Damage* and *Rebel OSV* negatively impact the chances of conflict termination in territorial conflicts, whereas the effects remain less visible in governmental conflicts. These contrasting results suggest that different dimensions of conflict intensity affect conflict duration when disputants fight over different issues, which would also warrant a focused analysis.

Nonetheless, the estimates for the two diffusion terms remain consistent across the subsamples: *Distant Diffusion* decreases the likelihood of conflict termination, whereas *Proximate Diffusion* may not have a substantial effect. These estimation results provide additional confidence that the differences in the disputed issues would not alter our main findings.

5.4 Conclusion

Recent advances in civil war studies have increasingly explored the micro-level battle dynamics in civil conflicts and their likely impacts on the termination and outcome of conflict at the macro level. Previous studies, however, only offer limited insights into the question of whether and how different spatio-temporal diffusion dynamics of violence have differing impacts on the chances of conflict termination. Building on the previous studies on conflict dynamics and the bargaining model of war, this chapter proposes and tests several preliminary hypotheses that relate the diffusion dynamics of battles to the likelihood of conflict termination. Drawing on a precisely geocoded event dataset on civil war battles and a nuanced typology of diffusion dynamics, it has then undertaken a first cut at examining the previously under-investigated determinants of conflict termination.

The results reveal two important empirical patterns. First, consistent with the credible-commitment account of war, escalating distant diffusion

Table 5.3: Discrete-time duration models of conflict termination, governmental and territorial conflicts

	Dependent variable: Termination	
	Model 4 Governmental conflict	Model 5 Territorial conflict
Violence diffusion		
Proximate Diffusion	−0.086 (0.500)	0.049 (0.671)
Distant Diffusion	-0.572^{**} (0.182)	-1.010^{**} (0.217)
Naive Diffusion	−0.072 (0.115)	0.008 (0.192)
Government attributes		
per capita GDP	−0.008 (0.174)	−0.213 (0.175)
Democracy	−0.005 (0.544)	0.620 (0.514)
Country Size	0.054 (0.113)	0.251 (0.193)
Rebel attributes		
Territorial Control	−0.359 (0.272)	0.014 (0.387)
Ethnic Claim	−0.013 (0.257)	−0.325 (1.172)
Rebel Much Weaker	−0.366 (0.284)	0.062 (0.336)
Multi Party	−0.127 (0.262)	0.079 (0.453)
Conflict dynamics		
Conflict Intensity	−0.037 (0.115)	0.277^{*} (0.139)
Cumulative Casualty	0.250^{**} (0.085)	0.007 (0.102)
Collateral Damage	−0.103 (0.187)	-0.939^{**} (0.347)
Govt OSV	−0.136 (0.127)	0.028 (0.159)
Rebel OSV	−0.238 (0.175)	-0.389^{*} (0.195)
Conflict geography		
CapitalDistance	−0.044 (0.136)	−0.468 (0.291)
Local Population	−0.110 (0.133)	0.191 (0.233)
Natural Resource Distance	−0.175 (0.131)	0.120 (0.172)
Ruggedness	−0.143 (0.241)	−0.122 (0.316)
Road Density	−0.208 (11.091)	14.253 (15.718)
Duration dependence		
t^1	-3.218^{**} (1.051)	-2.380^{*} (1.080)
t^2	1.847^{**} (0.681)	1.168 (0.932)
t^3	-0.294^{*} (0.123)	−0.157 (0.203)
Observations	4,138	3,203
Log Likelihood	−390.898	−271.665
Akaike Inf. Crit.	829.797	591.329

Note: $^{*}p < 0.05$; $^{**}p < 0.01$
Unit of analysis: conflict dyad–month. Robust standard errors clustered on dyad in parentheses. Intercepts are omitted for brevity.

dynamics, or spreads of battle activities toward non-adjacent areas, decrease, rather than increase, the chances of conflict termination, while informational account of war imply otherwise. Second, although distant diffusion has a substantial and negative impact on the likelihood of conflict termination across different geographic scales, the effect of proximate diffusion, or the spread of violence across geographically contiguous areas, is found to be sensitive to the spatial grid specification.

These empirical findings speak to scholarly and policy debates over conflict termination. First, this chapter provides compelling support for the bargaining accounts of war onset and termination based on a nuanced characterization of battle dynamics in civil conflicts. The empirical results are consistent with the earlier arguments that views conflict as a bargaining process, and relates battlefield outcomes to the prospects of conflict termination. Specifically, our results provide strong empirical support for the credible-commitment account of war that stress the role of temporary fluctuations in the government's capability and the exacerbated incredibility of its commitments. Second, the results highlight the role of the spatio-temporal diffusion of battles in determining the chances of conflict termination. Just as instances of "hurting stalemate" substantially shape the prospects for peace, the distant diffusion of combat activities invariably influences the future course of conflict. These dynamic determinants of conflict termination should not be neglected in future studies.

This chapter also yields implications beyond scholarly debates. The end of a civil war can depend on "ripe moments" for dialogue between the disputants (Zartman, 2001). These opportunities, however, may often be missed due to the warring parties' inability to credibly commit to following through the war-ending agreement in the absence of central enforcement. Previous studies highlight the role of mutually hurting stalemate as a signal of such moments (Greig, 2015; Ruhe, 2015; Zartman, 2001), which is consistent with our results regarding the impact of cumulative battle-imposed costs on conflict termination. In a sense, our study provides another indicator about where and when such ripe moments might occur. Somewhat counterintuitively, a particular type of escalation of battle activities, increasingly distant diffusion, may also be used as a signal to the international community about the appropriate timing to initiate interventions in order to shorten costly conflicts. In circumstances where there is increasingly distant diffusion of battle activities, both temporarily weakened governments and temporarily strengthened rebels have strategic incentives to stop inefficient fighting once an enforcement mechanism has been implemented. This is a situation where conflict termination is difficult without external enforcement devices to guarantee the implementation of the war-ending agreement, and therefore, where carefully-designed third-party intervention is most needed.

There are several avenues for future research. First, our empirical results demonstrate how short- and long-term conflict intensity can impact conflict termination differently. These differing impacts of conflict intensity, and its possible interaction effects with conflict geography, warrant further investigation. Second, investigating the empirical associations between diffusion patterns of violence and conflict outcomes is another promising pathway for future research. History tells us that civil conflicts can end in a variety of ways: some civil conflicts end in military victory, while others end through negotiated settlements. Still other conflicts terminate without clear outcomes (DeRouen and Sobek, 2004; Kreutz, 2010). Do different diffusion patterns of violence have differing impacts on the likelihood of specific conflict outcomes as well as conflict duration? Does violence diffusion shape not only *when*, but also *how* civil conflict ends? These questions, too, warrant focused analyses and will be addressed in the next chapter.

CHAPTER 6

Violence Diffusion Shapes How Civil Conflict Ends

Examining the Impacts of Microdynamics of Fighting on Conflict Outcome[†]

Violence, being instrumental by nature, is rational to the extent that it is effective in reaching the end which must justify it.

Hannah Arendt (1970, 79)

Chapter Abstract *How do different diffusion patterns of civil war violence influence the type and likelihood of conflict termination? Recent advances in the literature on micro-dynamics of civil wars have found that the location and intensity matters in resolving the bargaining problem between the warring parties. Building on such theoretical framework, this chapter argues that* whether *or not battles diffuse is less important for conflict outcomes and termination than* how *they diffuse. Different diffusion patterns of civil war battles create varying shifts in the underlying balance of power between the disputants and thus exasperate credible commitment problem and alter the chances of military victories, which in turn hamper conflict termination. The argument is tested by creating two distinct diffusion patterns of battles: distant diffusion and proximate diffusion. The empirical findings support the argument that distant*

[†]This chapter is an edited version of the coauthored manuscript in collaboration with Kaisa Hinkkainen (University of Leeds), originally entitled "Battle diffusion matters: Examining the impact of microdynamics of fighting on conflict outcome and termination."

diffusion of battles make civil conflicts less likely to terminate in both rebel and government favorable ways.

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CHAPTER 7

Conclusion and Outlook

War, to be abolished, must be understood.
To be understood, it must be studied.

Karl W. Deutsch (1970, 473)

The critical step in preventing the tragedy of war is to understand it (Deutsch, 1970, 473). Effective policy remedies for civil conflicts require concrete scholarly understanding, and deepening scholarly understanding requires the accumulation of research. Taking the recent advances in civil war study as the point of departure, this dissertation has explored the role of dynamic, endogenous, and relatively static, exogenous factors in altering the process and termination of civil conflicts. Specifically, it has addressed the following research questions on the micro- or subnational-level *causes* and macro- or country-level *consequences* of violence in civil conflicts: Why do the frequency and manner of civil war violence vary in single conflicts? What causes violence in civil conflicts in specific locations and manners at the local or micro level? Do the micro-level dynamics of battles significantly influence macro-level variations in conflict duration and outcome?

This dissertation has answered these questions by presenting a twofold argument: first, endogenous or dynamic factors such as a past history of violence as well as structural factors such as physical geography matter in determining micro-level battle dynamics and macro-level conflict termination; and second, the relative importance of the dynamic factors varies depending on how violence is applied. The first part of the empirical analysis focused on the micro-level causes of civil war violence, while the second part analyzed the impacts of micro-level battle dynamics on the variations in civil war duration and outcome at the macro level.

This chapter summarizes the main findings and highlights the scholarly and policy implications, followed by some avenues for future research.

7.1 Key Findings

The main findings can be summarized along the dual focus of this dissertation. First, and at the micro level, this study has demonstrated the critical but conditional role of endogenous factors in shaping future conflict trajectories. The empirically-grounded computational model has demonstrated the importance of endogenous diffusion dynamics in determining where and how violence unfolds during civil conflicts (Chapters 3 and 4). The simulation exercise also suggests that diffusion dynamics matter, as much as a standard set of structural correlates of civil war violence, in improving our capability to explain and predict insurgent violence (Chapter 3). Another significant finding lies in the conditional importance of these endogenous dynamics: while diffusion dynamics invariably matter in explaining selective violence, they matter less in predicting indiscriminate violence (Chapter 4). These conditional effects of endogenous diffusion dynamics on the future trajectories of violence can be attributed to the different incentives underlying different types of violence.

Second, and at the macro level, this dissertation has examined the consequences of civil war violence by analyzing how the micro-level dynamics of fighting translate into the macro-level variations of conflict duration and outcome. Building upon the bargaining model of war, the two chapters in the second part of the analysis posit that the spatio-temporal dynamics of violence that occur during conflict substantially influence when and how civil conflict ends by altering the severity of the underlying bargaining problems. The relative importance of diffusion dynamics depends on how battles diffuse rather than whether battles diffuse because the different diffusion dynamics affect the expectations and underlying power balance between disputants differently.

The empirical results provide strong support for the theoretical claim that the diffusion of battle activities across distant localities substantially lowers the likelihood of conflict termination (Chapter 5). While civil conflict can end in a variety of ways, the analysis has also demonstrated that the diffusion of battle activities across distant localities lowers the likelihood of conflict termination in both government-favorable *and* rebel-favorable ways (Chapter 6). The theoretical argument and empirical analysis suggest a two-fold logic of conflict termination: first, distant diffusion dynamics decrease the chances of conflict termination with government-favorable outcomes, primarily because the incumbent is likely to have difficulty restoring the monopoly of violence through coercive means when rebels are relatively successful in the battlefield and enjoy freedom of maneuver; and second, as the credible-commitment story of war termination illustrates, although battlefield success indicates fluctuations in government capability and enhances rebels' current bargaining position, the fear of a post-conflict power shift prevents rebels from ending inefficient conflict. In the former case, conflict may continue due to the government's inability to defeat rebels militarily, while in the latter, conflict is prolonged due to the government's inability to credibly commit to upholding a negotiated solution. The two-fold failure of military strategy and war-ending bargaining in turn prolongs civil conflicts.

7.2 Implications

Besides those discussed in previous chapters, this dissertation can offer several important implications for civil war study. First, the empirical analysis underscores the importance of the conceptually, as well as spatially and temporally, disaggregated approach to deepen our understanding of civil conflict. The micro-level analysis suggests that endogenous diffusion dynamics substantially shape our capability to explain and predict local-level variations in civil war violence, but the relative impact critically depends on the types of violence. As discussed in Chapter 4, most existing studies tend to emphasize either exogenous or endogenous factors; yet, this tendency may mask important heterogeneity in the determinants of civil war violence. Similarly, the macro-level analysis also highlights that the relative importance of diffusion dynamics in altering conflict termination depends on *how*, rather than *whether*, battles diffuse (Chapters 5 and 6). A nuanced conceptual disaggregation of battle activities would also deepen our understanding of the determinants of civil war termination.

Second, the macro-level analysis demonstrates the substantial impact of micro-level diffusion dynamics of violence on the chances of conflict termination. Combined with insights from the small but emergent body of literature (e.g., Greig, 2015; Greig, Mason, and Hamner, 2016; Ruhe, 2015; Wood and Kathman, 2014), this dissertation suggests that any study on civil war termination remains incomplete without examining how and why fighting shapes the prospects for domestic peace. The findings also speak to the broader literature on the links between the conflict process and conflict termination in inter- and intra-national conflicts (e.g., Leventoglu and Slantchev, 2007; Powell, 2004a, 2012; Reiter, 2009; Slantchev, 2003a,b; Wagner, 2000). As this dissertation and related studies on interstate conflict demonstrate (e.g., Ramsay, 2008; Weisiger, 2016), a systematic analysis of battlefield dynamics would help to dissect the pathways through which the conflict process shapes conflict termination.[1]

Third and methodologically, the two-part empirical analysis has un-

[1] Another but related implication is the effectiveness of intervention efforts. If the micro-dynamics of conflict shape conflict termination, external intervention efforts into civil conflicts may also alter the prospects for peace, not only by altering the credibility of war-ending agreements (e.g., Walter, 1997, 1999) but also by affecting the battlefield dynamics.

derscored the promises and pitfalls of using spatial data in civil war study. On the one hand, the increasingly available spatial data and related GIS tools enable researchers to explore the local-level realities of civil conflict. As demonstrated in Chapters 3 and 4, this methodological innovation offers a promising opportunity to deepen our understanding of the causes and consequences of violence. The methodological utility of the spatially-explicit approach, as demonstrated in Chapters 5 and 6, is substantial in studies of macro-level conflict termination, as well as the micro-level conflict process. On the other hand, the second part of the analysis reminds us that this methodological innovation comes with an additional methodological issue: the selection of the basic areal units can have a substantial impact on the estimation results of any statistical analysis employing discrete spatial units of analysis (modifiable areal unit problem, MAUP, Fotheringham and Wong, 1991; Jelinski and Wu, 1996; Openshaw, 1983; Openshaw and Taylor, 1979). As the analysis demonstrates, one cannot be sure that the empirical findings derived from spatial data are unbiased and robust if we fail to address this important methodological concern.[2]

7.3 Pathways for Future Research

In addition to those highlighted in each empirical chapter, there are several promising pathways for future research. An important research agenda is the impact that forms of foreign intervention can have on future trajectories of civil conflict. Admittedly, a huge body of literature has yielded valu-

[2]This methodological issue is visible in several studies on the micro-level impact of aid provision and counterinsurgency operations on subsequent patterns of civil war violence. For example, building upon the novel methodological approaches in Schutte and Donnay (2014), Schutte (2016), and Zhukov (2016), Ito (2017) examines the impact of foreign aid provision on the subsequent severity of rebel violence against civilians across different spatial and temporal windows. The empirical analysis reveals two patterns: first, humanitarian aid has a negative impact on the subsequent intensity of rebel violence against civilians at the local level, but the effect remains limited within small geographical and temporal distances; and second, the effect of conventional aid projects remains indeterminate across different spatial and temporal scales. The results suggest that the mixed empirical findings in previous studies may partly be driven by the reliance on different spatio-temporal units of analysis.

able insights into how external intervention shapes micro- and macro-level variations in civil conflict dynamics. The macro-level literature demonstrates how international mediation, peacekeeping operations, and aid inflows alter the prospects for conflict termination and recurrence at the macro level (e.g., Fortna, 2008; Greig and Regan, 2008; Narang, 2015; Sisk, 2009; Walter, 1997, 1999, 2002; Zartman, 2001). The rapidly growing micro-level literature highlights how peacekeeping operations and foreign aid provision can alter the subsequent intensity and dynamics of battle activities (e.g., Beardsley and Gleditsch, 2015; Crost, Felter, and Johnston, 2014; Gilligan, 2008; Ito, 2017; Ruggeri, Dorussen, and Gizelis, 2017; Wood and Molfino, 2016; Wood and Sullivan, 2015).[3]

What remains relatively under-explored, however, is scholarly investigation into how the micro-level impact of foreign intervention may "scale-up" to the macro-level variations. As this dissertation has demonstrated, the micro-level conflict dynamics invariably alter the macro-level conflict duration and outcome. The emerging micro-level literature shows how third-party intervention substantially shapes how battle activities unfold during civil conflicts. Collectively, these insights lead us to speculate that external intervention can alter the local battlefield dynamics, which, as this dissertation demonstrates, in turn shapes the severity of the underlying bargaining problems that need to be resolved for costly fighting to end. Such investigations into the micro-macro nexus that shapes intervention effectiveness would benefit both scholars and policymakers.

[3] See Zürcher (2017) for an overview of the recent advances in micro-level studies on the aid-conflict nexus.

Part IV

Appendix and Bibliography

APPENDIX A

Supplements to Chapters 3 and 4

The following sections illustrate the details of empirical data and report additional statistics and robustness checks for the simulation experiments in Chapters 3 and 4. Section A.1 provides an overview of the empirical data, followed by the supplemental statistics in Section A.3 and robustness checks in Sections A.4 and A.5.

A.1 Empirical Data

The computational experiments and empirical findings rely on a subset of the SIGACTs records in Afghanistan. The full SIGACTs dataset can be obtained at the WikiLeaks website (https://wikileaks.org/wiki/Afghan_War_Diary,_2004-2010). Note that the dataset containing the records of SIGACTs events is *not* included in the replication material, since the full dataset is still classified. To obtain the dataset used in this chapter, readers may download the dataset from Wikileaks or its mirror websites, and then filter and aggregate the entries following the coding rule explained below. In addition, the computational model contains a series of settlement-level structural covariates. The settlement-level dataset containing settlement IDs, structural covariates, and the inter-settlement network are included in the replication materials.

A.1.1 Event Coding

As noted in the main text, the SIGACTs dataset contains both violent and nonviolent incidents conducted by insurgents, counterinsurgent, and unknown actors. Following previous studies (e.g., Hirose, Imai, and Lyall, 2017; Lyall, Shiraito, and Imai, 2015; Schutte, 2016, 2017; Weidmann, 2013, 2015, 2016), the coding rule uses "Category," "Type," and "Affiliation" columns to generate the sub-sample of violent events from the whole database. Specifically, drawing on the "Category" column, entries in the following categories were divided into two major classes: insurgent-initiated violent incidents ($Violence_{INS}$) and ISAF-initiated violent incidents ($Violence_{ISAF}$):

- $Violence_{INS}$: "Other (Hostile Action)," "Assassination," "Attack," "Direct Fire," "IED Explosion," "IED False," "IED Found/Cleared," "IED Hoax," "Indirect Fire," "Mine Found/Cleared," "Mine Strike," "SAFIRE" (Surface-to-Air Fire), "Security Breach," "Unexploded Ordnance," and "Sniper Ops"
- $Violence_{ISAF}$: "Cache Found/Cleared," "Close Air Support," "Counter Insurgency," "Counter Terrorism," "Direct Fire," "Escalation of Force," "Indirect Fire," "Search and Attack," "Show of Force", "Small Unit Actions," "Sniper Ops," "Other Offensive," and "Raid."

Because "Direct Fire" and "Sniper Ops" categories are included in both $Violence_{INS}$ and $Violence_{ISAF}$, we further matched the subset of the data against "Affiliation" variable which contains information of the perpetrator ("FRIEND," "ENEMY," "NEUTRAL," "UNKNOWN"), and then code those records with "Affiliation"="FRIEND" as $Violence_{ISAF}$ and those with "Affiliation"="ENEMY" as $Violence_{INS}$.

A.1.2 Geocoordinates

As explained in Section 3.2, the records of insurgent-initiated violence $Violence_{INS}$ and ISAF-initiated violence $Violence_{ISAF}$ are aggregated to the settlement level using their reported geocoordinates, or "latitude" and "longitude" variables. This geo-processing was done in four steps. First, the international border of Afghanistan and SIGACTs event locations were projected to the standard UTM (Universal Transverse Mercator) coordinate system using the geographical information system (GIS). The entries not falling within Afghanistan's territory were carefully dropped from our dataset. Second, the settlement dataset (obtained from USAID) and entries of insurgent and ISAF violence were similarly projected to the standard UTM (Universal Transverse Mercator) coordinate system. Third, we computed the geodesic distance from each record of violence to all population settlements. Finally, we selected the settlements that are geographically closest to individual attack locations and aggregated the number of attacks at the settlement-level to generate the two count variables, $Violence_{INS}$ and $Violence_{ISAF}$.

A.2 Summary Statistics

The agent-based model is composed of a set $\boldsymbol{S} = \{S_1, \ldots, S_N\}$ of N population settlements resided by a set $\boldsymbol{I} = \{I_1, \ldots, I_M\}$ of M insurgent agents. To mimic the micro-geography of Afghanistan, population settlements S_i are seeded by empirical data, i.e., susceptibility covariates $\boldsymbol{x}$ and the road networks as explained in Section 3.3 in the main text. Tables A.1 and A.2 report and visualize the summary statistics and correlation estimates of $\boldsymbol{x}$ covariates incorporated with the computational model. Note that all covariates are log-transformed and rescaled to the range of $[-1, 1]$ when incorporated with the model to minimize the effects of marginal values and make them easily comparable.

A.3 Prediction Performance

As discussed in the main text, the model's capability to correctly classify the settlements with and without insurgent violence can be quantified us-

TABLE A.1: SUMMARY STATISTICS

Covariate (logged)	Mean	Std. Dev.	Median	Range
Socioeconomic conditions				
PopSize	5.695	1.103	5.749	[1.099, 14.750]
PashtunPop	2.424	2.997	0	[0, 12.690]
Development	9.201	0.389	9.265	[6.483, 9.703]
Geographic conditions				
Ruggedness	2.123	0.560	5.749	[0, 3.437]
RoadAccess (in logged km)	−0.026	1.461	0.034	[−5.817, 3.881]
KabulDist (in logged km)	5.425	0.742	5.518	[−6.908, 6.723]
APborder (in logged km)	5.017	1.021	5.224	[−0.962, 6.466]

Note: All covariates are logged. The unit of observation is population settlement.

TABLE A.2: CORRELATION MATRIX

	Socioeconomic conditions			Geographic conditions		
	PopSize	*PashtunPop*	*Development*	*Ruggedness*	*Road*	*CapDist*
PopSize						
PashtoPop	0.357					
Development	−0.003	0.096				
Ruggedness	0.010	−0.379	0.102			
Road	−0.212	−0.010	0.007	−0.171		
CapDist	0.019	−0.111	−0.545	−0.064	0.008	
APborder	−0.063	−0.437	−0.297	0.229	0.012	0.609

Note: Spearman's ρ estimates are reported.

ing the Receiver Operating Characteristic (ROC) curve and the area under the ROC curve (AUC) score. An ROC curve plots TPR and FPR as the output of each possible probability threshold for positive prediction. The resultant plot displays the balance between TPR and FPR where a highly predictive model (with high TPR and low FPR) produces the curve up in the top left corner. The AUC score, which is defined as the area covered by the corresponding ROC curve, ranges between 0 and 1, and provides a single number summary of the model's classification performance. A random coin toss produces an AUC score of 0.5, whereas a model with higher

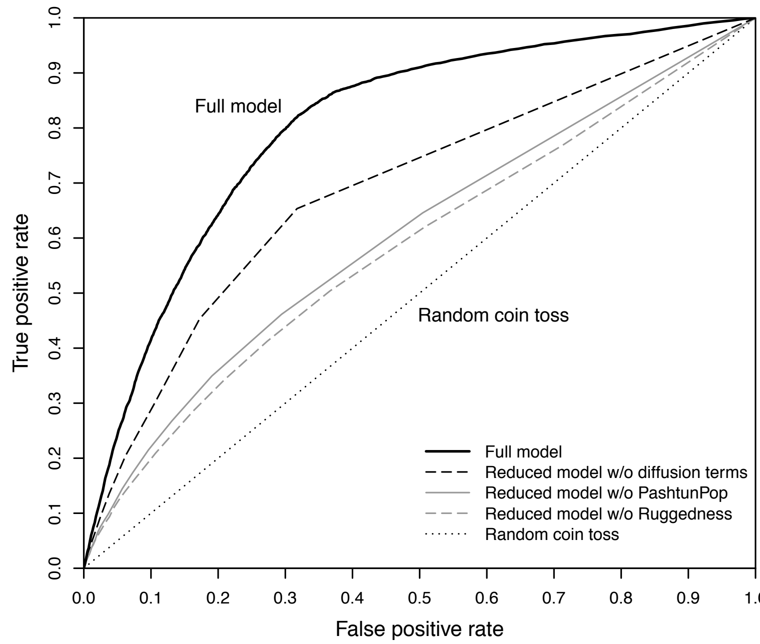


Figure A.1: ROC curves for in-sample prediction accuracy across different model specifications

Note: Individual curves represent the estimated in-sample ROC curves for the full model with all covariates (black solid), the reduced model without diffusion terms (γ parameters; black dashed), the reduced model without diffusion terms and *PashtunPop* (gray solid), the reduced model without diffusion terms, *PashtunPop*, and *Ruggedness* (gray dashed), and a random coin toss (0.5 AUC score; black dotted).

classification performance should yield an AUC score of greater than 0.5.

As reported in main text, the model yields fairly high in-sample classification performance and substantially outperforms random guesses. Figure A.1 plots the (in-sample) ROC curves for the baseline model with all covariates and reduced models reported in Sections 3.5.1 and 3.5.2. The solid and dashed curves in Figure A.1 represent the ROC curves generated by our computational model across different model specifications, while the black dotted curve indicates the reference of 0.5 AUC score obtained by a random coin toss. 50,000 simulation runs were conducted for each parameter setting to gain these estimates. The contribution of each covariate measured as the corresponding change in the in-sample AUC score is reported in the main text and Figure 3.6.

