

# Diffusion Patterns of Violence in Civil Wars

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## Abstract

Much of the current conflict literature attempts to explain the occurrence of violence as the result of determinants exogenous to the conflict process. This paper takes a different approach and analyzes how violence in civil wars spreads in space and time, drawing on earlier work on micro diffusion of violence in criminology as well as high resolution conflict data. Two general scenarios are distinguished in our analysis: the relocation and the escalation of conflict. Relocation diffusion corresponds to a shift in the location of violence, whereas escalation diffusion refers to the spatial expansion of the conflict site. We argue that unconventional warfare in civil wars without demarcated front-lines should primarily lead to the second type of pattern. We describe an extension to a joint count statistic to measure both diffusion types in conflict event data. Monte Carlo simulation allows for the establishment of a baseline for the frequency of contiguous conflict events under the assumption of independence, and thus provides a significance test for the observed patterns. Our results suggest that violence in civil wars exhibits patterns of diffusion, and in particular, that these patterns are primarily of the escalation type, driven by the dynamic expansion of the scope of the conflict.

Keywords: conflict diffusion, conflict event data, civil war, Monte Carlo simulation.

## INTRODUCTION

More than forty years ago, the geographer Robert [McColl \(1969\)](#) noted that “the geographic aspect in the evolution [...] of revolutionary movements” (p. 614) failed to be systematically examined, pointing to a lack of scientific attention devoted to how rebellions unfold in time and space. This criticism remains as valid today as it was back in 1969. Much of the current literature attempts to explain conflict and the occurrence of violence as the result of determinants exogenous to the process. This is especially true for the macro-literature on civil war, which typically attributes conflict to poverty ([Collier and Hoeffler 2004](#)), lack of state control ([Fearon and Laitin 2003](#)), ethnic divisions in a country ([Cederman and Girardin 2007](#)), or the existence of non-democratic institutions ([Hegre et al. 2001](#)). Surprisingly, however, even the emerging research on the micro-foundations of internal conflicts tends to assume that violent outcomes are exclusively caused by specific conditions existing prior to the conflict, as Kalyvas (2008) critically notes. Rather, he argues, violence may better be explained as the result of a particular history of conflict, where prior violence conditions future events.

This paper makes a first attempt to disentangle this temporal and spatial dependence in contemporary civil wars. While scholars acknowledge that conflict displays these dependencies and have adapted their statistical models accordingly ([Weidmann and Ward 2010](#)), the dynamics of violence is rarely the focus of investigation. This paper shows what we can learn from an analysis of these patterns. In the spirit of previous research on diffusion ([Hägerstrand 1967](#); [Gould 1988](#); [Morrill et al. 1988](#)), we provide a systematic discussion of the spatial-temporal diffusion of internal conflicts. The diffusion of conflict has received attention primarily by studying contagion effects between countries, explaining the finding that a civil war in one country increases the risk of neighboring countries to also experience internal armed conflict ([Buhaug and Gleditsch 2008](#)). What we are interested in is

the spatial-temporal dynamics of violence *within a single conflict*, rather than its spread beyond country borders.

Empirical datasets on conflict have developed to a point where patterns of violence can be analyzed, but researchers have not made much use of this potential. So far, disaggregated analyses of civil war have almost exclusively studied the impact of exogenous factors on violence, such as population ([Raleigh and Hegre 2009](#)) or poverty ([Hegre et al. 2009](#)). If these studies incorporate the endogeneity of violence, they only do so by controlling for spatial autocorrelation rather than studying in detail how violence unfolds in space and time. We take these studies as our point of departure and make a first step toward filling this gap.

While often portrayed as chaotic episodes of turmoil in fragile states, we show that civil wars exhibit characteristic patterns of diffusion. There are several related studies that contribute to the analysis of diffusion of violence in civil wars. O’Loughlin and Witmer (2011) analyzed “Hot Spots” of violence in the North Caucasus and found that violent events in the context of the ongoing fighting in Chechnya diffuse into neighboring republics. Also, [Townsend et al. \(2008\)](#) analyzed IED attacks in Iraq and showed that follow-up attacks are most probable in the immediate spatio-temporal vicinity of an initial strike. Although both studies make important contribution to the understanding of micro-dynamics in armed conflict, they cannot provide a more general characterization of the spatial-temporal footprints of different types of warfare. This study introduces a statistical technique that is capable of telling apart the characteristic properties of conventional maneuver warfare and guerrilla war.

We distinguish between two patterns of diffusion—*relocation* and *escalation*. These patterns should be related to how the territorial zones of control change as a result of fighting between two conflict parties, and thus reflect to a certain extent the type of warfare.