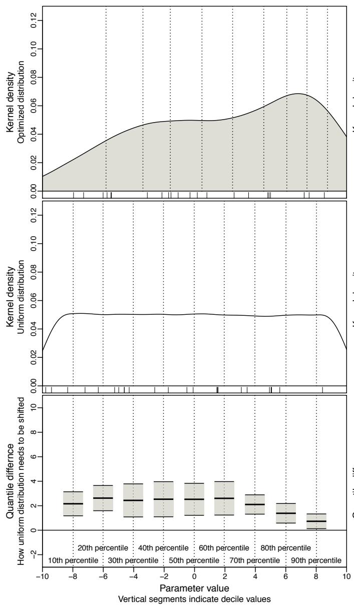
A.4 Robustness Checks

The main simulation results reported above do not on their own preclude the potential sensitivities of the simulation results. Consequently, one may reasonably wonder whether and how the "moving parts" or parameter settings of the simulation model change the results. Four model parameters and assumptions warrant investigation to examine the robustness of the main results: (1) neighborhood size k, (2) number of agents M, (3) the attack-or-relocate dichotomy in the behavior algorithm, and (4) exponential weight ϕ for $Spread$ and $History$. In order to examine the robustness of the main results, $350,000$ additional simulations were conducted, varying these parameter settings and assumptions. Reassuringly, none of these sensitivity tests reported in Appendix A.4 yielded results that deviate markedly from the main results reported above. These results provide confidence that the specific parameter settings and assumptions are not driving the main findings.

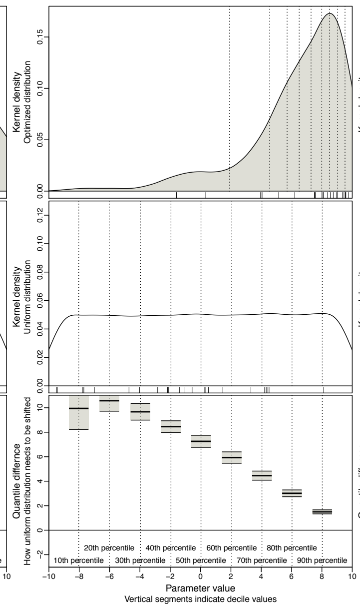
A.4.1 Neighborhood Size

The neighborhood networks are the pathways through which insurgent agents move around and violence diffuses. In order to examine potential sensitivities of the results to the definition of neighborhood network, additional $50,000 \times 2 = 100,000$ simulation runs have been conducted using alternative network sizes $k = 10$ and $k = 30$ instead of the baseline value of $k = 20$, with all other parameters held at the baseline values.

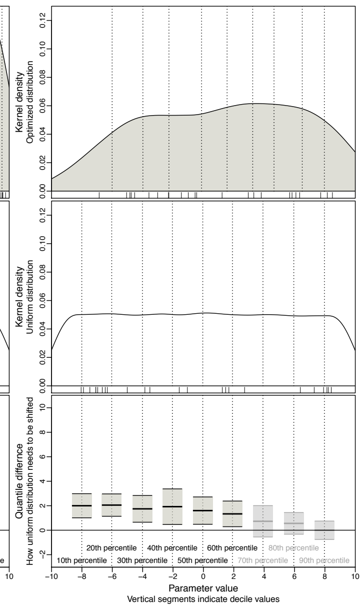
Figures A.2 and A.3 plot the density estimates for simulation runs with these alternative network sizes. As these estimates are substantially indistinguishable from those with $k = 20$, it can be concluded that the parameter estimates are fairly robust to the changes of neighborhood definitions.



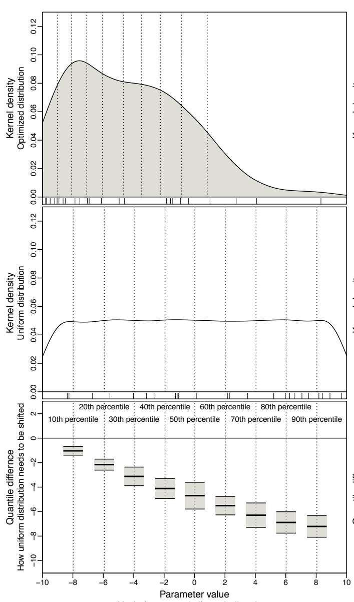
(a) *PopSize*



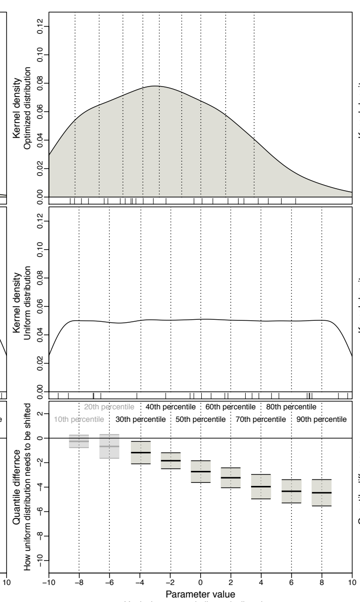
(b) *PashtunPop*



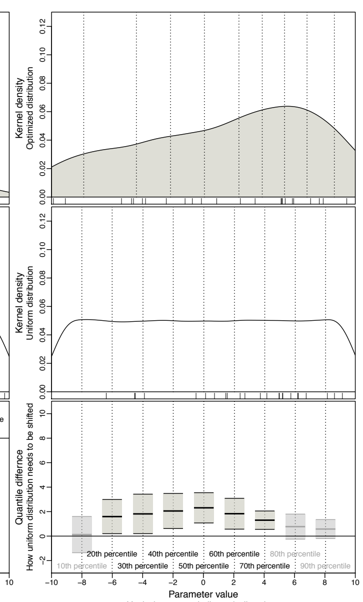
(c) *Development*



(d) *Ruggedness*

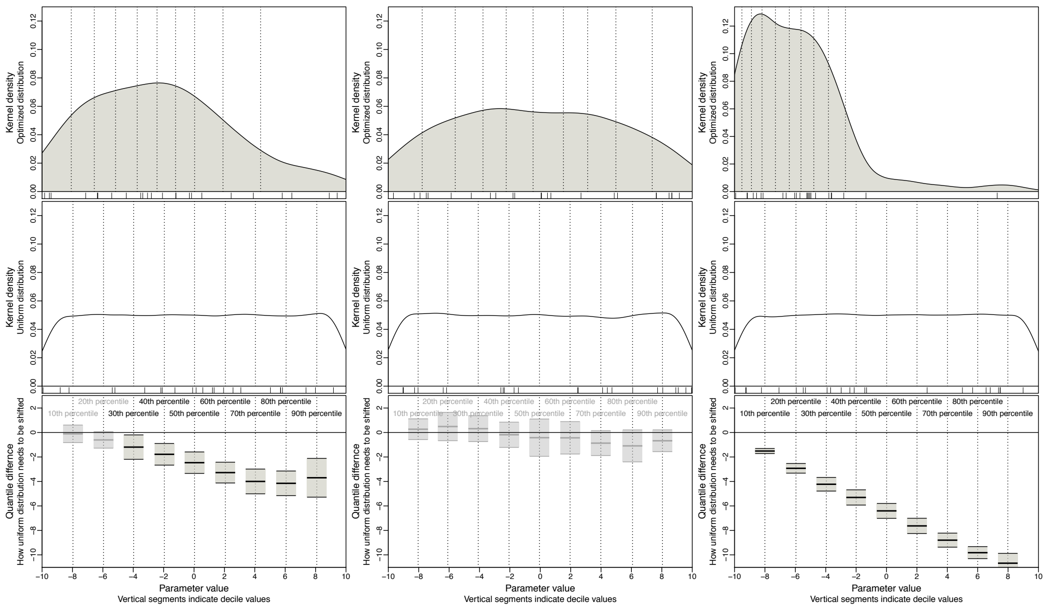


(e) *RoadDist*



(f) *CapDist*

Figure A.2: Optimized parameter distribution with $k = 10$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.2 (cont.): Optimized parameter distribution with $k = 10$

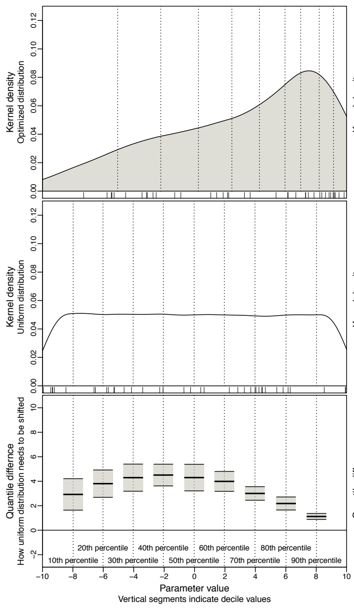
Note: See notes in Figure 3.4

A.4.2 Number of Agents

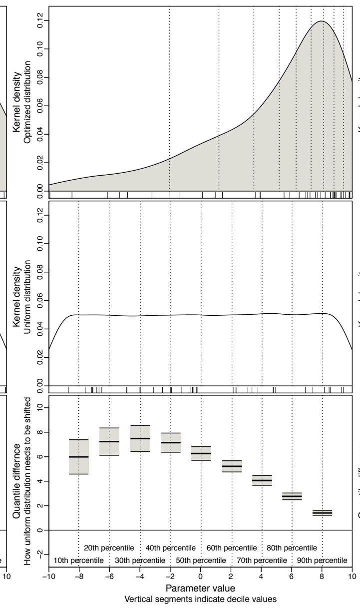
We also run additional simulation runs varying the number of insurgent agents. Specifically, another $50,000 \times 2 = 100,000$ runs have been conducted with the number of agents M set to 18,000 (−10%) and 22,000 (+10%). Again, the results remain largely unchanged. Figures A.4 and A.5 represent density estimates for β and γ parameters for the runs with smaller and larger numbers of agents. The same set of covariates are found to have significant impacts on the simulation results.

A.4.3 Behavior Algorithm

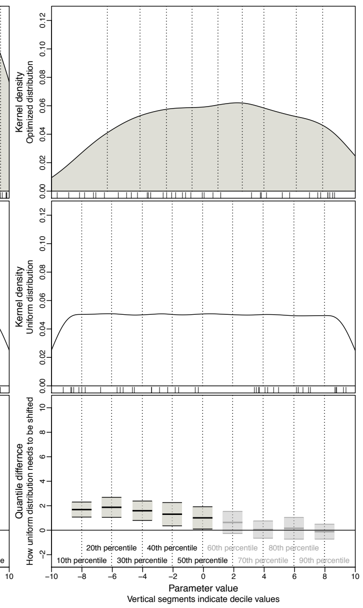
The baseline model assumes insurgent agents to make binary decisions at every time period: carry out an attack at the current location or relocate to a randomly chosen neighbor settlement. Although this dichotomy applies as long as there are several actions of which only one is subject to the



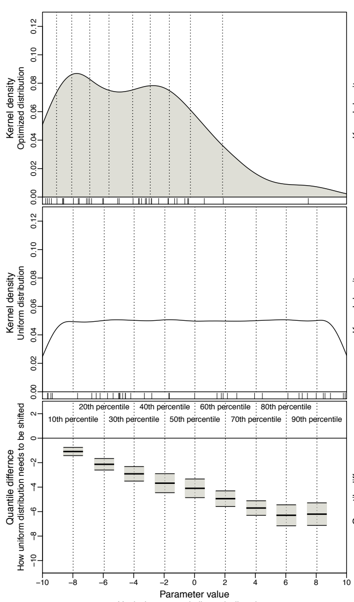
(a) *PopSize*



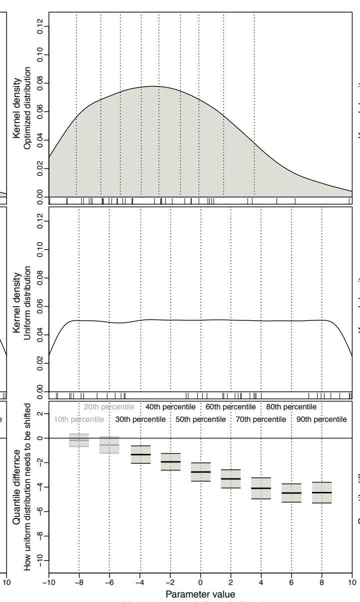
(b) *PashtunPop*



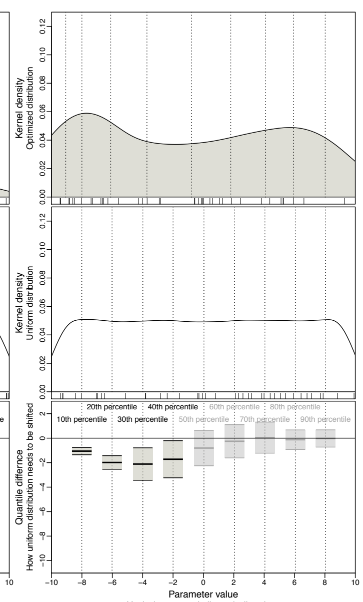
(c) *Development*



(d) *Ruggedness*

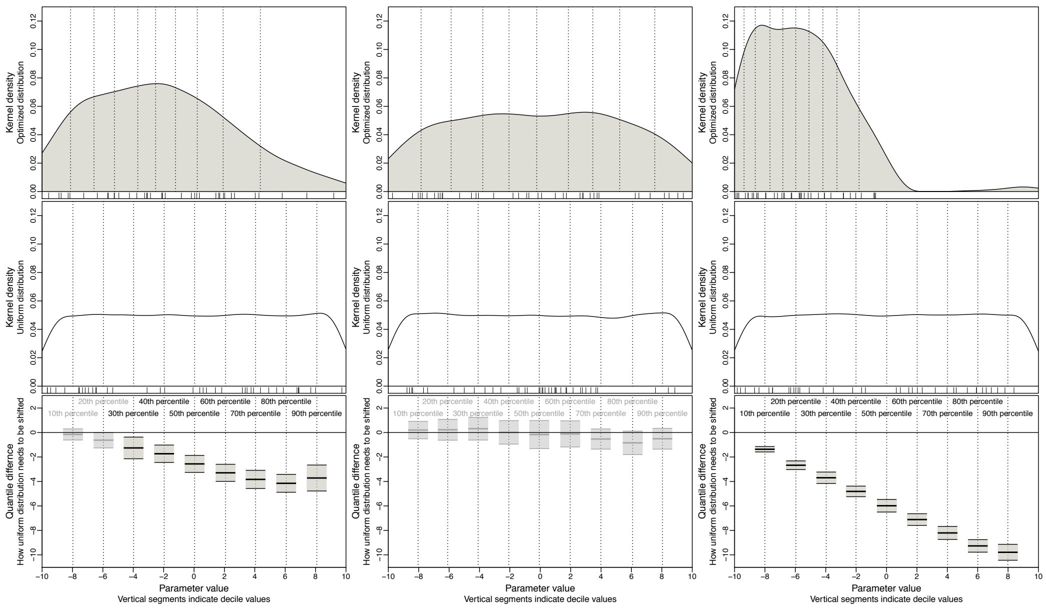


(e) *RoadDist*



(f) *CapDist*

Figure A.3: Optimized parameter distribution with $k = 30$



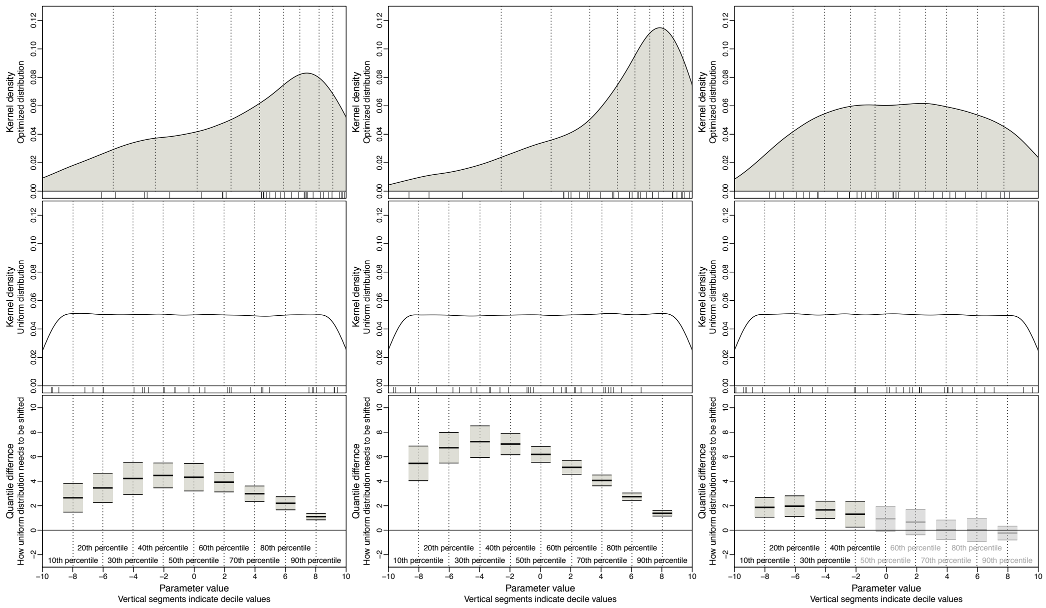
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.3 (cont.): Optimized parameter distribution with $k = 30$

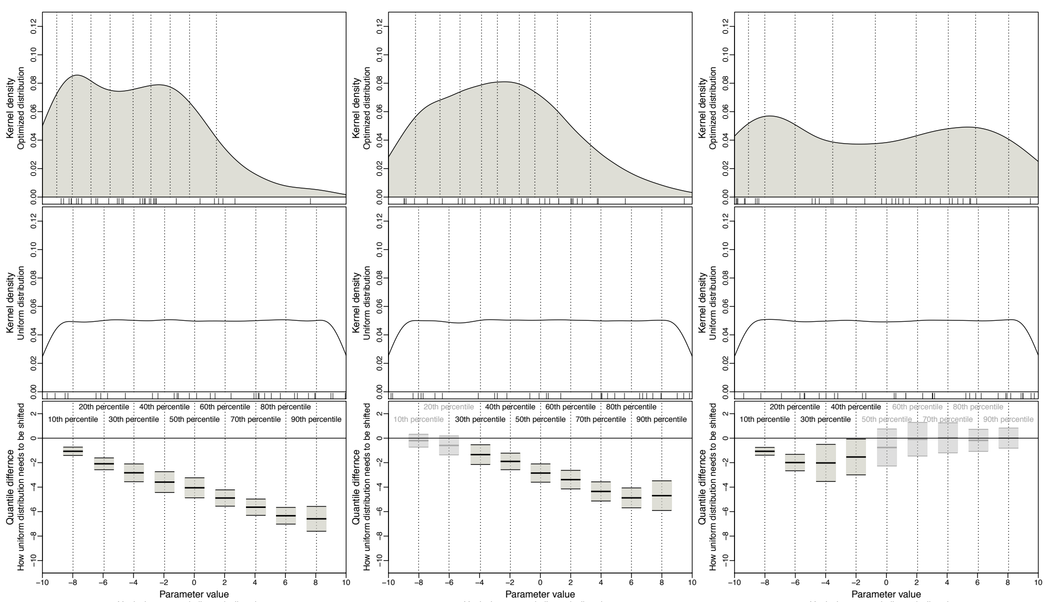
Note: See notes in Figure 3.4

analysis (Siegel, 2011, 995), insurgents, in reality, may alternatively decide to just stay and hide among civilians or mobilize them while not conducting attacks. By allowing for this third option, we examine the potential sensitivity of the simulation results to the dichotomy assumption. Specifically, we extend the baseline model such that it incorporates an additional model parameter q which determines the probability that insurgent agents decide to stay at their current locations. If insurgent agent I_j decides not to conduct an attack with probability $1 - p_{ijt+1}$, then I_j makes another decision whether to stay at its current location S_i or migrate to randomly chosen neighbor settlement S_l. Exogenous model parameter q determines this second round of decision-making: I_j stays at S_i with probability q; otherwise, it decides to migrate to S_l with probability $1 - q$. This extended model coincides with the baseline model when $q = 0$.

Another 50,000 simulation runs have been conducted with q set at 0.5 while holding all other parameters as in the baseline setting to obtain the

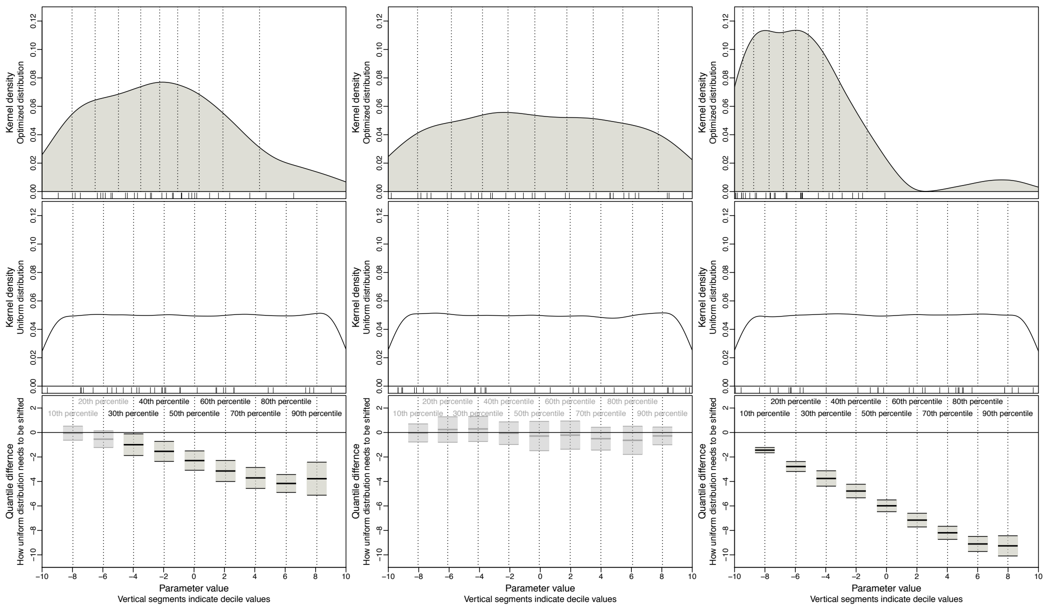


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

FIGURE A.4: OPTIMIZED PARAMETER DISTRIBUTION WITH $M = 18,000$



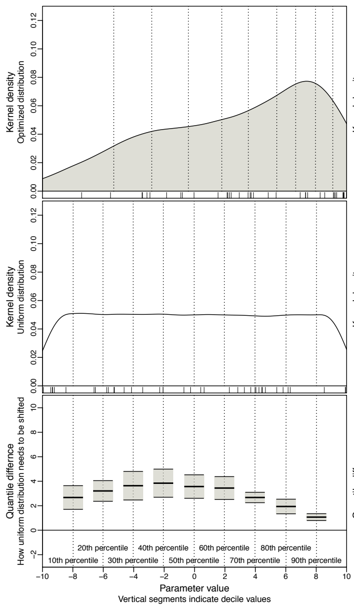
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.4 (cont.): Optimized parameter distribution with $M = 18,000$
Note: See notes in Figure 3.4

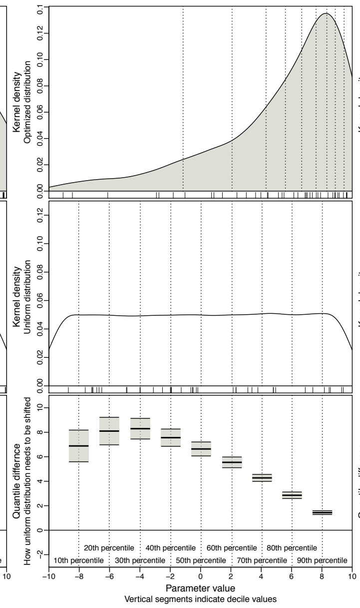
estimates in represented in Figures A.6. While the effect-sizes of individual parameter change, the decile-shift estimates generally agree with the baseline results reported in Section 3.4 in main text, suggesting that our results do not depend crucially on the binary-decision assumption.

A.4.4 Exponential Weight

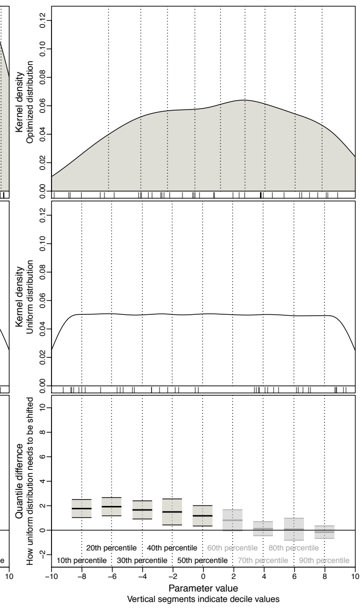
Another model assumption that warrants a sensitivity analysis is the exponential weight ϕ used to construct the diffusion terms, namely *Spread* and *History*. In the baseline setting, the impact of violence the nearby settlements on the subsequent decision making of a given agent decays according to an exponential decay function. Similarly, the impact of the occurrence of violence in a settlement impacts the subsequent behavior of agents located in the same settlement, but its impact decays with the number of lags.



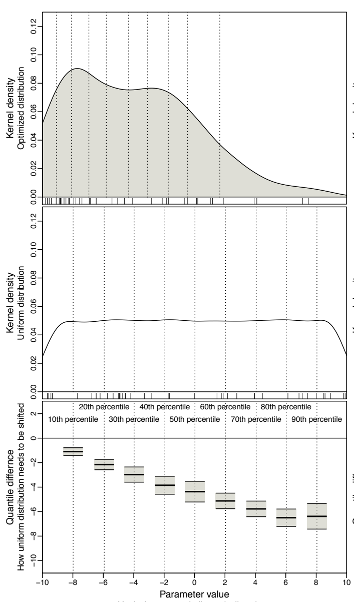
(a) *PopSize*



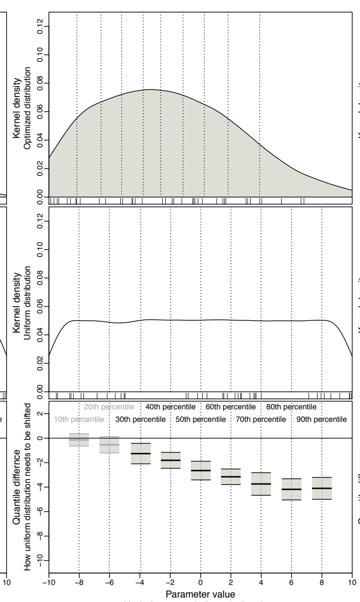
(b) *PashtunPop*



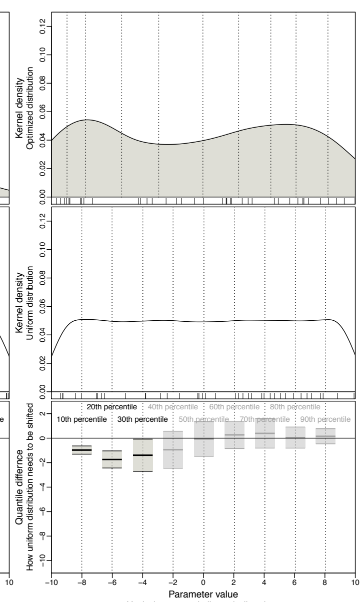
(c) *Development*



(d) *Ruggedness*

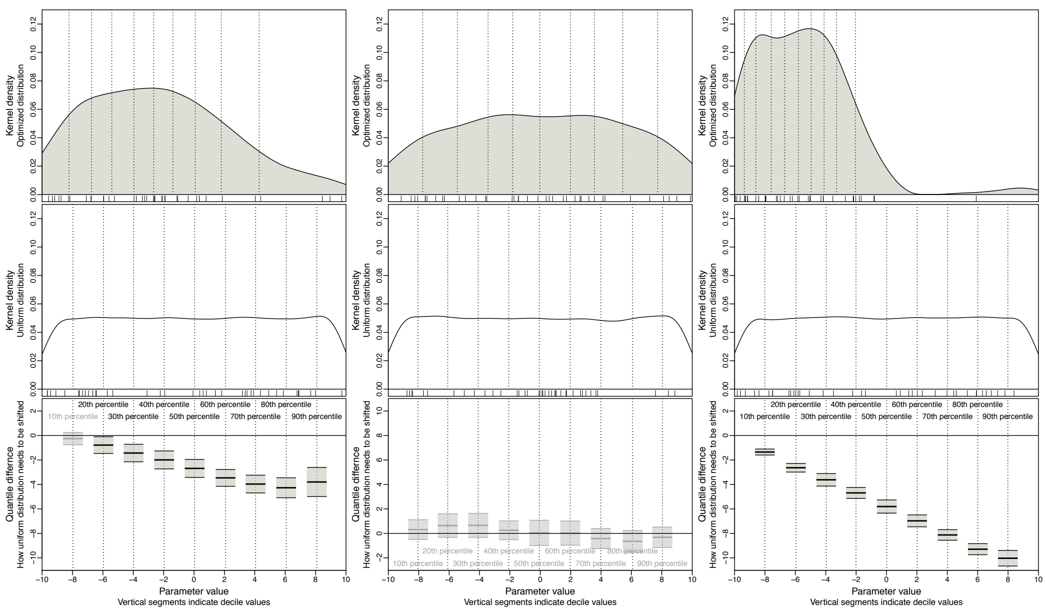


(e) *RoadDist*



(f) *CapDist*

Figure A.5: Optimized parameter distribution with $M = 22,000$

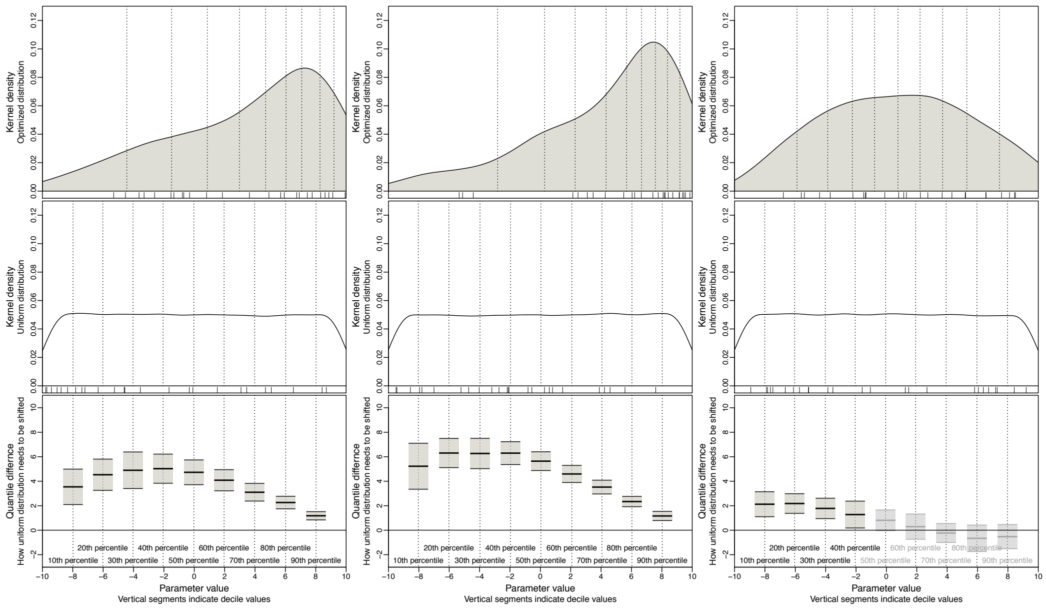


(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

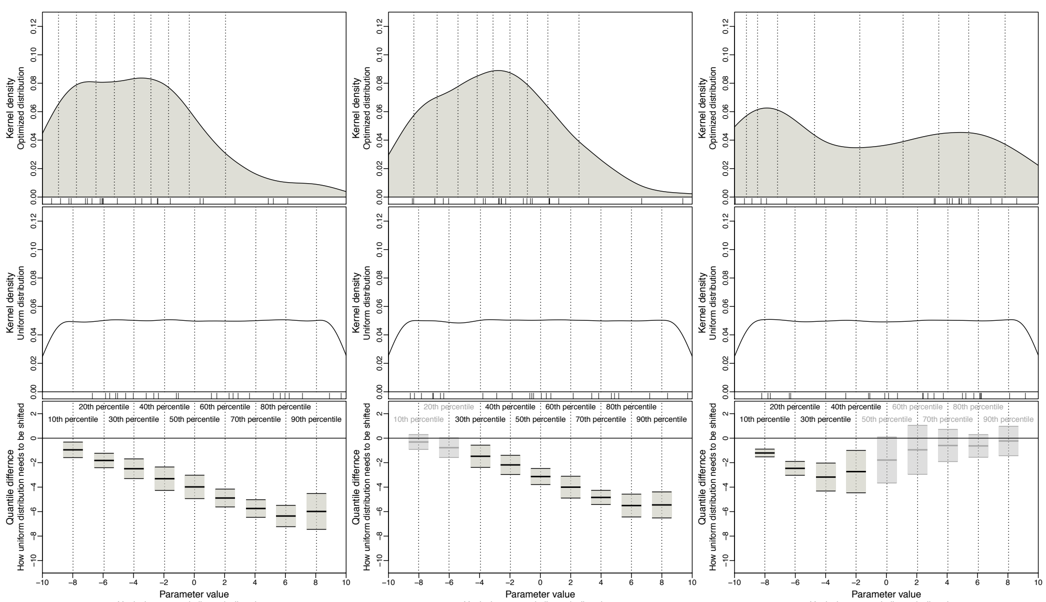
Figure A.5 (cont.): Optimized parameter distribution with $M = 22,000$

Note: See notes in Figure 3.4

In order to examine the robustness of the main results to the choice of the exponential weight, we conduct $50,000 \times 2 = 100,000$ additional simulation runs with alternative weights of $\phi = 0.5$ and $\phi = 2$ instead of the baseline value of $\phi = 1$, with all other parameter values set at the baseline setting. As shown in Figures A.7 and A.8, these alternative parameter settings do not affect the baseline results.

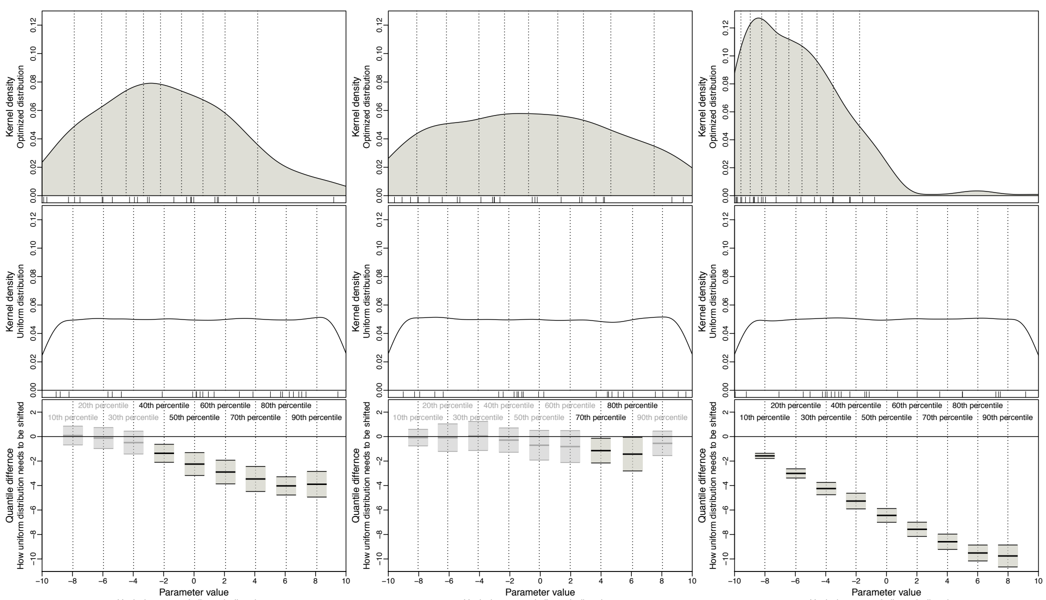


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

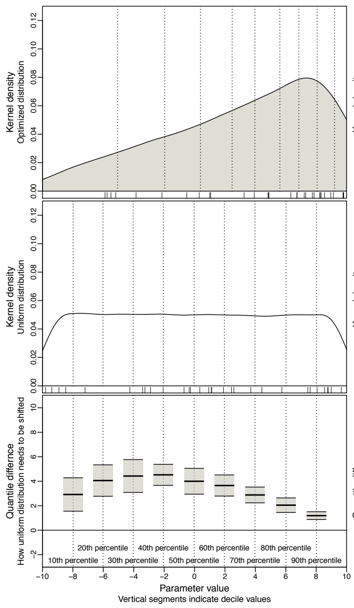
Figure A.6: Optimized parameter distribution with $q = 0.5$



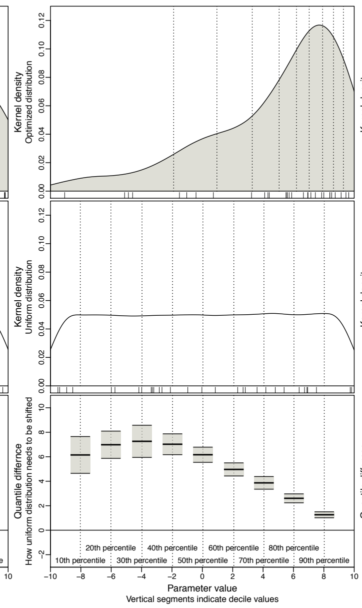
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.6 (cont.): Optimized parameter distribution with $q = 0.5$

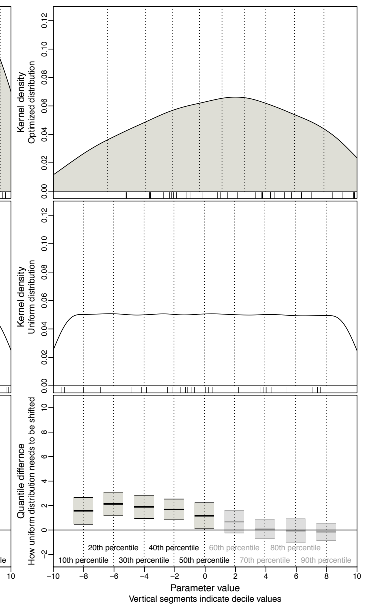
Note: See notes in Figure 3.4



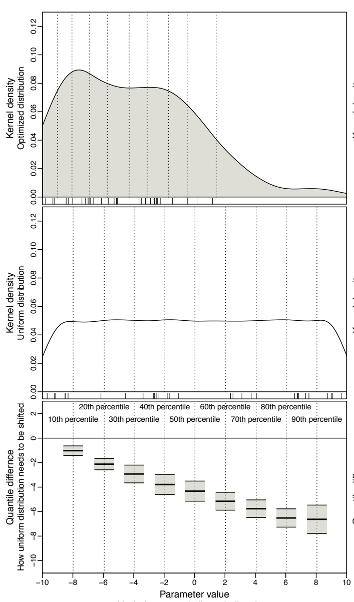
(a) *PopSize*



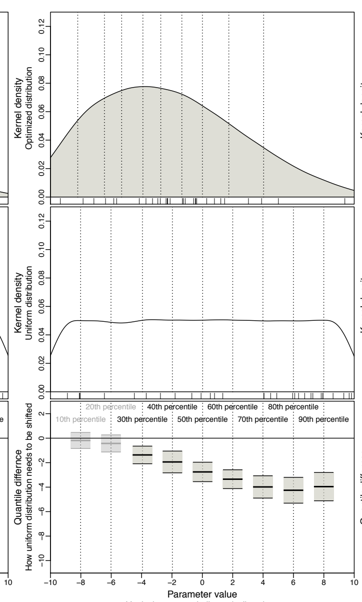
(b) *PashtunPop*



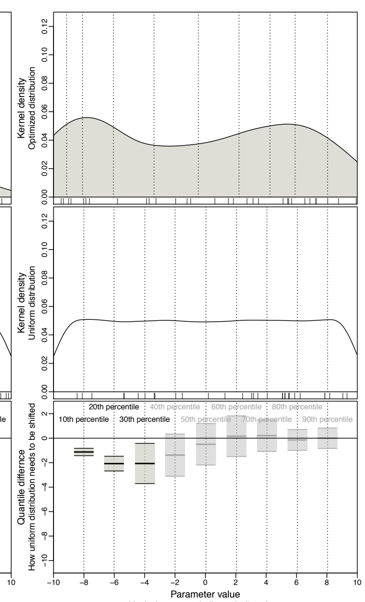
(c) *Development*



(d) *Ruggedness*

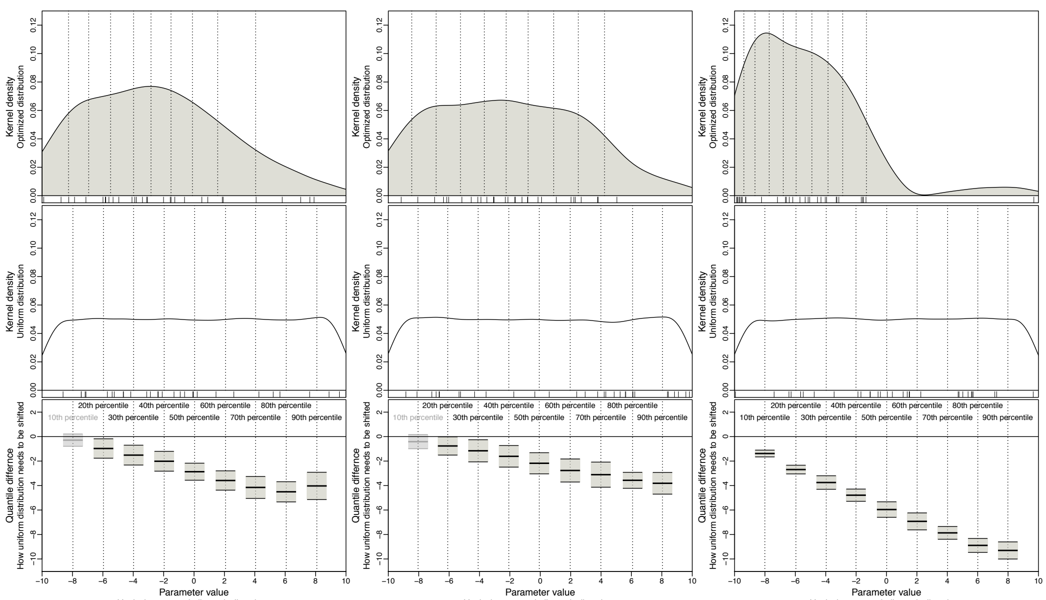


(e) *RoadDist*



(f) *CapDist*

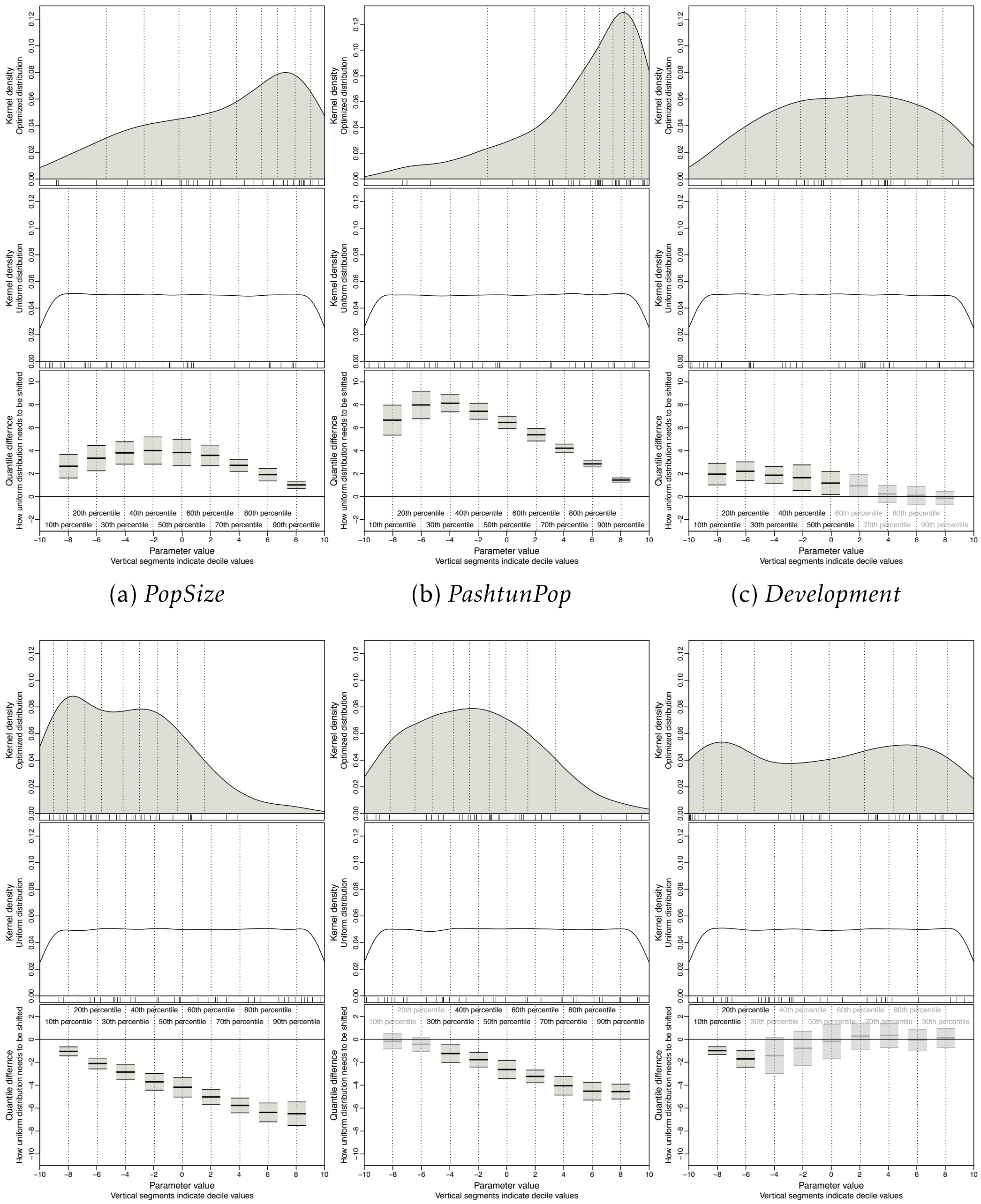
Figure A.7: Optimized parameter distribution with $\phi = 0.5$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.7 (cont.): Optimized parameter distribution with $\phi = 0.5$

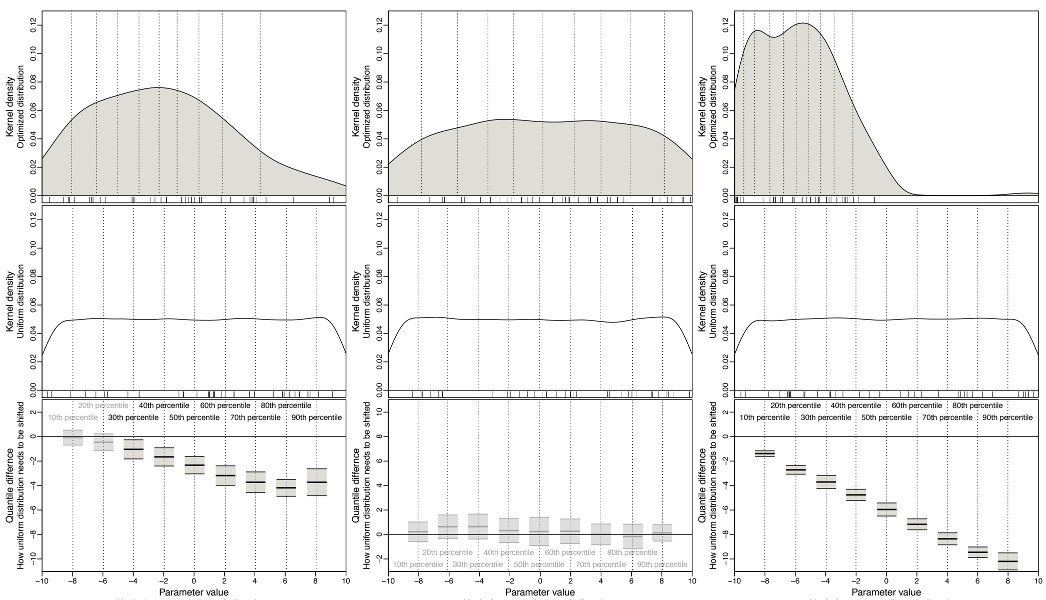
Note: See notes in Figure 3.4



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

Figure A.8: Optimized parameter distribution with $\phi = 2$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.8 (cont.): Optimized parameter distribution with $\phi = 2$

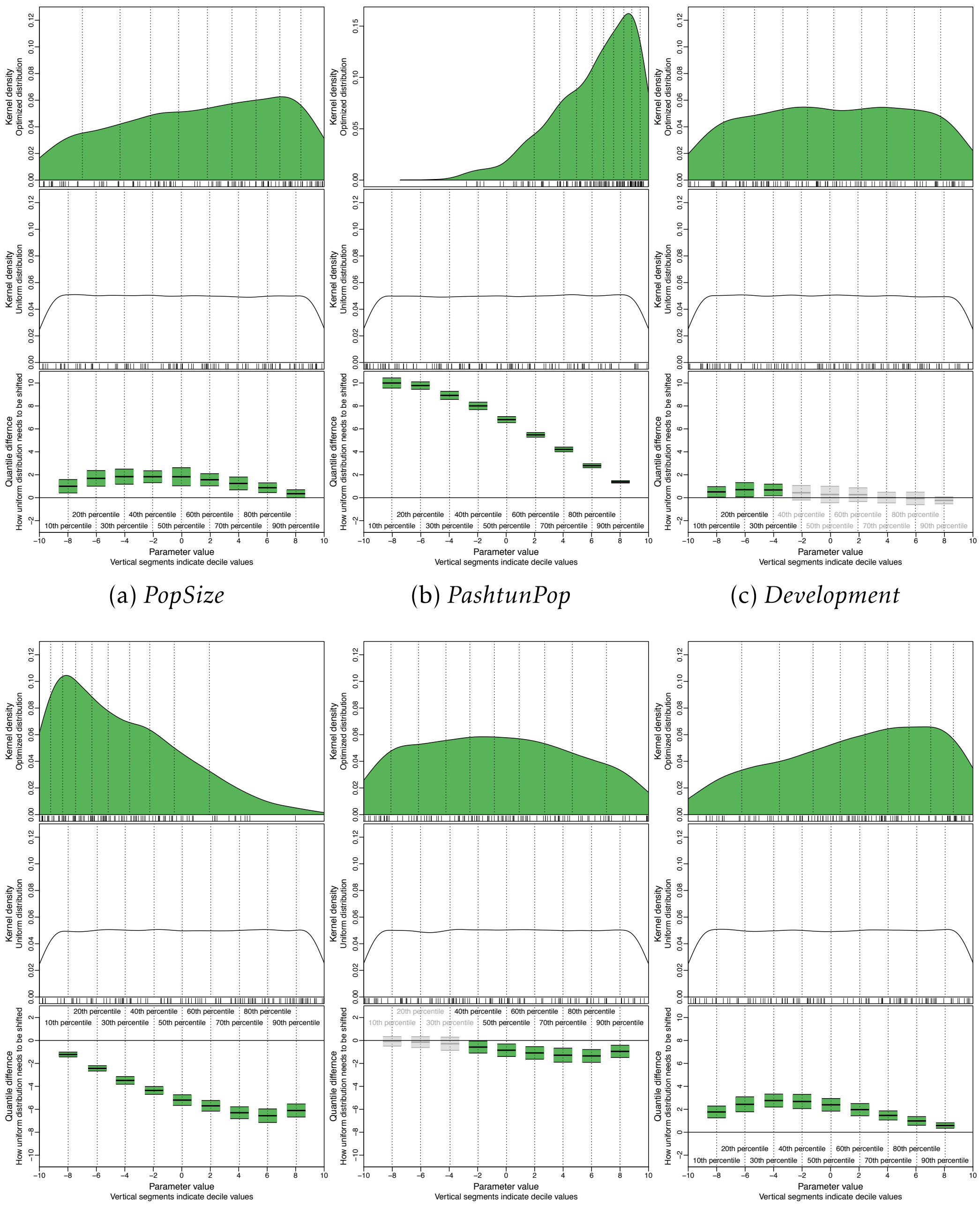
Note: See notes in Figure 3.4

A.5 Robustness Checks for Type-Specific Modeling

Chapter 4 extends the analysis in Chapter 3 to decompose the determinants of selective (non-IED) and indiscriminate (IED) insurgent violence. Similar to the analysis in Chapter 3, four model parameters and assumptions warrant investigation to examine the robustness of the main results: (1) neighborhood size k, (2) number of agents M, (3) the attack-or-relocate dichotomy in the behavior algorithm, and (4) exponential weight ϕ for $Spread$ and $History$.

in order to examine the robustness of the main results, 700,000 additional simulations were conducted, varying these parameter settings and assumption. As briefly reported in Section 4.7, none of these sensitivity tests yielded results that deviate markedly from the main results reported in the main text. These results provide confidence that the specific parameter settings and assumption are not driving the main findings.

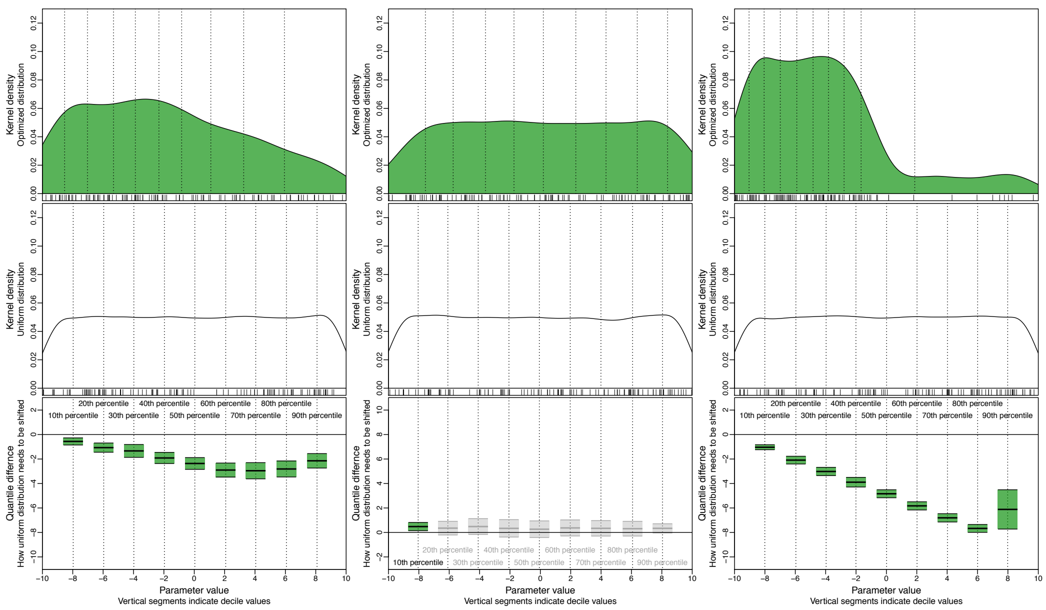
A.5.1 Robustness Checks: Determinants of Non-IED Incidents



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

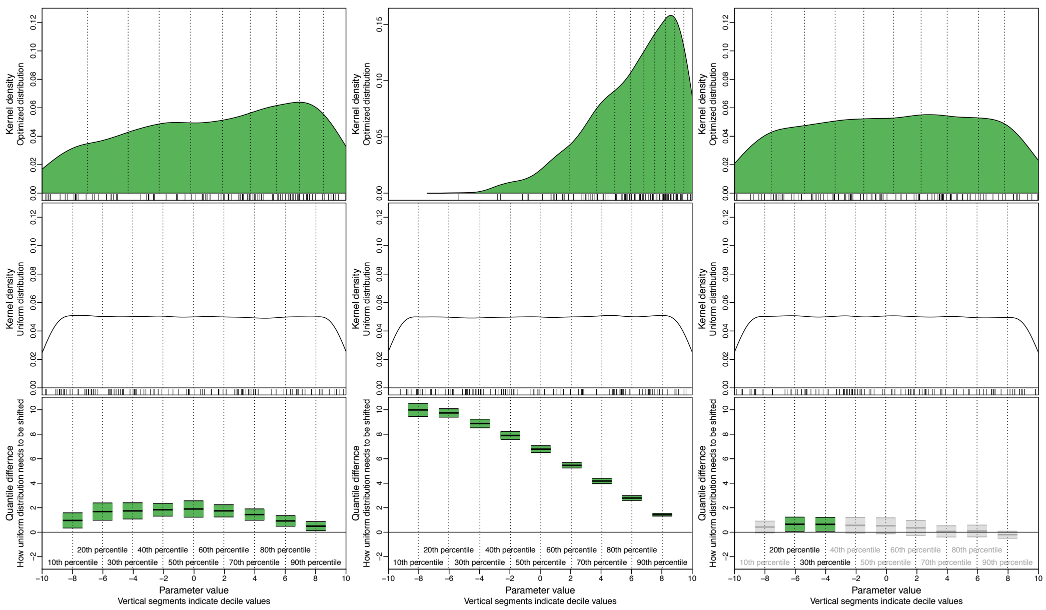
Figure A.9: Optimized parameter distribution, non-IED attacks, with $k = 10$



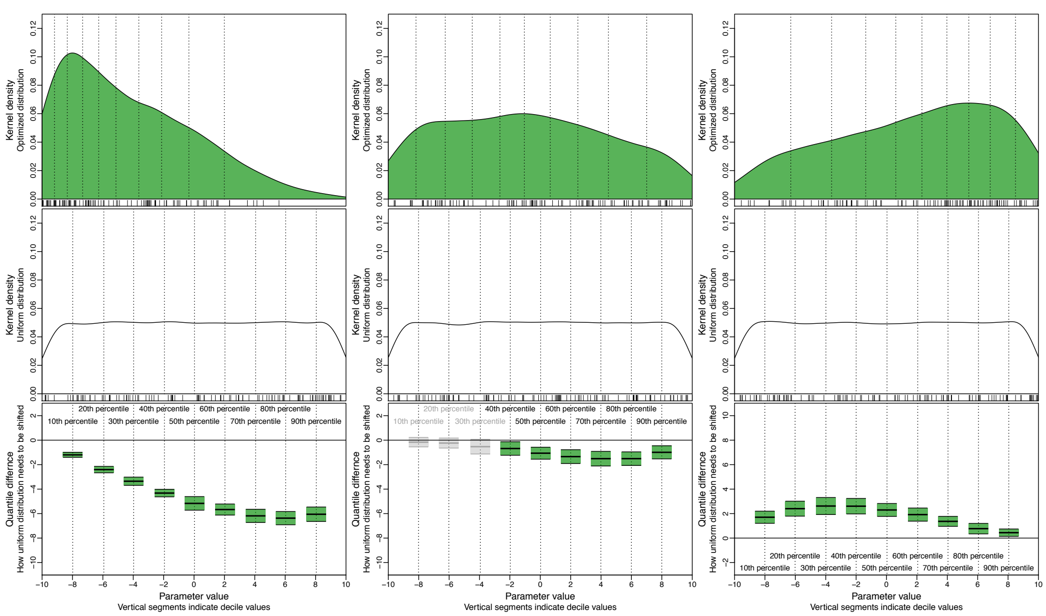
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.9 (cont.): Optimized parameter distribution, non-IED attacks, with $k = 10$

Note: See notes in Figure 3.4

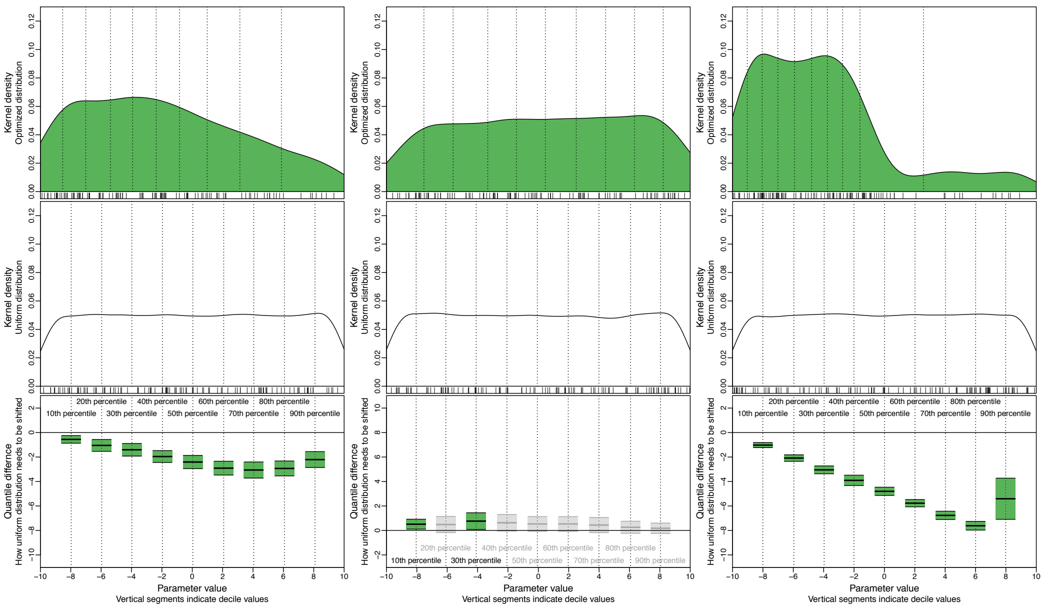


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

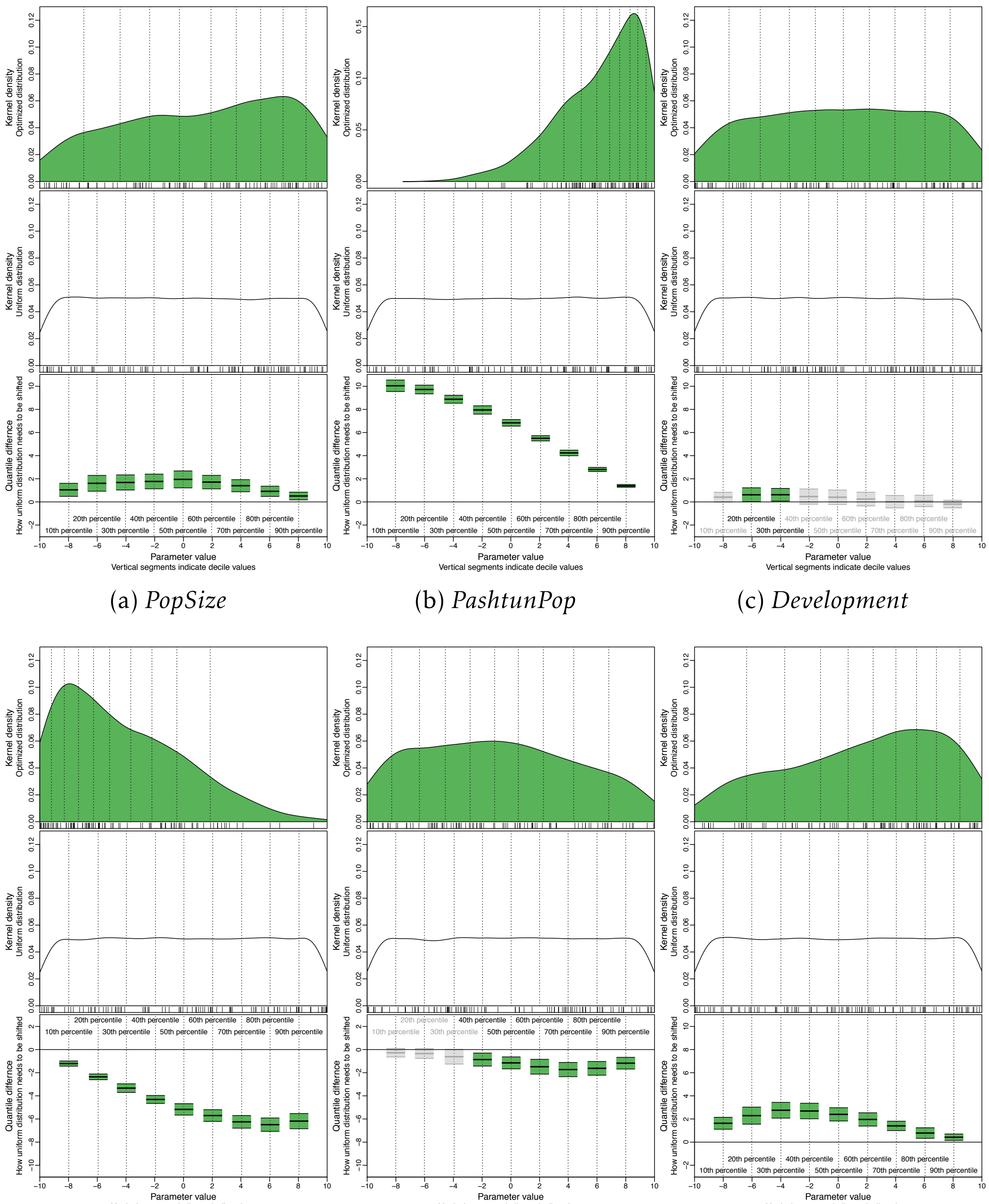
Figure A.10: Optimized parameter distribution, non-IED attacks, with $k = 30$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.10 (cont.): Optimized parameter distribution, non-IED attacks, with $k = 30$

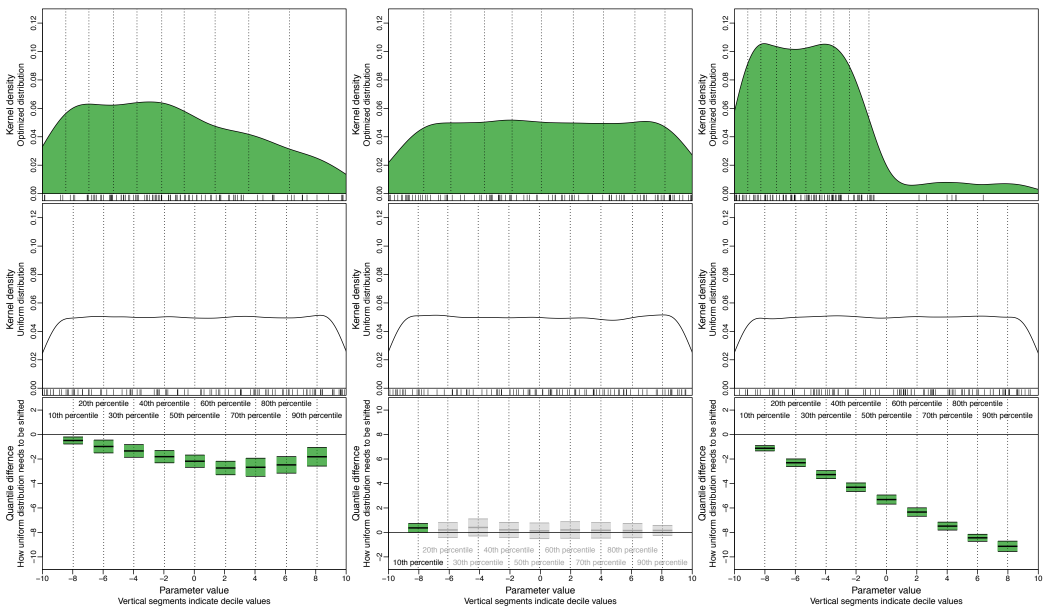
Note: See notes in Figure 3.4



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

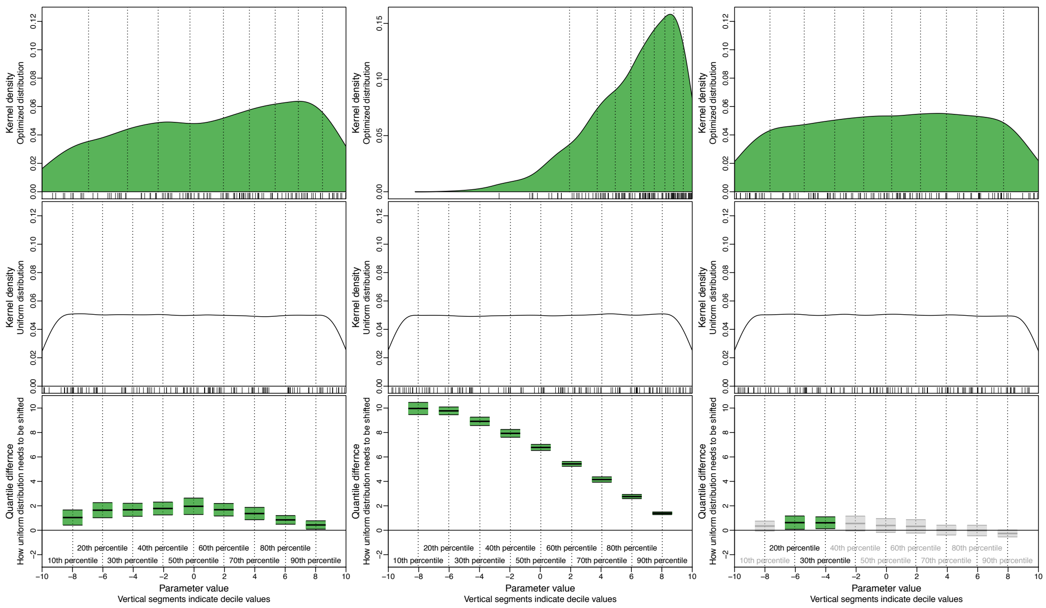
Figure A.11: Optimized parameter distribution, non-IED attacks, with $m = 18,000$



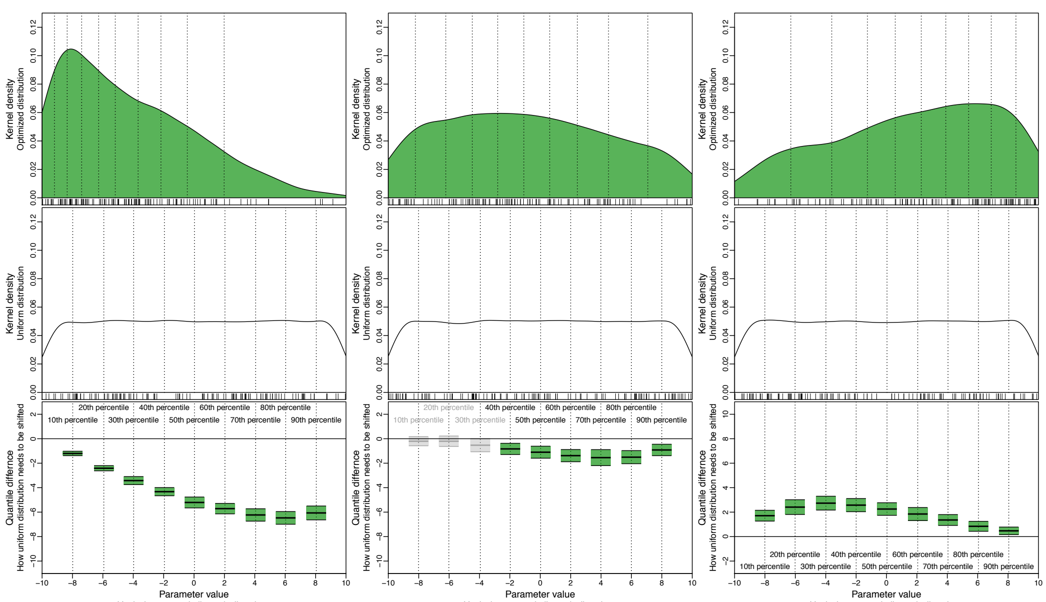
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.11 (cont.): Optimized parameter distribution, non-IED attacks, with $m = 18,000$

Note: See notes in Figure 3.4

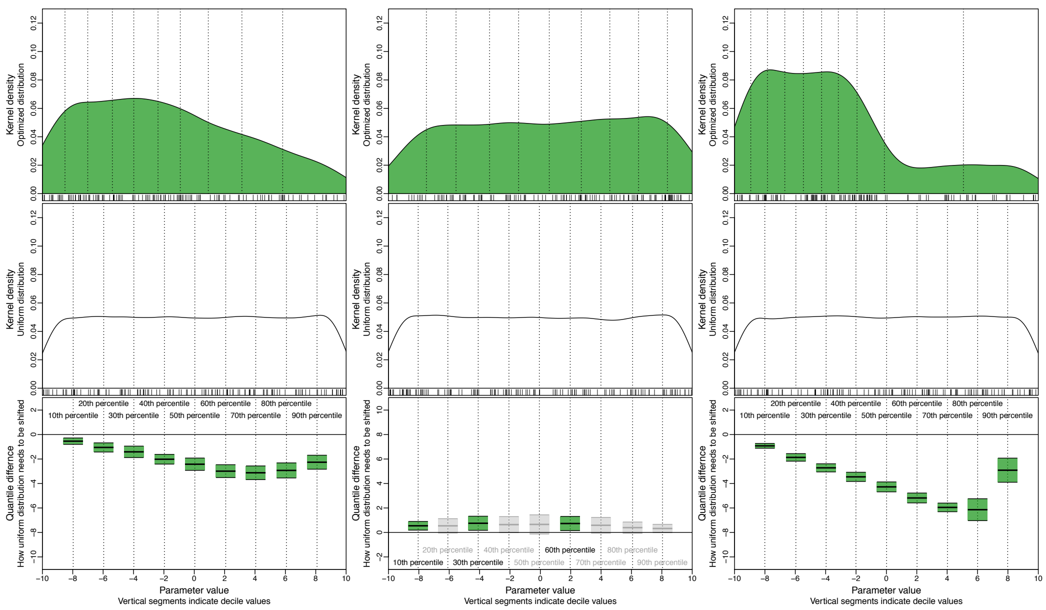


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

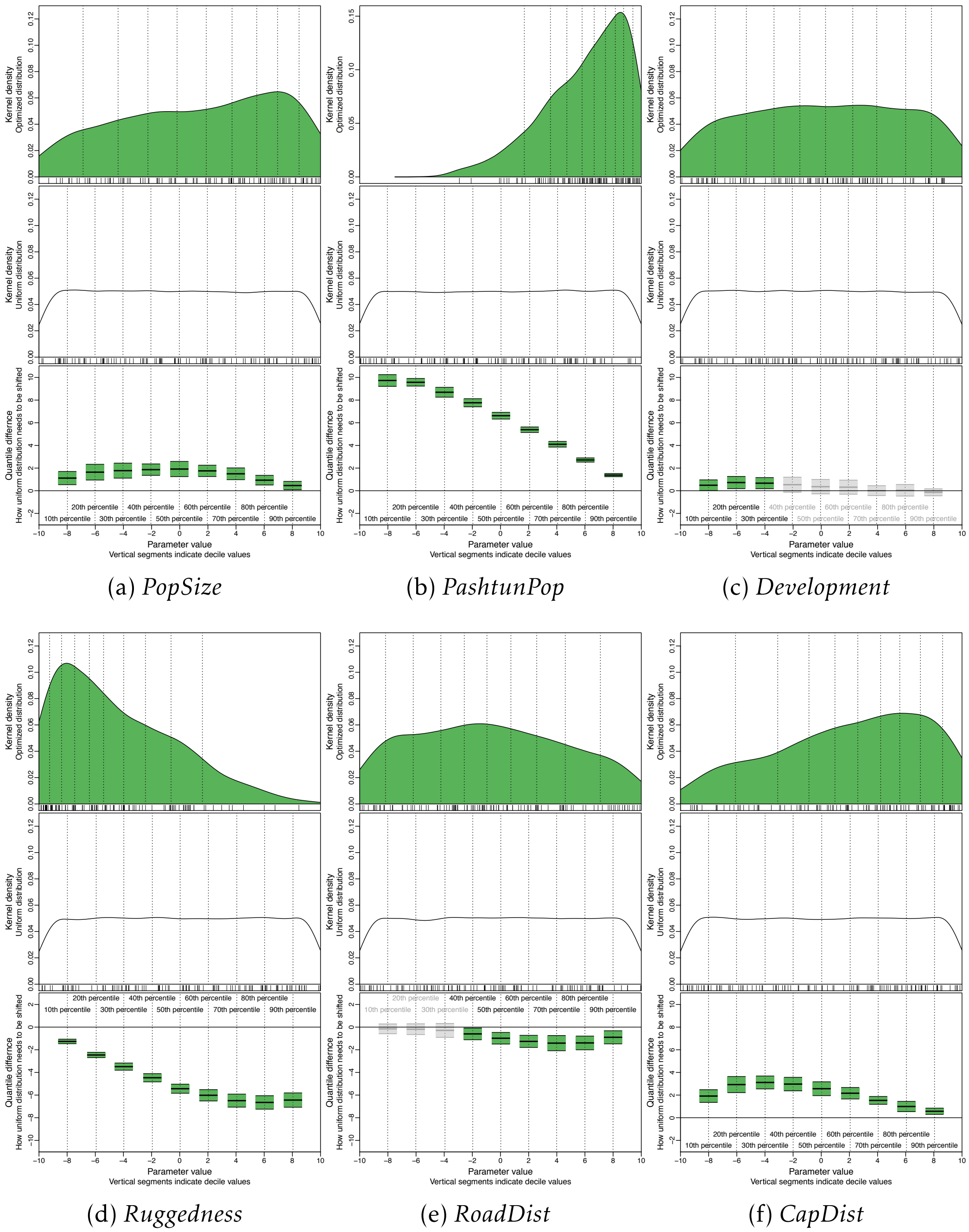
Figure A.12: Optimized parameter distribution, non-IED attacks, with $m = 22,000$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.12 (cont.): Optimized parameter distribution, non-IED attacks, with $m = 22,000$

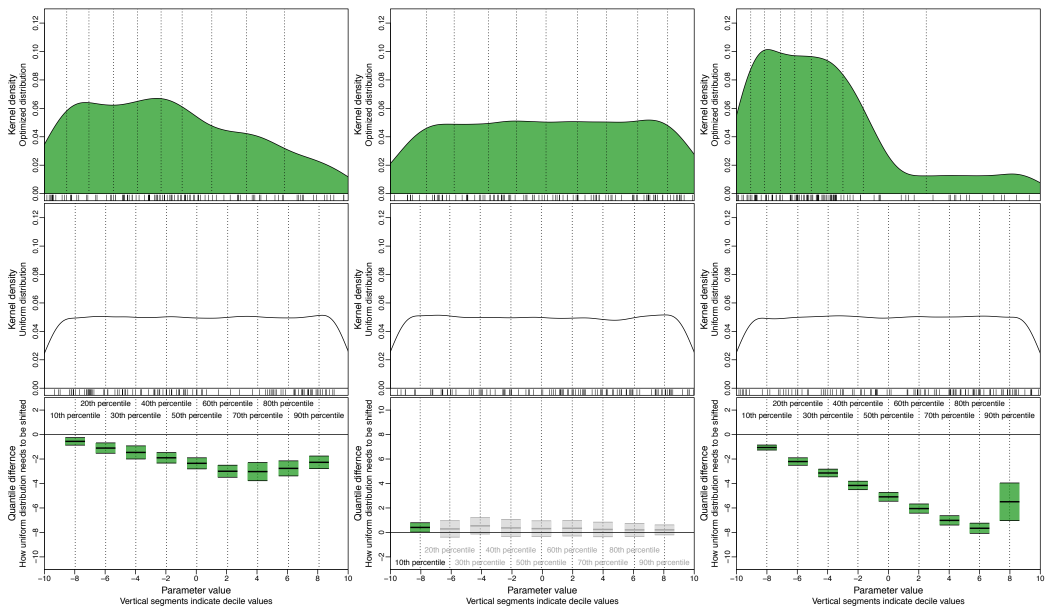
Note: See notes in Figure 3.4



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

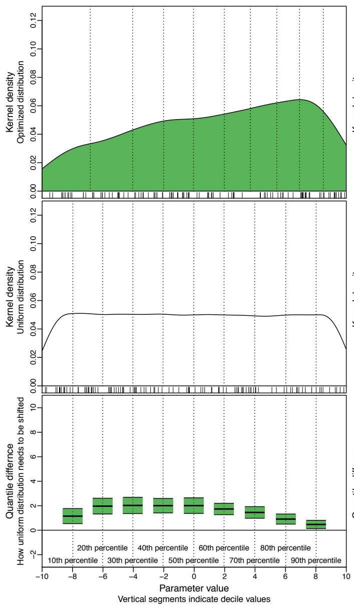
Figure A.13: Optimized parameter distribution, non-IED attacks, with $q = 0.5$



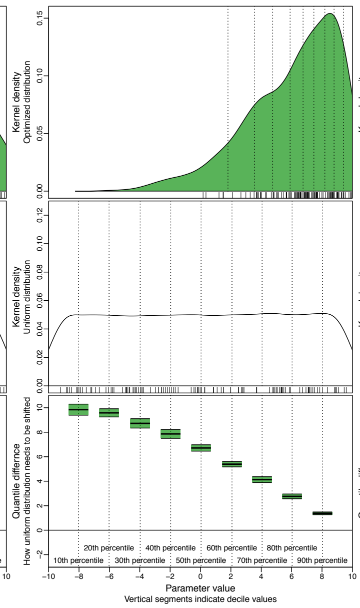
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.13 (cont.): Optimized parameter distribution, non-IED attacks, with $q = 0.5$

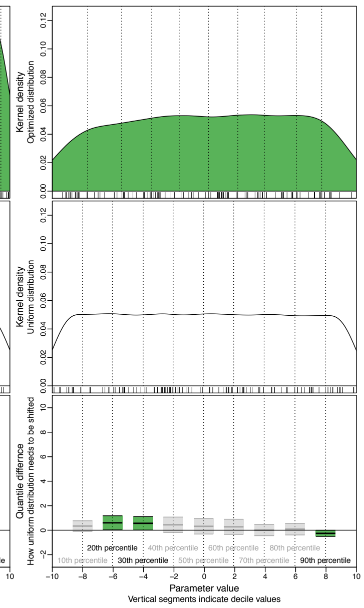
Note: See notes in Figure 3.4



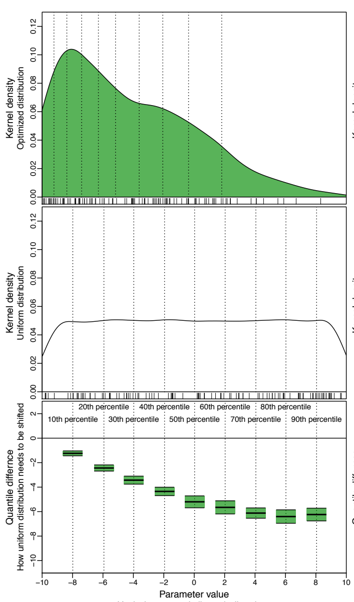
(a) *PopSize*



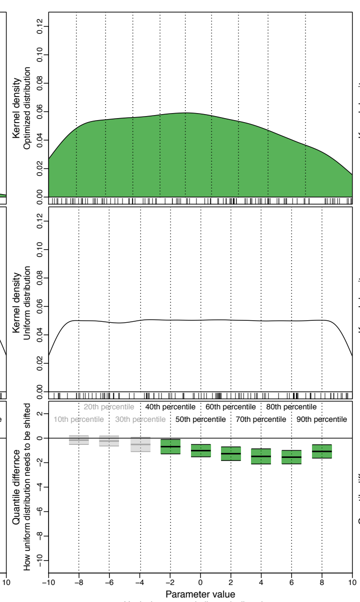
(b) *PashtunPop*



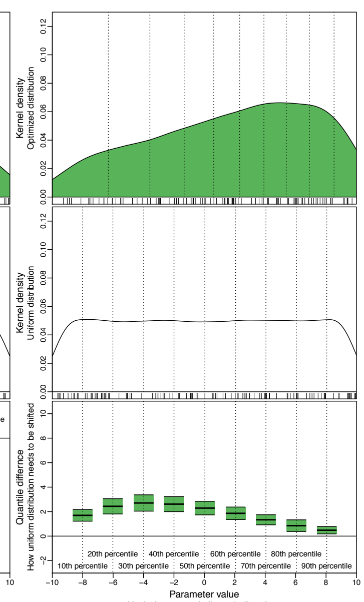
(c) *Development*



(d) *Ruggedness*

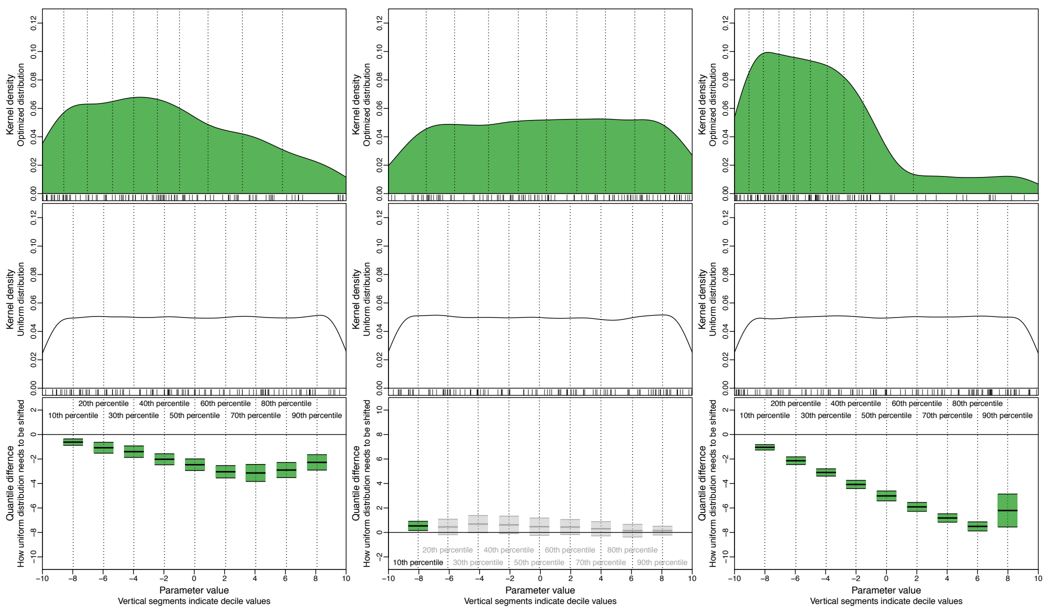


(e) *RoadDist*



(f) *CapDist*

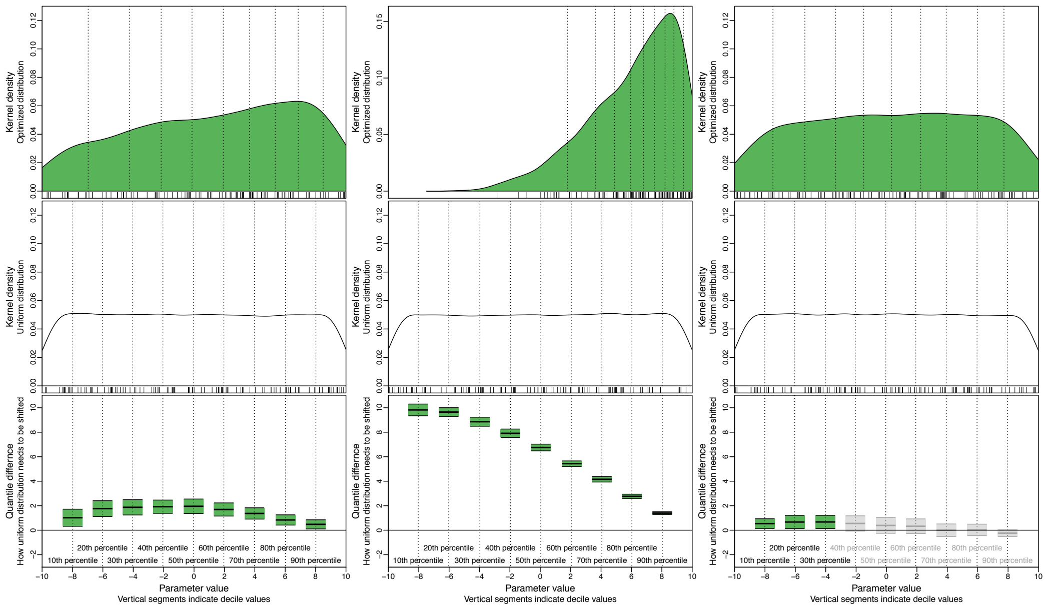
Figure A.14: Optimized parameter distribution, non-IED attacks, with $\phi = 0.5$



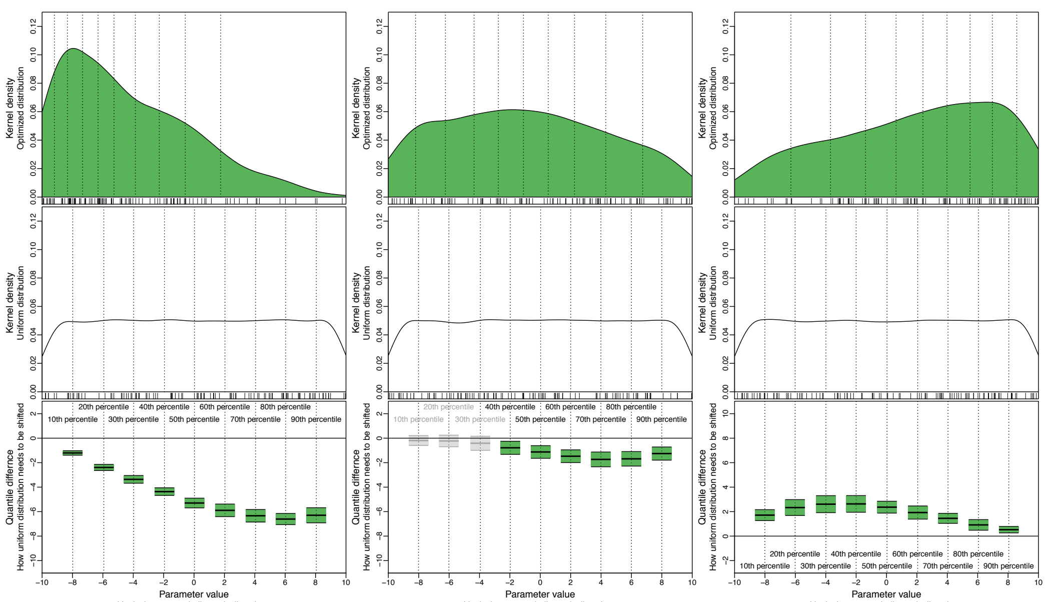
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

FIGURE A.14 (cont.): OPTIMIZED PARAMETER DISTRIBUTION, NON-IED ATTACKS, WITH $\phi = 0.5$

Note: See notes in Figure 3.4

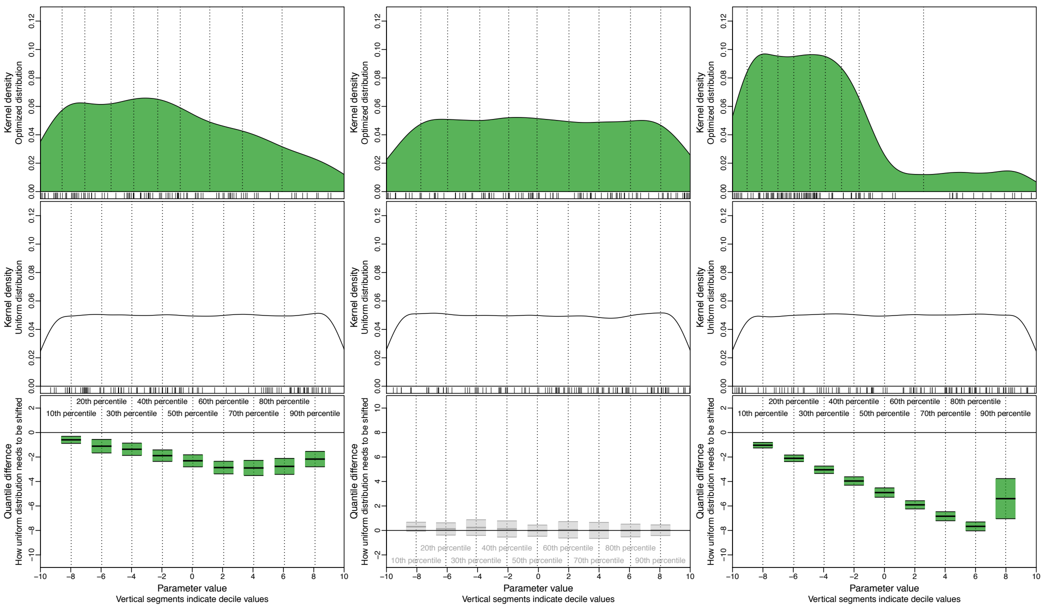


(a) *PopSize* (b) *PashtunPop* (c) *Development*



(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

Figure A.15: Optimized parameter distribution, non-IED attacks, with $\phi = 2$

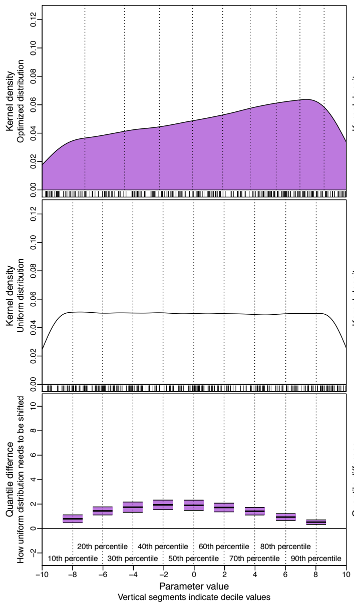


(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

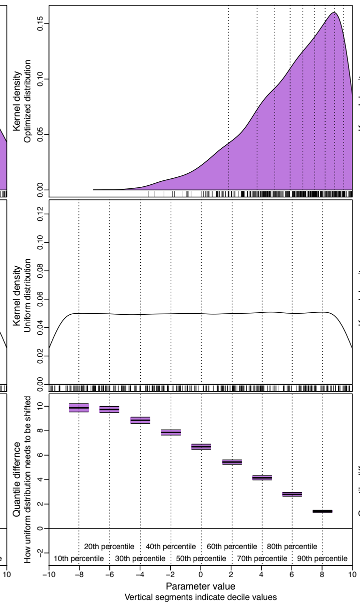
Figure A.15 (cont.): Optimized parameter distribution, non-IED attacks, with $\phi = 2$

Note: See notes in Figure 3.4

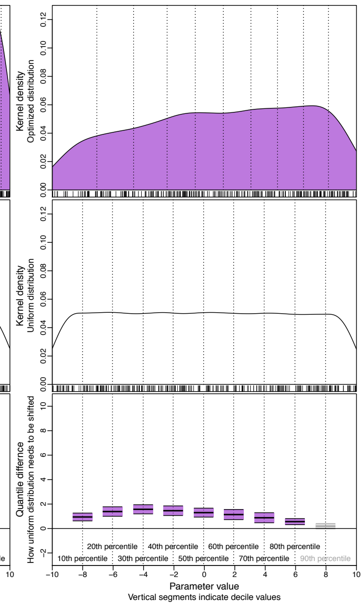
A.5.2 Robustness Checks: Determinants of IED Incidents



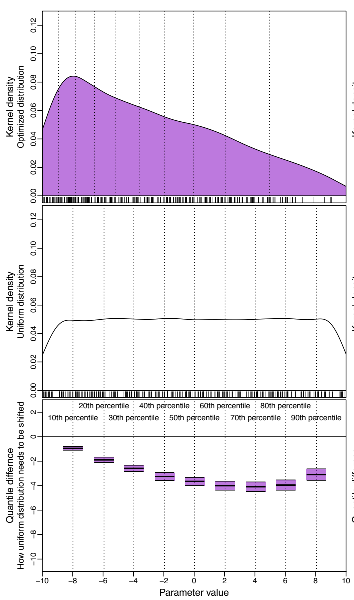
(a) *PopSize*



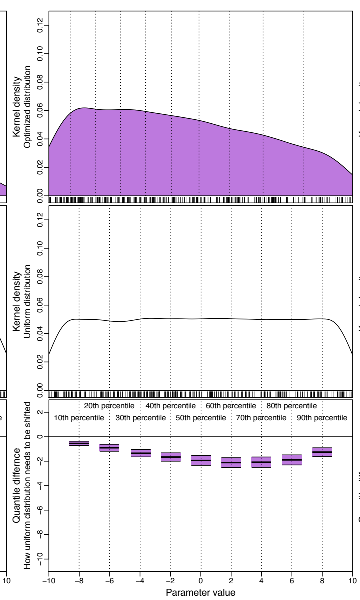
(b) *PashtunPop*



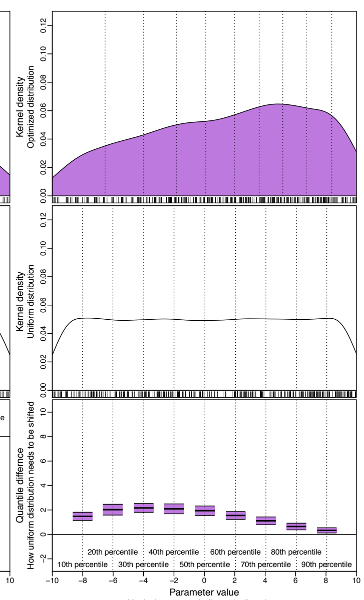
(c) *Development*



(d) *Ruggedness*

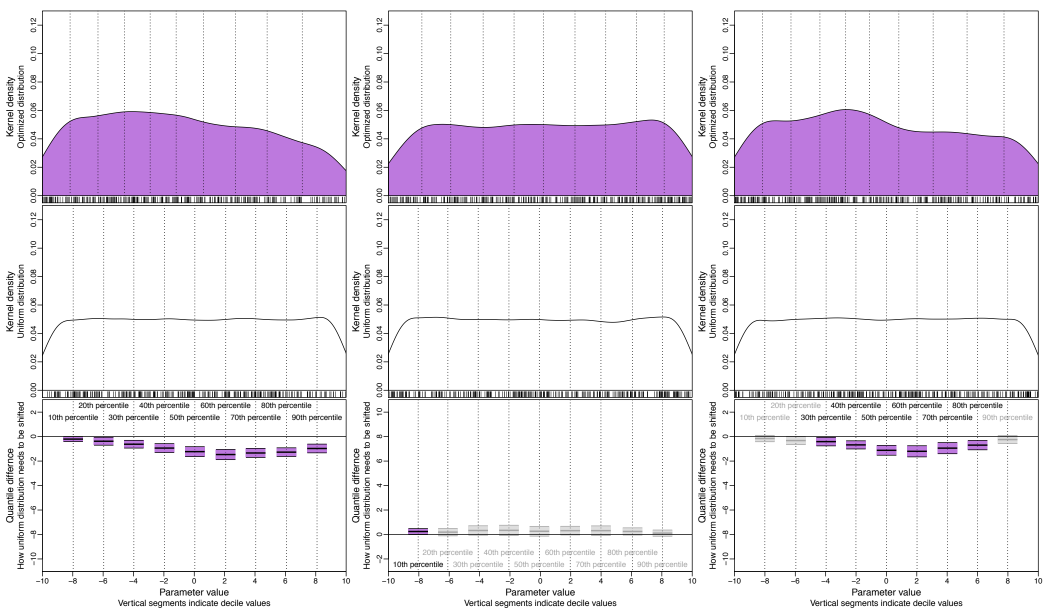


(e) *RoadDist*



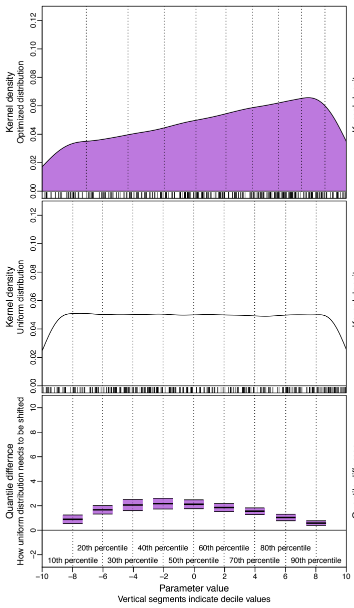
(f) *CapDist*

Figure A.16: Optimized parameter distribution, IED attacks, with $k = 10$

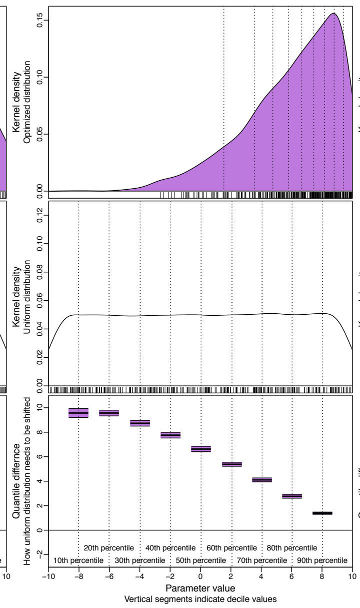


(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

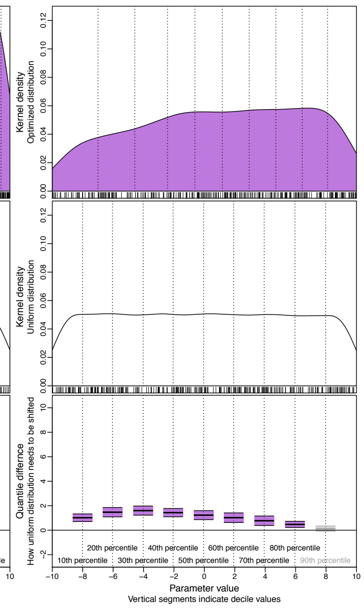
Figure A.16 (cont.): Optimized parameter distribution, IED attacks, with $k = 10$
Note: See notes in Figure 3.4



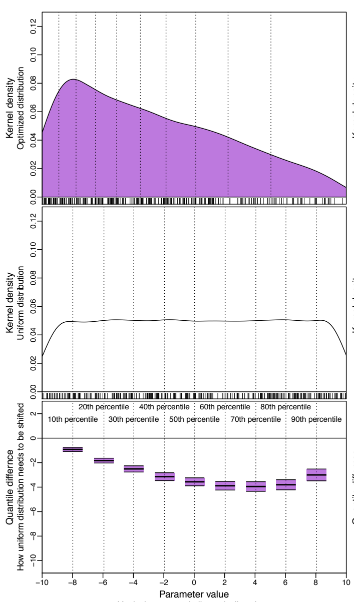
(a) *PopSize*



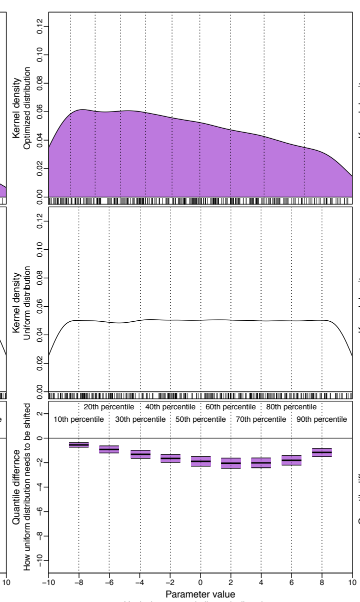
(b) *PashtunPop*



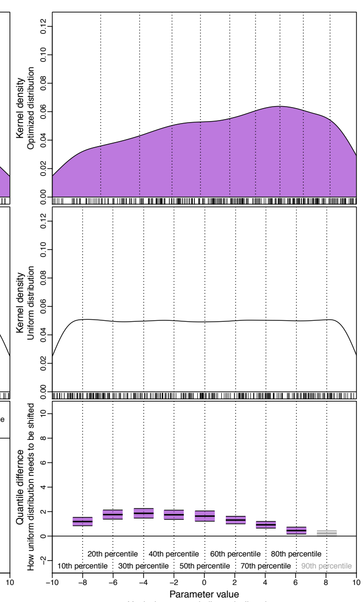
(c) *Development*



(d) *Ruggedness*

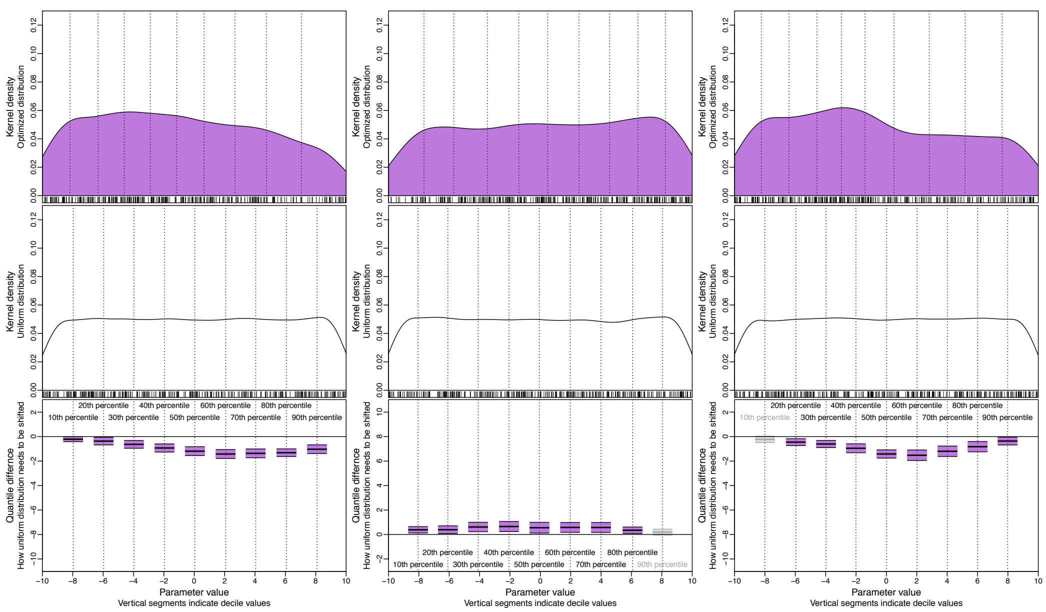


(e) *RoadDist*



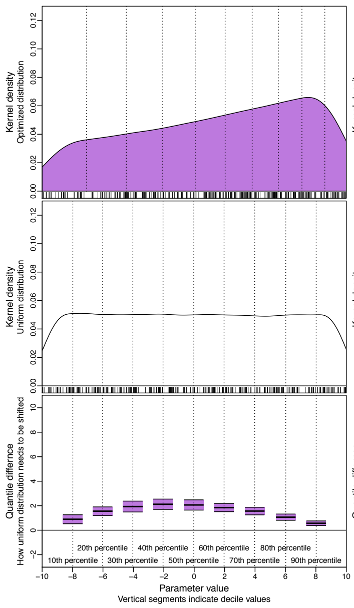
(f) *CapDist*

Figure A.17: Optimized parameter distribution, IED attacks, with $k = 30$

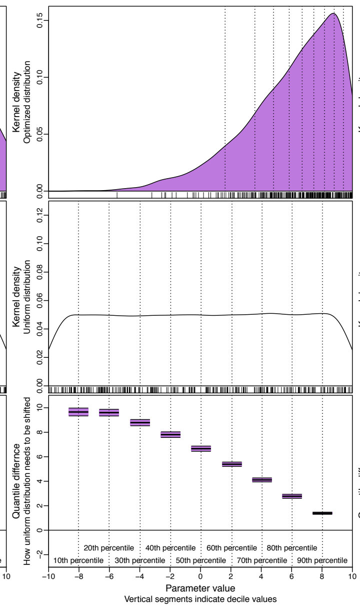


(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

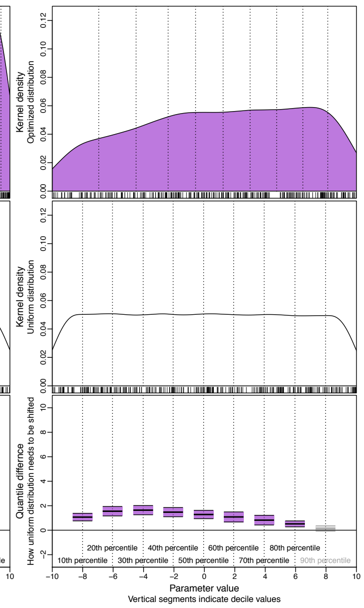
Figure A.17 (cont.): Optimized parameter distribution, IED attacks, with $k = 30$
Note: See notes in Figure 3.4



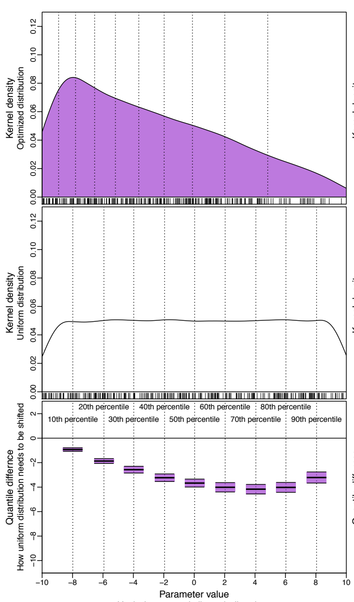
(a) *PopSize*



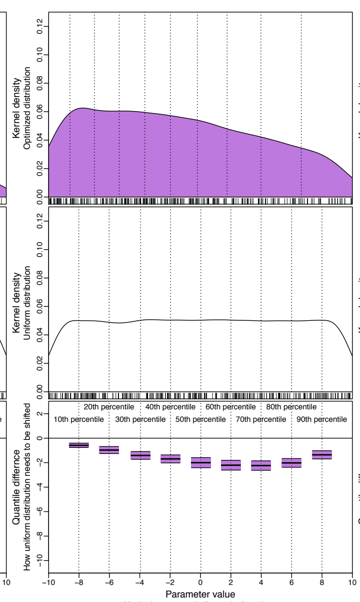
(b) *PashtunPop*



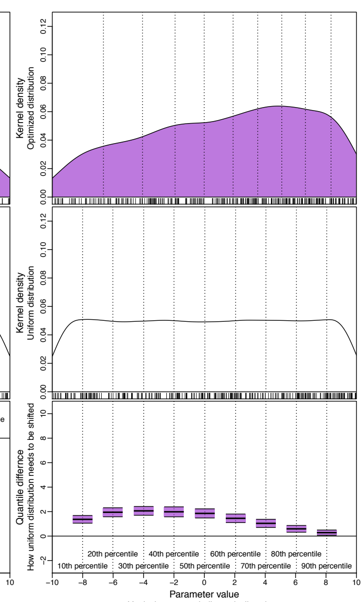
(c) *Development*



(d) *Ruggedness*

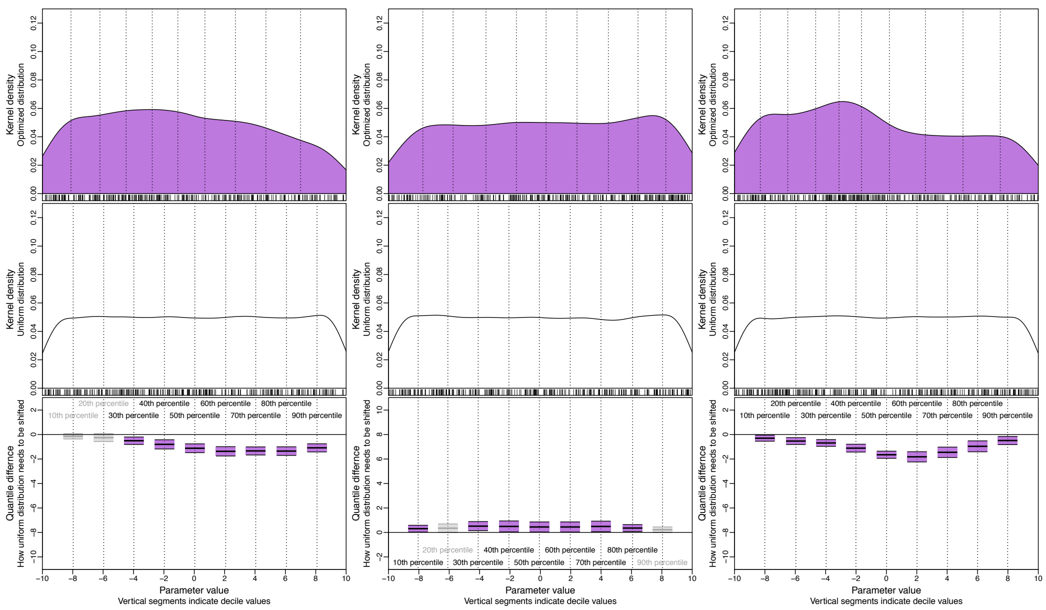


(e) *RoadDist*



(f) *CapDist*

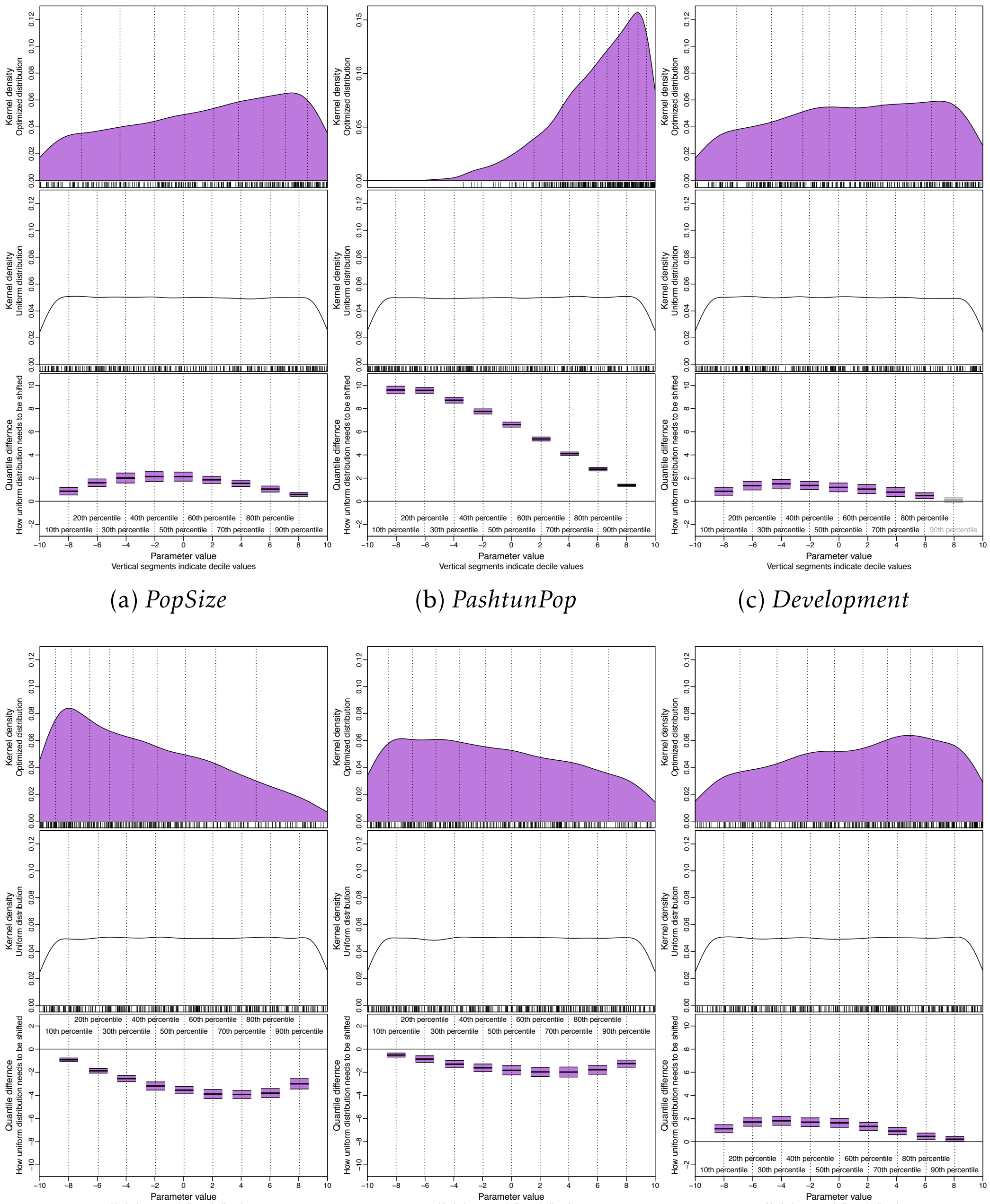
Figure A.18: Optimized parameter distribution, IED attacks, with $m = 18,000$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.18 (cont.): Optimized parameter distribution, IED attacks, with $m = 18,000$

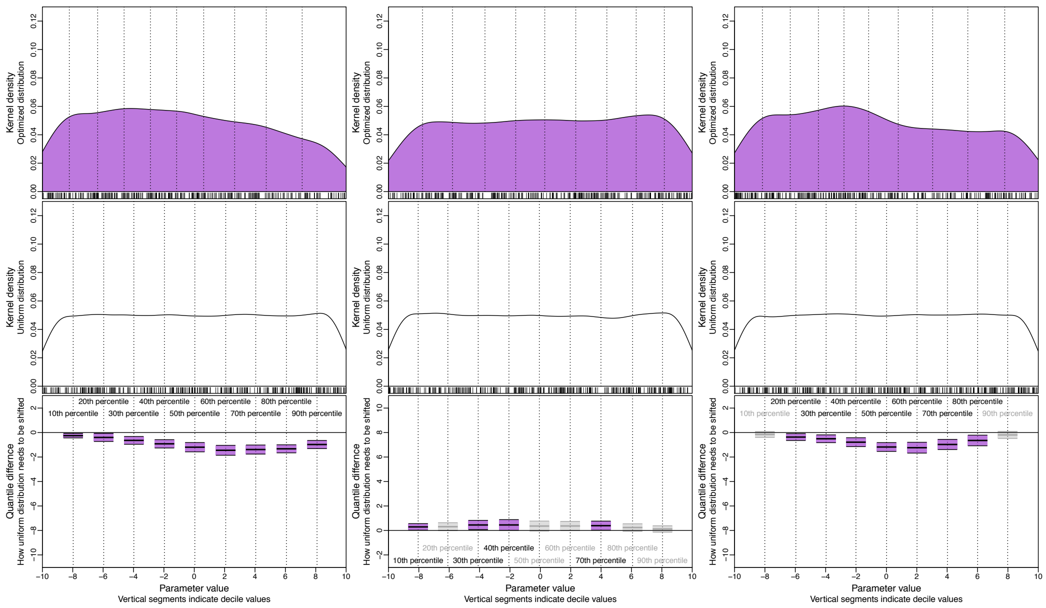
Note: See notes in Figure 3.4



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

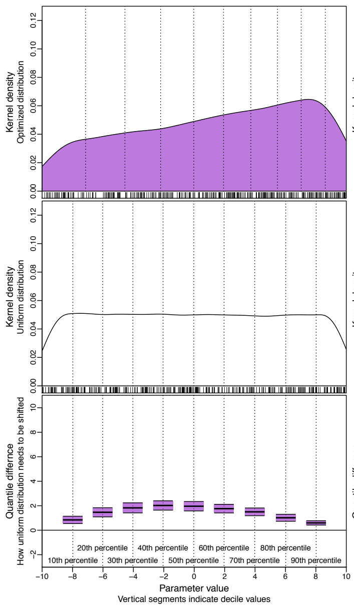
FIGURE A.19: OPTIMIZED PARAMETER DISTRIBUTION, IED ATTACKS, WITH $m = 22,000$



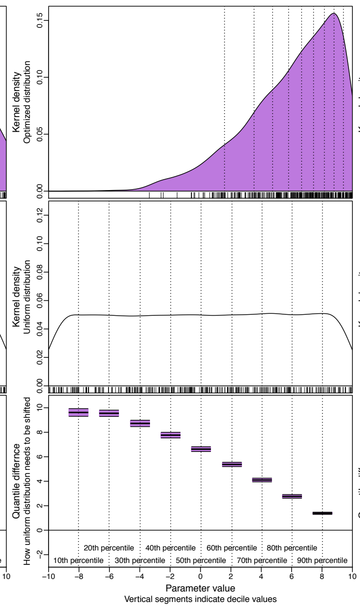
(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.19 (cont.): Optimized parameter distribution, IED attacks, with $m = 22,000$

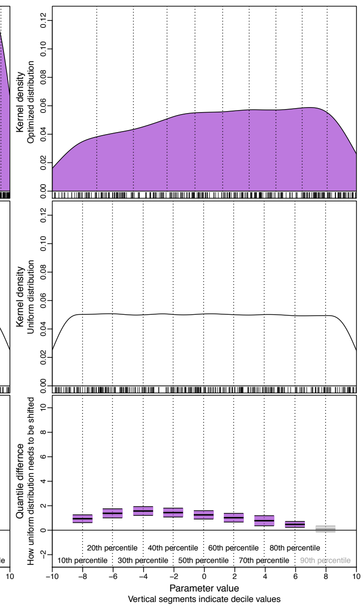
Note: See notes in Figure 3.4



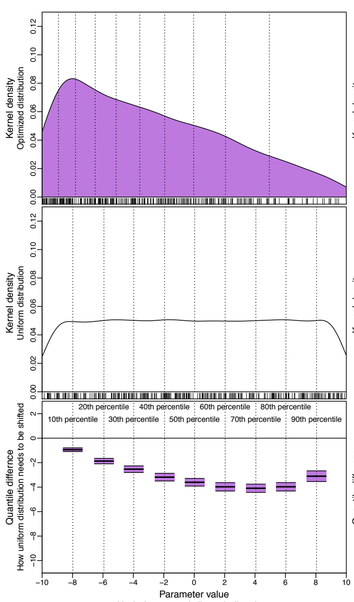
(a) *PopSize*



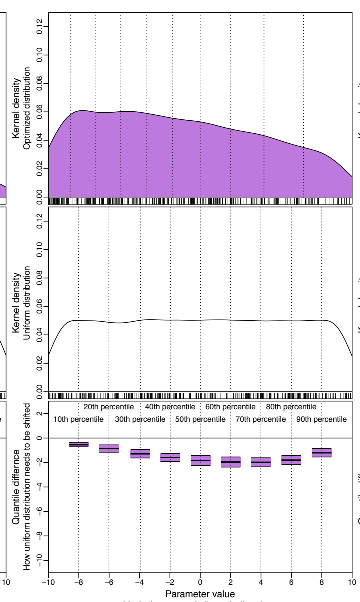
(b) *PashtunPop*



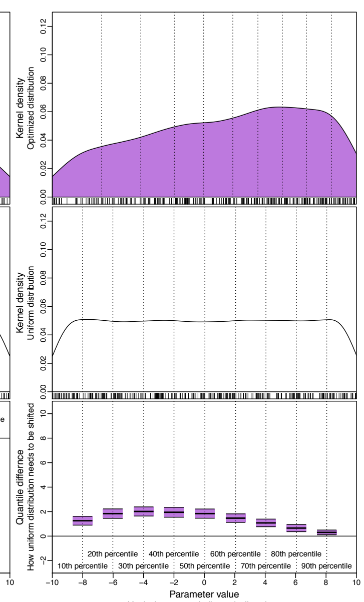
(c) *Development*



(d) *Ruggedness*

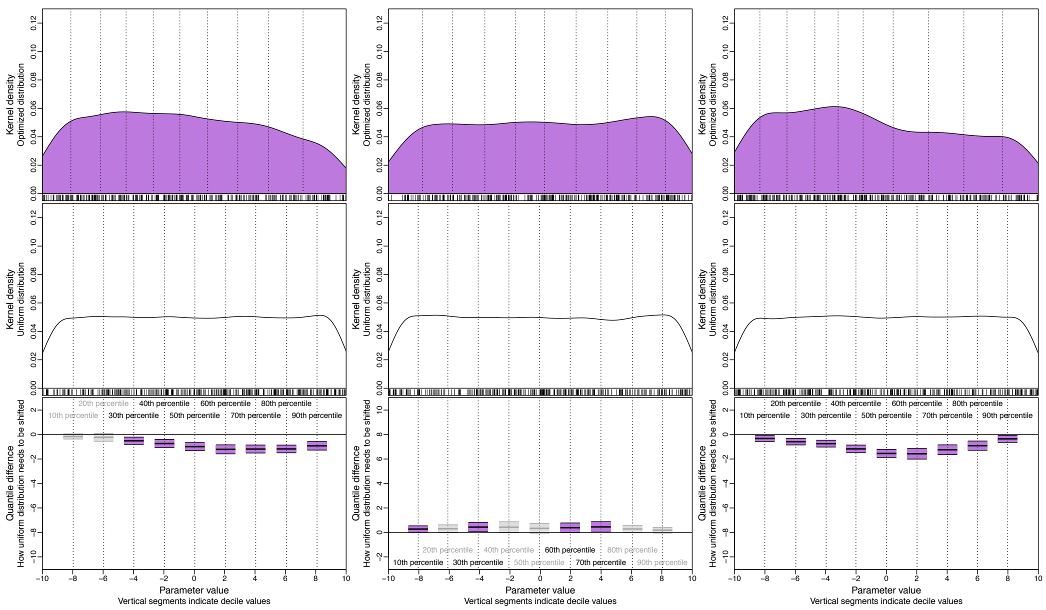


(e) *RoadDist*



(f) *CapDist*

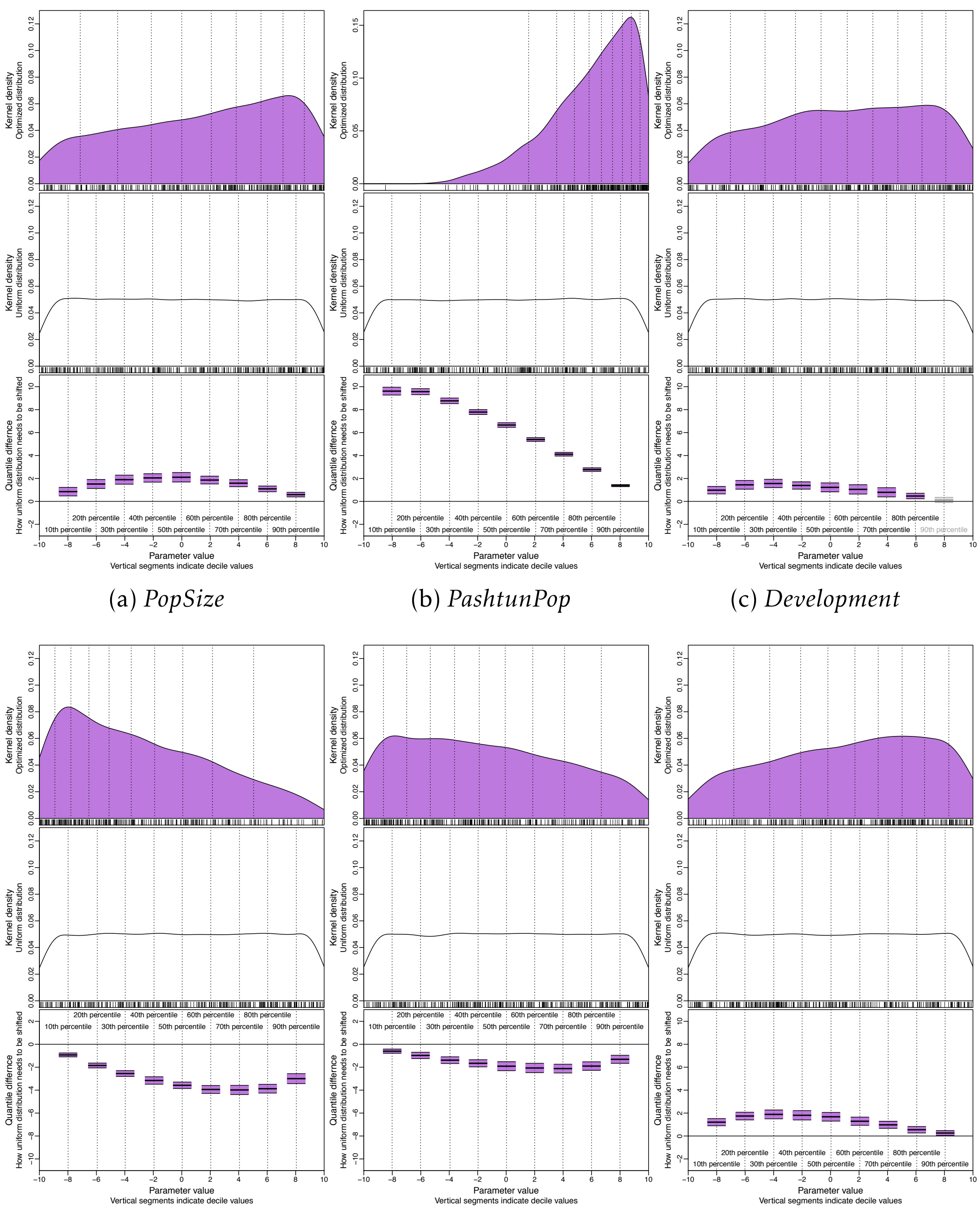
Figure A.20: Optimized parameter distribution, IED attacks, with $q = 0.5$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

Figure A.20 (cont.): Optimized parameter distribution, IED attacks, with $q = 0.5$

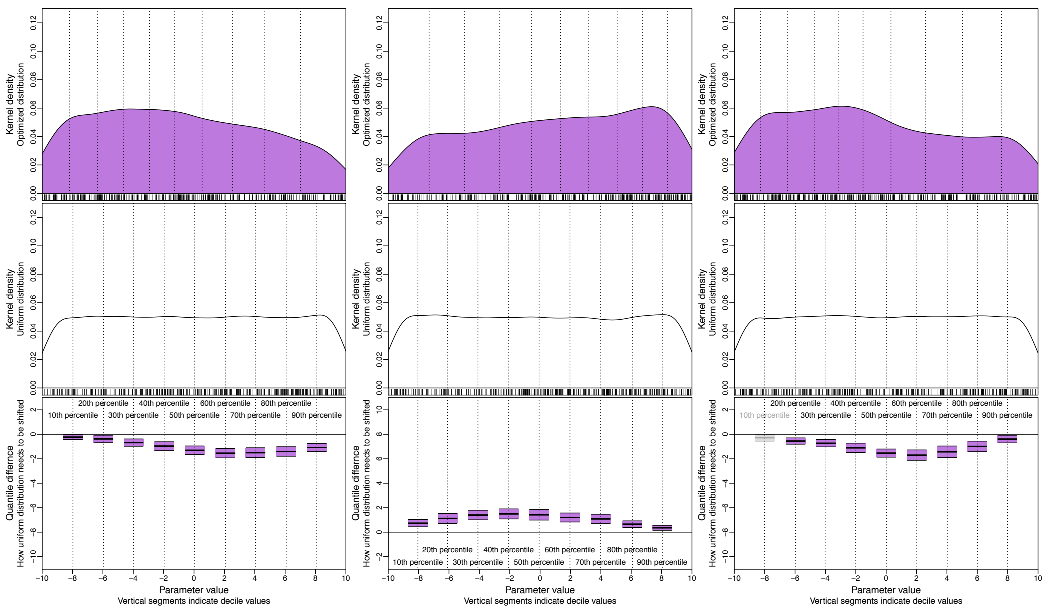
Note: See notes in Figure 3.4



(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

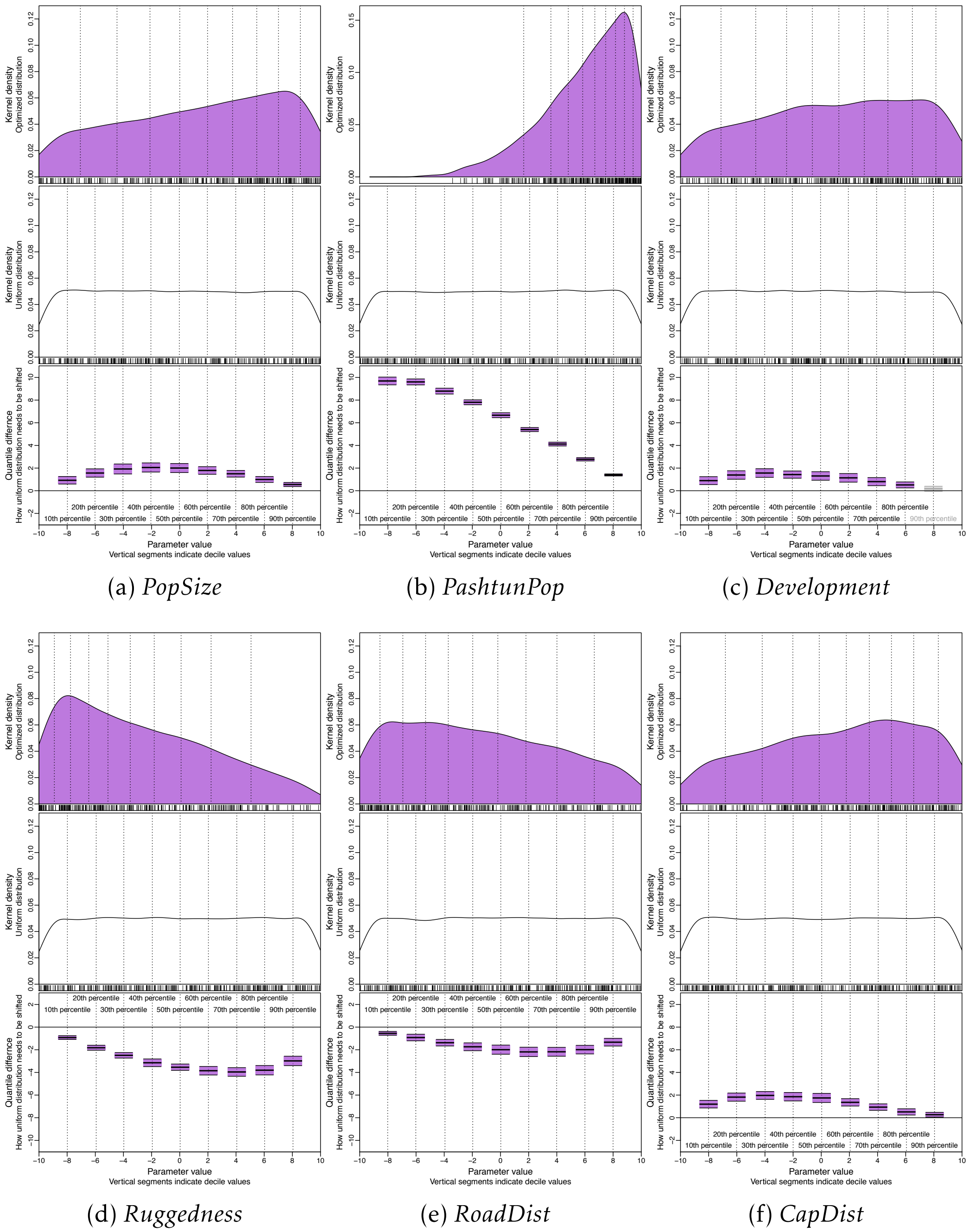
Figure A.21: Optimized parameter distribution, IED attacks, with $\phi = 0.5$



(m) (cont.) *APborder* (n) (cont.) *Spread* (o) (cont.) *History*

FIGURE A.21 (cont.): OPTIMIZED PARAMETER DISTRIBUTION, IED ATTACKS, WITH $\phi = 0.5$

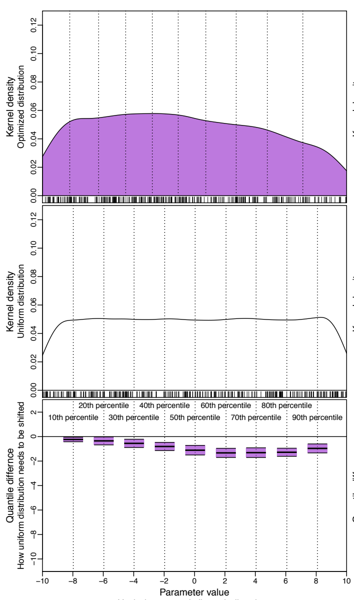
Note: See notes in Figure 3.4



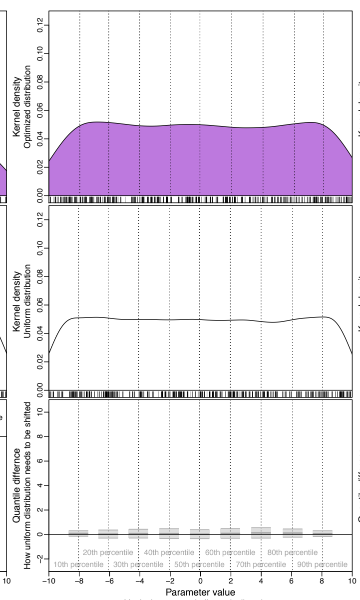
(a) *PopSize* (b) *PashtunPop* (c) *Development*

(d) *Ruggedness* (e) *RoadDist* (f) *CapDist*

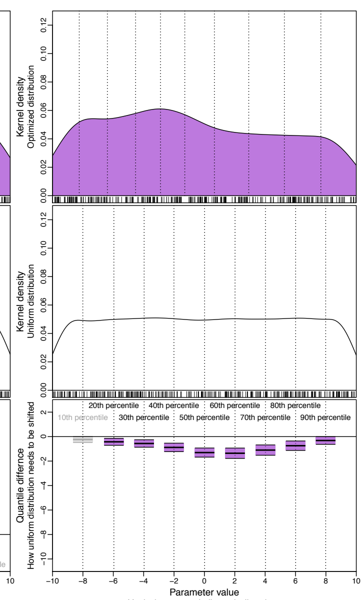
Figure A.22: Optimized parameter distribution, IED attacks, with $\phi = 2$



(m) (cont.) *APborder*



(n) (cont.) *Spread*



(o) (cont.) *History*

Figure A.22 (cont.): Optimized parameter distribution, IED attacks, with $\phi = 2$
Note: See notes in Figure 3.4

APPENDIX B

Supplements to Chapters 5 and 6

The following sections report additional estimation results to assess the robustness of our results reported in Chapters 5 and 6. Section B.1 reports the estimation results for *Naive Diffusion* across different spatial grid settings, and Sections B.2 to B.5 address the major sensitivity concerns of the main empirical results. Reassuringly, none of these sensitivity tests yield results that deviate markedly from the main results reported above. These results provide confidence that the specific parameter settings and assumption are not driving our main empirical findings. Note also that we relied on sp package in R (Bivand, Pebesma, and Gomez-Rubio, 2013; Pebesma and Bivand, 2005) and original R implementations in the geoprocessing operations.

B.1 Effect of Naive Diffusion

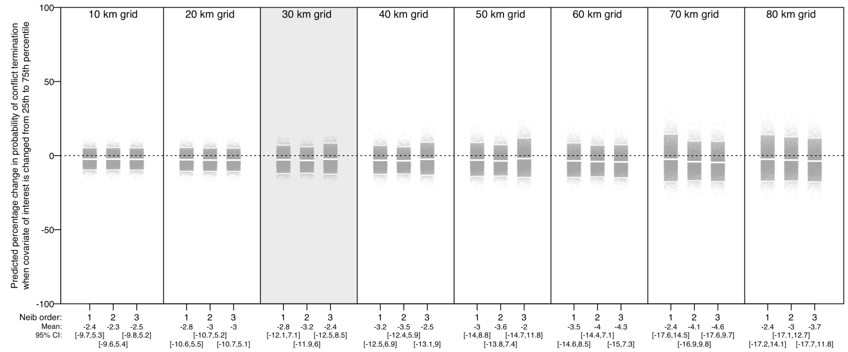
Our empirical suggests that *Naive Diffusion*, or the changes in the scope of conflict zones, would unlikely alter the prospects of conflict termination. Yet, as the MAUP suggests, it is possible that the null findings are specific to the baseline spatial grid setting with resolution $r = 30$ km and neighborhood order $k = 1$. To address this issue, Figure B.1 replicates the estimates of *Naive Diffusion* on conflict termination and outcomes varying the spatial grid specification. As the results indicate, the effect of *Naive Diffusion* on the chances of conflict termination and rebel- and government-favorable outcomes remain statistically and substantially insignificant across different spatial grid settings, suggesting that the baseline null finding is not likely to be the product of the arbitrary selection of grid resolution and neighborhood order.

B.2 Alternative Spatial Grid Specification

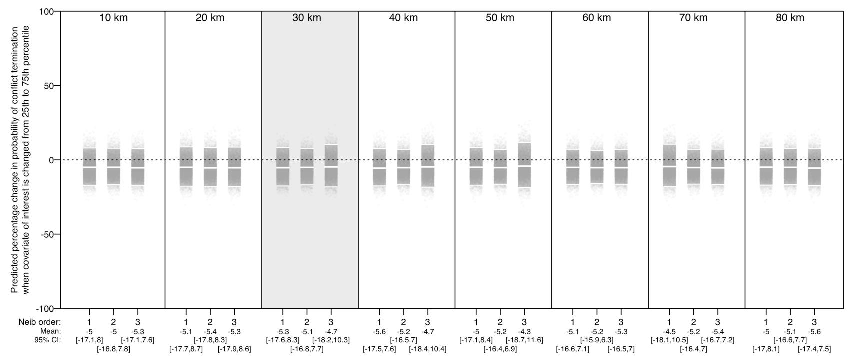
The results reported in the main text suggest that the estimations on the effect of diffusion terms can vary, either qualitatively or quantitatively, depending on the selection of gird resolution and neighborhood order. Because the selection of grid *shape* as well as grid resolution and neighborhood size could alter when detecting instances of proximate diffusion and distant diffusion, an explicit statistical examination is needed to ensure that the main findings reported in the main text are not results of arbitrary spatial grid definition. While the analysis in the main text employs hexagonal grid to detect diffusion patterns, the following robustness check measures battle diffusion using rectangular grids and replicate the main regression models to explore the effect of the selection of spatial units on estimation results. Figure B.2 replicates the estimation reported in Table 6.1 and Figure 6.1 using differently specified rectangular grids.[1] Reassuringly, the estimation results in Figures B.2(a) and B.2(b) do not deviate markedly from the main results: *Distant Diffusion* consistently has a substantial and negative impact on the probability of conflict termination across different grid settings, while the effect of *Proximate Diffusion* remains indeterminate or sensitive to the grid specifications. These additional results provide confidence that the specific parameter settings are not driving the main findings.

As in the results on conflict termination, one may reasonably wonder if the grid-shape specification alters the estimation results reported above.

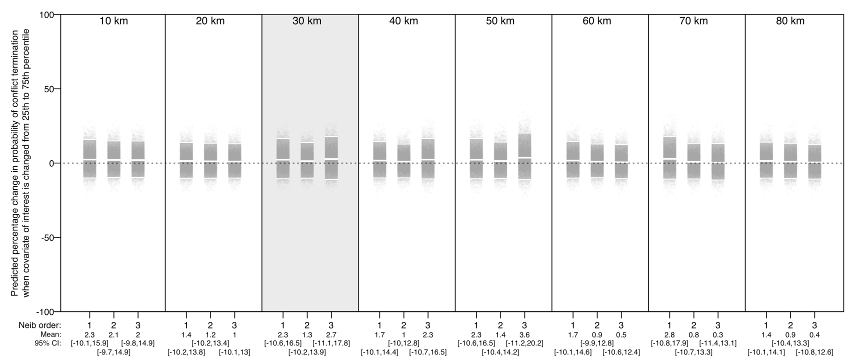
[1] Neighborhood in a rectangular grid is defined as the Moore (Queen) neighborhood, where the neighborhood includes four orthogonal and four diagonal neighbors.



(a) First difference estimates for naive diffusion (conflict termination)



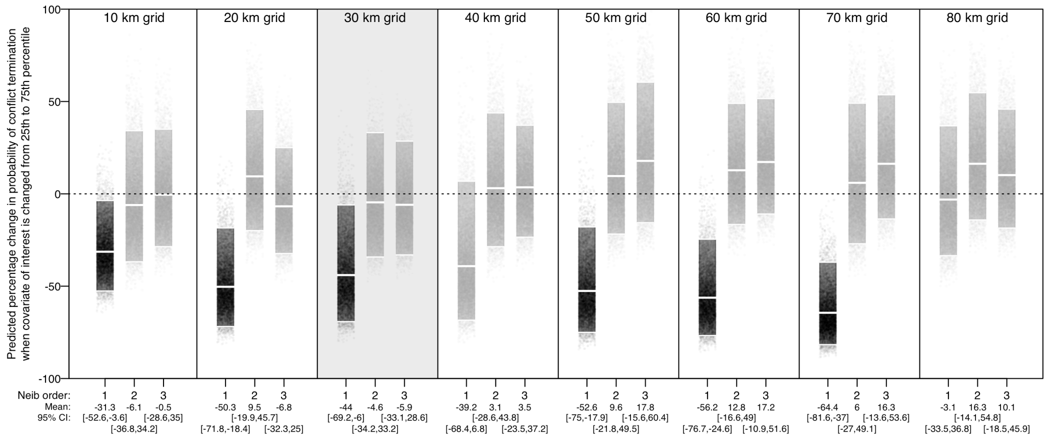
(b) First difference estimates for naive diffusion (rebel-favorable outcome)



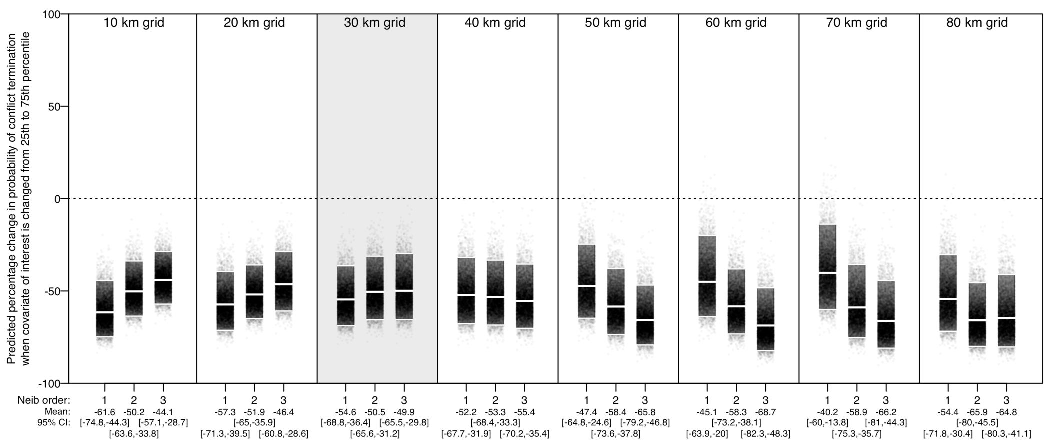
(c) First difference estimates for naive diffusion (government-favorable outcome)

Figure B.1: Effect of *Naive Diffusion* as percentage change in probability of conflict termination and outcome across differently specified rectangular grids

Notes: See notes in Figure 6.1.



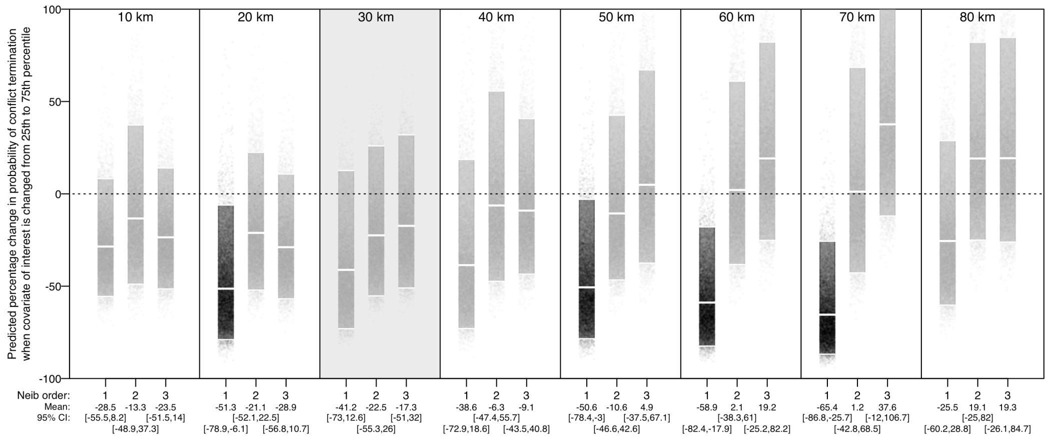
(a) First difference estimates for proximate diffusion



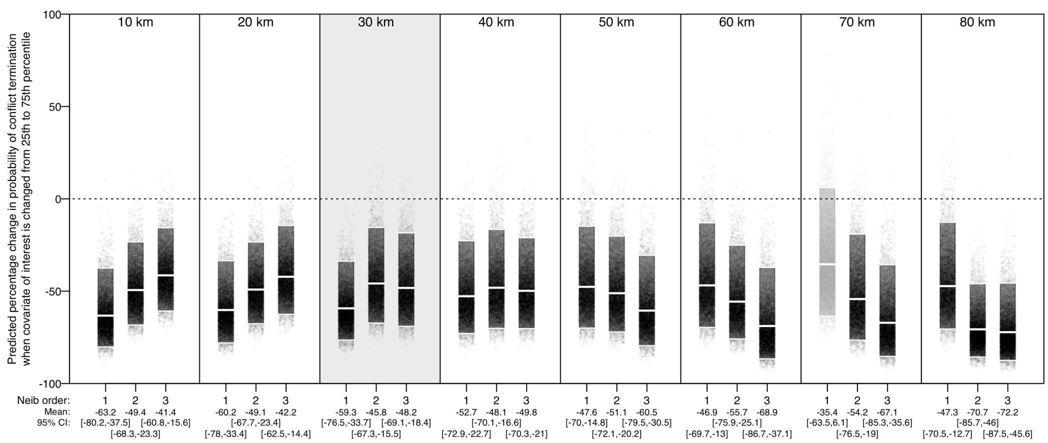
(b) First difference estimates for distant diffusion

Figure B.2: Effect of violence diffusion as percentage change in probability of conflict termination across differently specified rectangular grids
Notes: See notes in Figure 6.1.

As Figures B.3 and B.4 depict, the results remain qualitatively unchanged when employing differently-sized rectangular grids instead of hexagonal grids as in the previous analysis, rendering additional empirical support for our theoretical arguments.



(a) First difference estimates for proximate diffusion



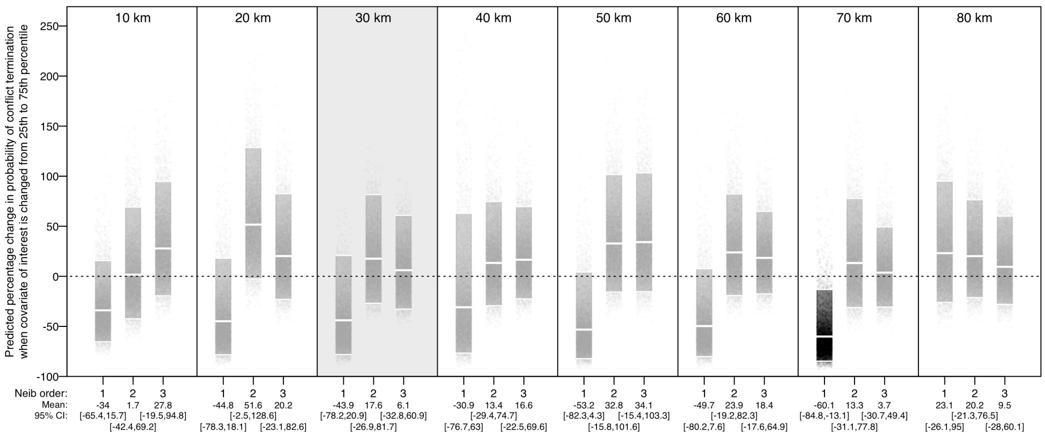
(b) First difference estimates for distant diffusion

Figure B.3: Effect of violence diffusion as percentage change in probability of rebel favorable conflict outcomes across differently specified rectangular grids

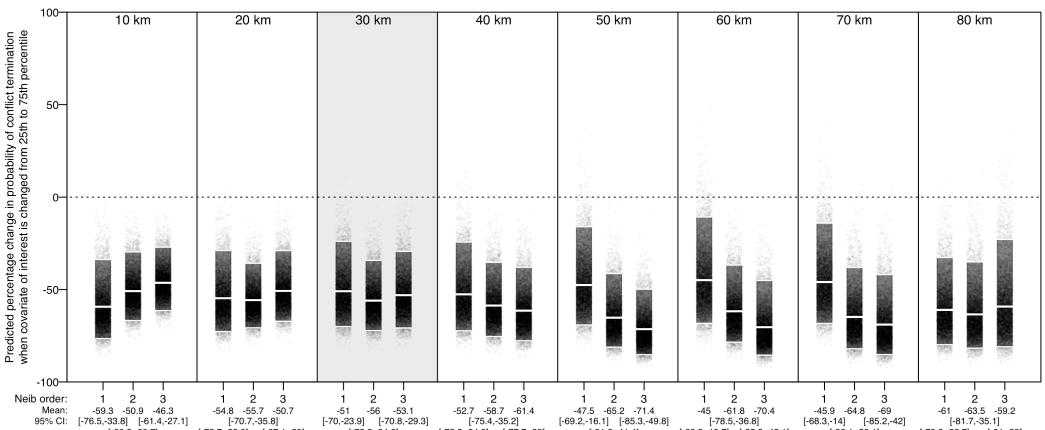
Notes: See notes in Figure 6.1.

B.3 Alternative Temporal-Window Specification

The baseline setting measures the diffusion terms as moving average over previous Δt months with $\Delta t = 6$. As the size of temporal window can affect the detection of the diffusion terms (and the estimates for all other covariates measured as moving-average), Figure B.5 replicates the main



(a) First difference estimates for proximate diffusion

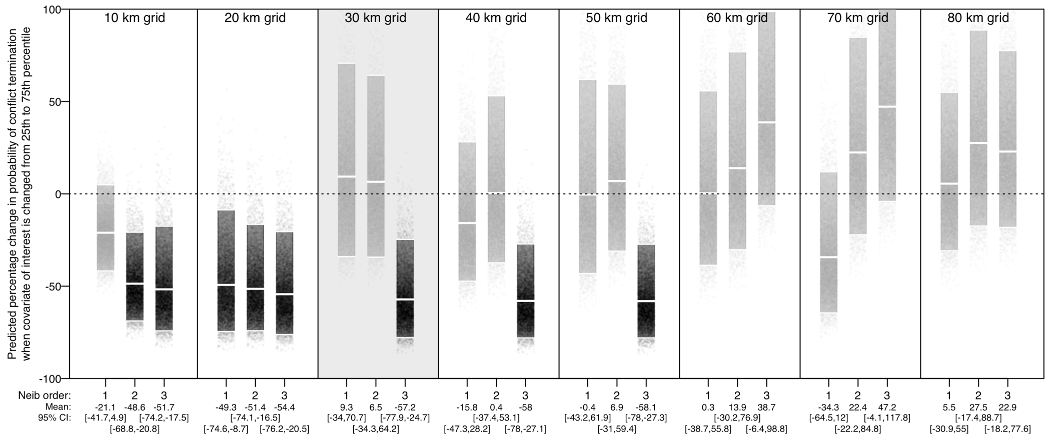


(b) First difference estimates for distant diffusion

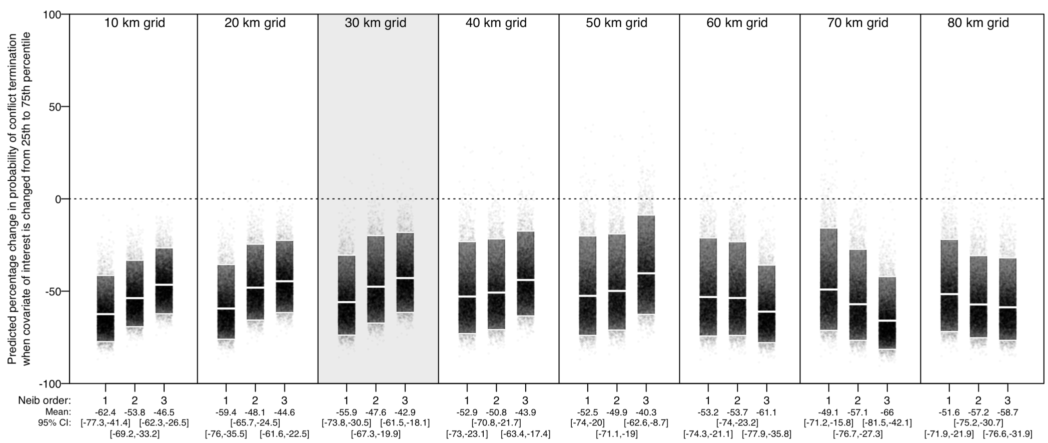
Figure B.4: Effect of violence diffusion as percentage change in probability of government favorable conflict outcomes across differently specified rectangular grids

Notes: See notes in Figure 6.1.

regression models with an alternative window size $\Delta t = 12$. These robustness checks do not alter the main findings qualitatively. Although the marginal effect estimates vary depending on the temporal window sizes, the results remain substantially unchanged across different temporal window settings.



(a) First difference estimates for proximate diffusion



(b) First difference estimates for distant diffusion

Figure B.5: Effect of violence diffusion as percentage change in probability of conflict termination with $\Delta t = 12$
Notes: See notes in Figure 6.1.

B.4 Competing-Risks Regression

The main estimation results rely on the logit estimator. In the following, we report the additional results using the competing-risks Cox regression model as our dataset contains two possible conflict outcomes or competing risks, *Government-favorable* and *Rebel-favorable outcomes*. mstate package in R is used to obtain the estimates (de Wreede, Fiocco, and Putter, 2010, 2011; Putter, Fiocco, and Geskus, 2007). The competing-risks estimates are obtained using the model specification in Table 6.2 in the main text.[2] Table B.1 reports the cause-specific hazard ratio estimates and corresponding 95% confidence intervals. The spatial grid is specified as in the baseline setting with grid resolution $r = 30$ km and neighborhood order $k = 1$. The cause-specific hazard for cause j refers to the hazard of failing (conflict termination) from cause (outcome type) j in the presence of J competing risks (causes; Putter, Fiocco, and Geskus, 2007, 2397). Similar to standard Cox proportional hazard models in the absence of competing risks, cause-specific hazard ratios can be interpreted relative to 1. Cause-specific hazard ratios less than 1 indicate covariates associated with longer duration until conflict termination with a particular outcome, whilst those with cause-specific hazard ratios greater than 1 with shorter duration.[3] As these estimations show, the main empirical results remain qualitatively unchanged: *Distant Diffusion* has a statistically and substantially negative impact on the chances of both *Government-favorable* and *Rebel-favorable outcomes*, while the cause-specific hazard ratio estimates for *Proximate Diffusion* and *Naive Diffusion* remain statistically indistinguishable from 1 at the conventional 5% level.[4]

Nonetheless, in the presence of competing risks, the (cause-specific) hazard ratio estimates alone only allow for limited interpretation of the substantial impacts of the corresponding covariates. This is primarily because the effect of a given covariate is modeled for more than one cause

[2]The multinomial logit model in main text can be thought as a discrete-time survival model in the presence of competing risks, with t^1, t^2, and t^3 mimicking the baseline hazard. See Barnett, Batra, Graves et al. (2009) and Beyersmann, Schumacher, and Allignol (2012, 164–166) for a discussion.

[3]The key assumption in the competing-risks Cox regression model is the proportional hazard assumption that the effect of a covariate on the baseline cause-specific hazard of cause j is constant over time. Schoenfeld residual-based tests detect no statistically significant violations of the assumption of proportional (cause-specific) hazards at the 5% level.

[4]We also estimated the competing risks model with frailty (random effect) to account for unobserved heterogeneity across rebel-government dyads using coxme package in R (Therneau, 2015). The results for the diffusion terms remained qualitatively unchanged.

Table B.1: Competing-risks estimates of conflict outcome

	Conflict outcome	
	Government-favorable Cause-specific hazard ratio [95% CI]	*Rebel-favorable* Cause-specific hazard ratio [95% CI]
Violence diffusion		
Proximate Diffusion	1.810 [0.589, 5.565]	0.487 [0.148, 1.602]
Distant Diffusion	0.501** [0.347, 0.723]	0.587** [0.409, 0.843]
Naive Diffusion	1.033 [0.852, 1.252]	0.981 [0.778, 1.238]
Government attributes		
per capita GDP	0.833 [0.668, 1.039]	0.833 [0.566, 1.226]
Democracy	0.704 [0.344, 1.442]	2.026 [0.886, 4.633]
Country Size	0.913 [0.757, 1.100]	1.119 [0.895, 1.399]
Rebel attributes		
Territorial Control	0.666 [0.379, 1.170]	1.032 [0.588, 1.811]
Ethnic Claim	1.018 [0.641, 1.616]	0.972 [0.537, 1.761]
Rebel Much Weaker	1.732* [1.030, 2.912]	0.321** [0.165, 0.625]
Multi Party	1.322 [0.731, 2.391]	0.806 [0.438, 1.484]
Conflict dynamics		
Conflict Intensity	0.894 [0.643, 1.241]	1.031 [0.825, 1.289]
Cumulative Casualties	1.137 [0.987, 1.308]	1.215* [1.023, 1.443]
Collateral Damage	0.545* [0.303, 0.980]	1.039 [0.720, 1.500]
Govt OSV	0.801 [0.629, 1.020]	0.960 [0.738, 1.248]
Rebel OSV	0.787 [0.542, 1.142]	0.880 [0.629, 1.230]
Conflict geography		
Capital Distance	1.084 [0.853, 1.377]	0.856 [0.615, 1.191]
Local Population	1.134 [0.931, 1.381]	0.779 [0.543, 1.118]
Natural Resource Distance	1.041 [0.799, 1.357]	0.816* [0.668, 0.997]
Ruggedness	0.913 [0.603, 1.383]	1.136 [0.693, 1.862]
Road Density	1.115 [0.870, 1.430]	0.936 [0.716, 1.222]
Observations (months at risk)	7,341	7,341
# Spells (conflict dyads)	199	199
# Failures	82	67
Log Likelihood	−304.975	−241.940
Wald Test (df = 20)	65.930**	67.340**
LR Test (df = 20)	73.336**	46.330**
Score (Logrank) Test (df = 20)	63.229**	45.821**

Note: $^{*}p < 0.05$; $^{**}p < 0.01$
Unit of analysis: conflict dyad–month. 95% confidence intervals computed using robust standard errors clustered on dyad in square brackets.

of failure (conflict outcomes) in competing-risks Cox regression models. Consequently, the substantial or marginal effect of a change in a given covariate on cause j depends on its effect on the baseline hazards of all other causes as well as cause j (Beyersmann, Schumacher, and Allignol, 2012, 89–121; Putter, Fiocco, and Geskus, 2007, 2403–2409). In other words, while a change in a given covariate can simultaneously affect the baseline cause-specific hazard of more than one cause, the cause-specific hazard ratio estimate indicates its effect on the hazard of cause j without taking account for its effect on other causes.[5]

In order to facilitate better understanding of the effects of *Distant Diffusion*, the two panels in Figure B.4 plot the cumulative incidence functions (CIFs) of *Government-favorable* and *Rebel-favorable Outcomes*, for median (dashed) and 99th percentile (solid) values of *Distant Diffusion* holding all other variables constant at their median (continuous) or mode (binary), respectively. Cumulative incidence functions in Figure B.4 represent the probability that conflict termination with *Government-favorable* (left) and *Rebel-favorable Outcomes* (right) occur before time (conflict month) t for a given levels of covariates. Because cumulative incidence functions take account for the covariate effects for more than causes, these estimates allow for intuitive interpretation of substantial effect of *Distant Diffusion* on different conflict outcomes.

Figure B.4 plots the stacked transition probabilities to give another graphical representation of the competing-risks regression estimates, with median (left) and 99th percentile (right) values of *Distant Diffusion*. The left panel of Figure B.4 plots the dashed curves in the two panels of Figure B.4 in a single figure, whilst the right panel stacks the probabilities represented by solid curves in Figure B.4. As in Figure B.4, all other continuous variables are held constant at their median and binary variables at their mode. In both panels, the horizontal axis indicates the number of months since the conflict onset, while the distance between two adjacent curves on the vertical axis indicates the estimated probability of being in the corresponding state (*Continuation*, *Government-favorable Outcome*, and *Rebel-favorable Outcome*). As noted in the main text, the average duration of dyadic conflict episodes (spells) is 59.34 months (4.95 years), and the median duration is 30 months (2.5 years).

As Figures B.4 and B.4 show, escalating *Distant Diffusion* of battle ac-

[5] Alternative approaches include regressing directly on cumulative incidence functions rather than cause-specific hazards (Fine and Gray, 1999) and reduced rank proportional hazards models (Fiocco, Putter, van de Velde et al., 2006).

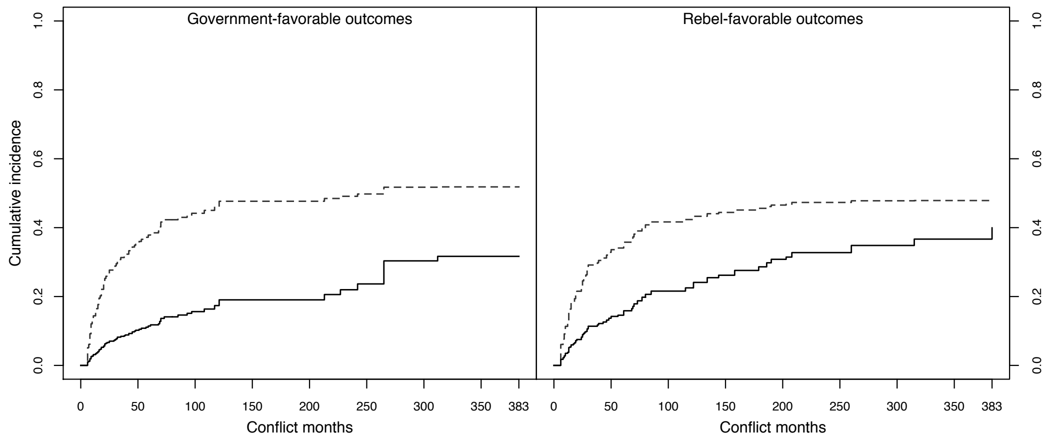


Figure B.6: Cumulative incidence functions for conflict outcomes across different values of distant diffusion

Notes: Cumulative incidence functions for *Government-favorable* (left) and *Rebel-favorable Outcomes* (right). Solid curves indicate the cumulative incidence functions with *Distant Diffusion* at its 99th percentile value, whilst dashed curves indicate the estimates with *Distant Diffusion* at its median value while holding all other continuous variables constant at their median and binary variables at their mode.

tivities is followed by substantial declines in the probabilities of failure (conflict termination) from *Government-favorable* and *Rebel-favorable Outcomes* and a corresponding increase of probability of conflict continuation. These figures graphically demonstrate the substantial and negative impact of *Distant Diffusion* on conflict termination with different outcomes and provide further empirical support for our argument.

B.5 Sample Selection and Outliers

Fourth sensitivity concern is that the sample selection, or the inclusion of outliers with a large number of diffusion observations in a single conflict may have a disproportionate effect on our estimates. To test whether these outliers drive our results, we report a series of subsample coefficient estimation results for the diffusion terms excluding one conflict episode at a time, or groupwise jackknifing of our sample by conflict dyads. As our

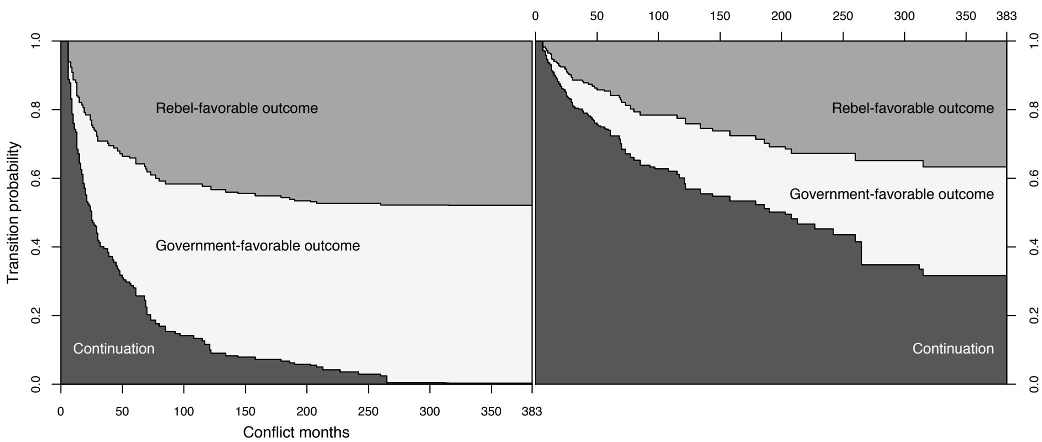


Figure B.7: Stacked transition probabilities of conflict outcomes across different values of distant diffusion

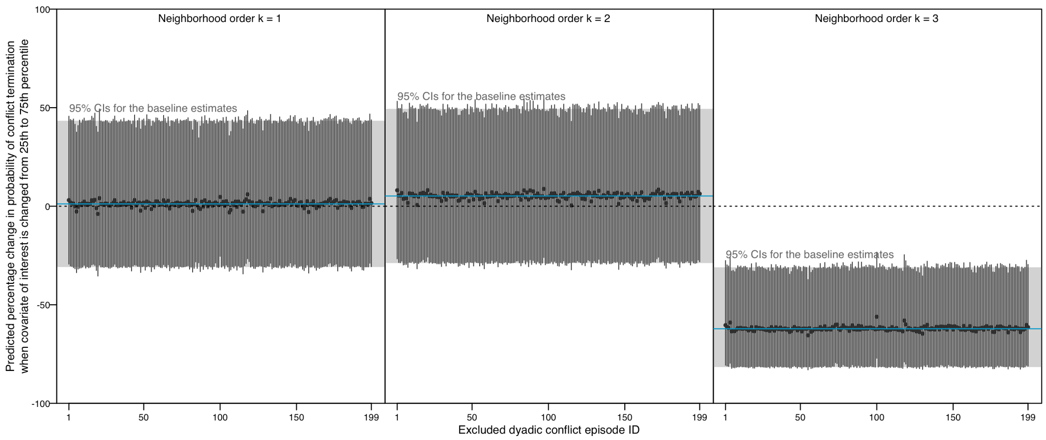
Notes: The distance between two adjacent curves indicates the estimated probability of being in the corresponding state (*Continuation*, *Government-favorable Outcome*, and *Rebel-favorable Outcome*), with median (left) and 99th percentile (right) values of *Distant Diffusion*. All other continuous variables are held constant at their median and binary variables at their mode.

dataset contains 199 unique dyadic conflict episodes, this dyad-wise jackknife procedure yields 199 distinct subsamples.

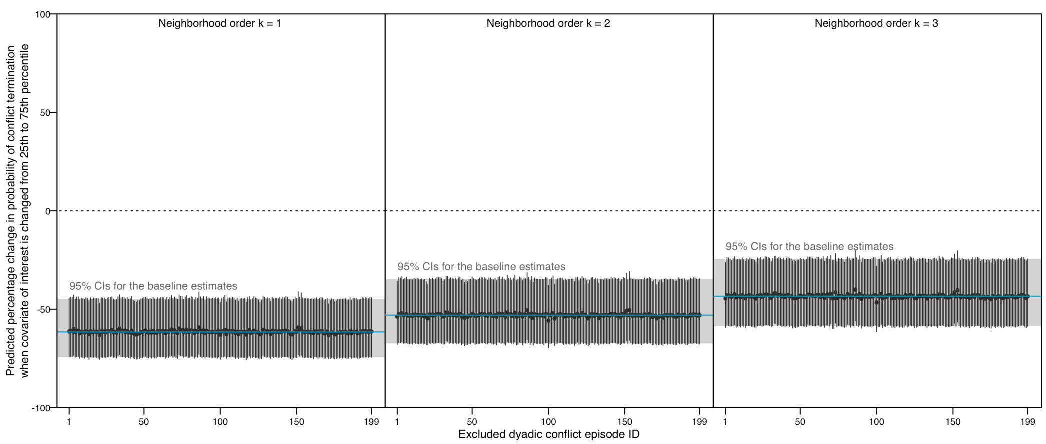
Figure B.8 uses a graph to summarize the results of 199 distinct estimations with a different conflict episode excluded from the sample, with reference to the baseline full sample estimates. Specifically, it plots how a specific amount of increase in *Proximate Diffusion* and *Distant Diffusion* (25th to 75th percentile) changes the probability of conflict termination, holding all other continuous variables constant at their median and binary variables at their mode (first difference estimate). Each dot and vertical segment indicates the median estimates and corresponding 95% confidence intervals for a regression estimate excluding a single episode of dyadic conflict. Three panels represent the estimation results across different neighborhood orders. The grid specification is set as the baseline setting, or $r = 30$ km resolution hexagonal grid with neighborhood order k varying from 1 to 3. Uncertainty estimates for the predicted values are obtained via 10,000 simulations following the recommendation of King, Tomz, and Wittenberg (2000).[6] Blue solid horizontal segment in each panel indicates the mean estimate for the full sample (baseline) regression, whereas gray shade represents the corresponding 95% confidence intervals. Similarly, Figures B.9 and B.10 plot the simulated impact of diffusion terms on *Government-favorable* and *Rebel-favorable Outcomes* across different subsamples, respectively.[7]

Rather than simply reporting the jackknife estimates, the graphical approach in Figures B.8 to B.10 allows us to easily detect the potential outliers on the estimation results. These three figures indicate heavy overlaps of the confidence intervals in the full sample and individual subsample estimations, suggesting that the main findings are not driven by outliers with an exceptional number of battle diffusion events.

[6]Simulations are based on the model specification of Model 3 in Table 6.1 in main text.
[7]Simulations are based on the model specification in Table 6.2 in main text.



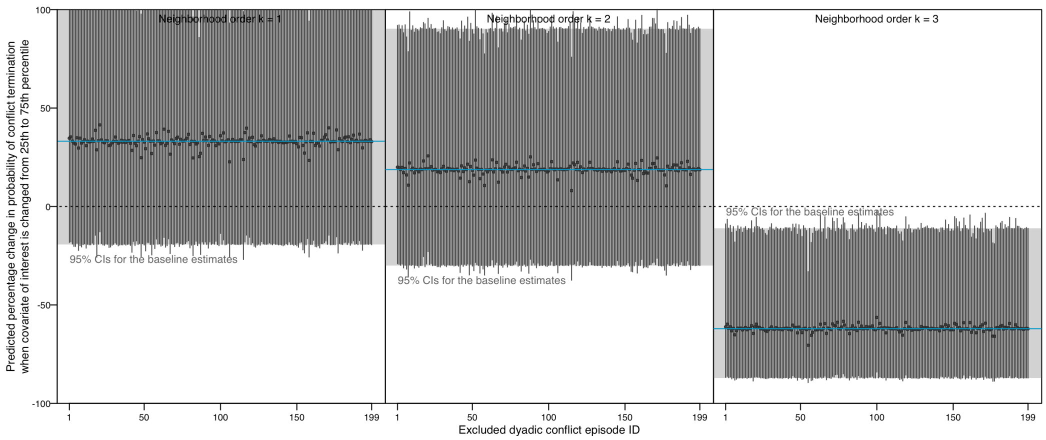
(a) Effect of proximate diffusion on probability of conflict termination



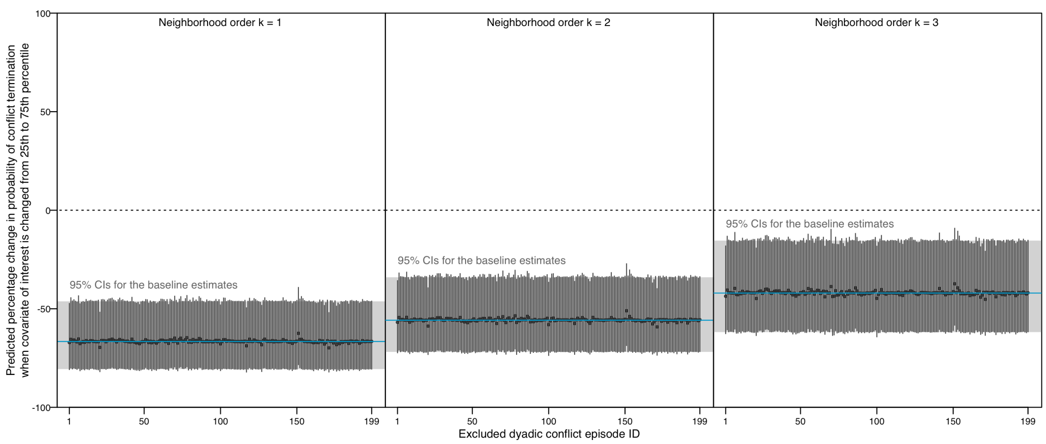
(b) Effect of distant diffusion on probability of conflict termination

Figure B.8: Effect of proximate diffusion as percentage change in probability of conflict termination across subsamples (dyad-wise jackknifing)

Notes: Each dot indicates a predicted change in probability of conflict termination drawn from a single simulation when *Proximate Diffusion* (*Distant Diffusion*) is changed from the 25th to 75th percentile (first difference estimate), holding all other variables constant at their median (continuous) or mode (binary). Vertical segments indicate the corresponding 95% confidence intervals of predicted values. Blue solid horizontal segment indicates the mean estimate for the full sample (baseline) regression, whereas gray shade represents the corresponding 95% confidence intervals. Black horizontal segment running through each panel indicates the zero-reference line. Uncertainty estimates are obtained by 10,000 simulations. Simulations are based on the model specification of Model 3 in Table 6.1 with grid resolution $r = 30$ km.



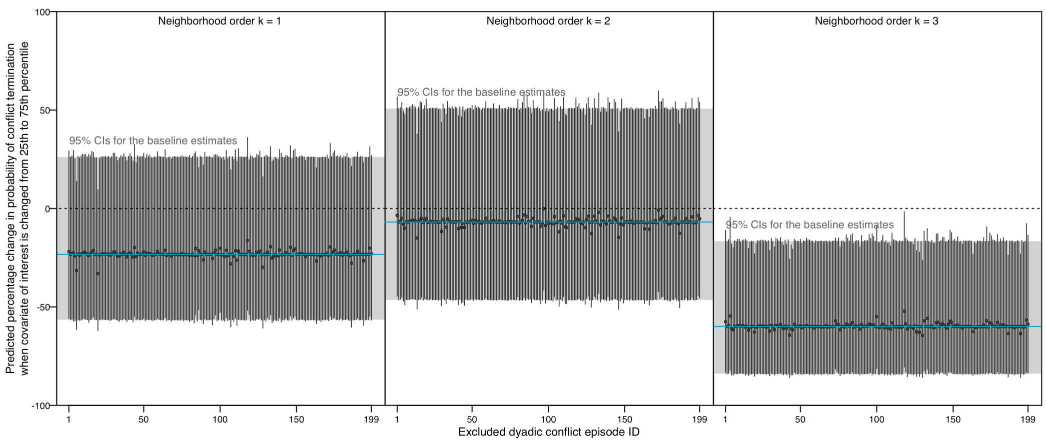
(a) Effect of proximate diffusion on probability of government-favorable outcomes



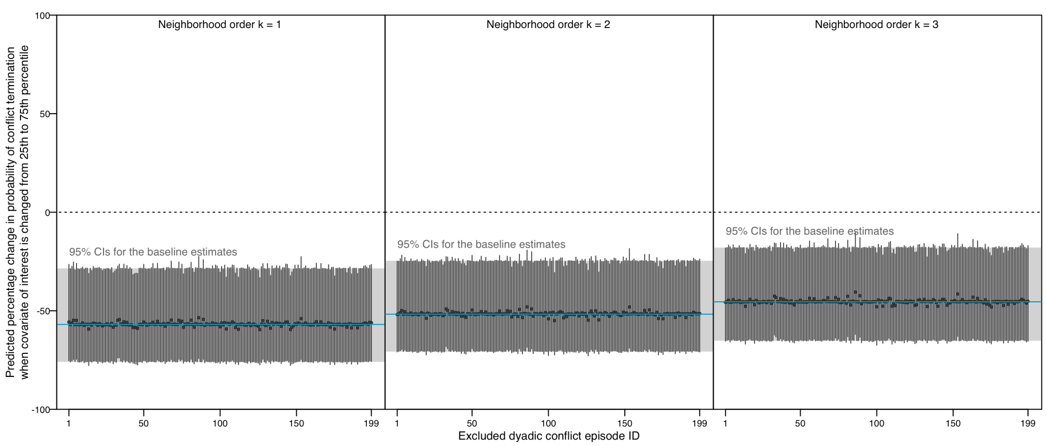
(b) Effect of distant diffusion on probability of government-favorable outcomes

Figure B.9: Effect of proximate diffusion as percentage change in probability of government-favorable conflict outcomes across subsamples (dyad-wise jackknifing)

Notes: See notes in Figure B.8. Simulations are based on the model specification in Table 6.2 with grid resolution $r = 30$ km.



(a) Effect of proximate diffusion on probability of rebel-favorable outcomes



(b) Effect of distant diffusion on probability of rebel-favorable outcomes

Figure B.10: Effect of proximate diffusion as percentage change in probability of rebel-favorable conflict outcomes across subsamples (dyad-wise jackknifing)

Notes: See notes in Figure B.8. Simulations are based on the model specification in Table 6.2 with grid resolution $r = 30$ km.

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