Conventional maneuver warfare with clear front lines should exhibit relocation diffusion, whereas mobile guerilla war with fast growing and shrinking islands of control should result in patterns of escalation diffusion. While this distinction covers only a subset of diffusion types the literature has described so far ([Hägerstrand 1967](#); Gould 1988), we believe that these are the ones we can most clearly link to patterns of warfare, and thus to a key question in the current literature on civil war (Kalyvas and Balcells 2010). We argue that civil wars should predominantly exhibit the second type, escalation diffusion. For a test of this proposition, our analysis takes advantage of recent progress in the quantitative study of violent conflict. While first attempts to code civil war exclusively aimed at the country level (e.g. [Singer and Small 1972](#)), much work has recently been dedicated to the disaggregation of civil war at the subnational level. Currently, the finest level of disaggregation pinpoints individual conflict events along with their spatial and temporal coordinates, and it is this type of data that we aim to explore in this study.

The article proceeds as follows. First, we discuss diffusion patterns in civil war and introduce our typology. We then test whether current conflicts exhibit particular diffusion types. For this purpose, we adopt a method developed by criminologists and modify it to make it applicable to our analysis. Using fine-grained event data, we demonstrate this method on four recent conflicts. This exercise is meant to be a feasibility test of our approach, rather than a general test. Still, in line with our expectation, the results show that these conflicts predominantly exhibit patterns of escalation diffusion.

## **HOW CIVIL WARS DIFFUSE**

Diffusion and diffusion processes have long been the focus of different subfields in geography and political science. Interest in diffusion is oftentimes motivated by the need to explain the frequently observed spatial *clustering* of social phenomena. As recognized by

Sir Francis Galton in the late 19th century, it is difficult to draw inferences from spatially autocorrelated data, which led researchers to give more attention to the mechanisms generating this correlation. The international relations literature, for example, has shown that proximate countries are oftentimes similar with respect to their institutional setup ([Gleditsch 2002](#)), their economic policies ([Simmons and Elkins 2004](#)), or their involvement in civil war ([Buhaug and Gleditsch 2008](#)). The similarity of spatially proximate outcomes can be explained by two broad categories of approaches: The first one assumes that spatial clustering occurs because the phenomenon to be explained results from factors which are themselves spatially clustered. For example, if democracy leads to peace, and democracy is spatially clustered, we should see clusters of peace on our world map. The second category of approaches assumes that the phenomenon is “contagious”, such that its occurrence in one case causes nearby countries to be affected as well. In the context of civil war, this means that the occurrence of conflict in one country infects nearby states. This infection or transmission of a phenomenon between close units is typically what is referred to as a “diffusion process” ([Elkins and Simmons 2005](#)).

Much of the research on diffusion of conflict has made attempts to uncover the underlying mechanisms that facilitate its spread between countries, such as transnational ethnic linkages ([Lake and Rothchild 1998](#); [Buhaug and Gleditsch 2008](#)) or migration ([Salehyan and Gleditsch 2006](#)). In contrast to this macro-diffusion, little attention has been devoted to the micro-diffusion of conflict. How do conflict events at a particular location affect the likelihood of future ones? A first intuition might be that if conflicting parties have clashed at a particular location, they are likely to do so again. The resulting pattern should be one of repeated conflict activity at this location until one of the actors is defeated. Alternatively, one could portrait civil wars as chaotic episodes of violence. Along these lines, violence in contemporary civil wars should be carried out by highly fragmented military

groups carrying out multiple isolated attacks. Consequently, there should be little if any spatial dependence between the incidents. If spatio-temporal patterns of violence were highly deterministic as suggested above, or completely random, their analysis would either be trivial or futile.

In the following two paragraphs, we describe a more nuanced perspective on patterns of violence in civil wars. As motivated above, we do not aim to explain *why* particular locations see conflict in the first place, but rather how conflict activity evolves over space and time, once it has started. In line with previous research on internal conflict ([McColl 1969](#); [Kalyvas 2006](#)), our stylized description of the conflict dynamics assumes two zones of territorial control, one for the government and one for the rebel group. Violent clashes between the government’s armed forces and the rebel group occur at the boundary between the two zones, with both groups struggling to expand their control. Obviously, this stylized model neglects the possibility that rebels fight each other. Although cases of rebel-rebel encounters are known, we only focus on the classic civil war scenario in which the state’s monopoly on violence is challenged by a non-state actor.

Spatial diffusion of conflict is created by dynamic changes of the zones of control. Previously unaffected areas will now see violence, as violence spills over from one place to proximate ones. These dynamics play out both spatially and temporally, as the process of “infecting” neighboring areas typically takes time. To clarify this point, consider two spatial units  $s_x$  and  $s_y$  (e.g. villages) located next to each other, observed over two subsequent time periods  $t_0$  and  $t_1$ . Assume further that location  $s_x$  experiences conflict at time  $t_0$ . A diffusion process can now lead to conflict at unit  $s_y$  at time  $t_1$ , as a result of spillover from  $s_x$ . By aggregating temporally and then testing for spatial correlation in conflict—as some studies do (see e.g. [Buhaug and Rød 2006](#); [Raleigh and Hegre 2009](#))—we would see two proximate units affected by violence, but fail to get to the basic patterns of how this

diffusion occurs. The following paragraphs outline two possible mechanisms of how this can happen. Our approach shares much with a typology of (contagious) diffusion patterns introduced by [Cohen and Tita \(1999\)](#) in a study on the spread of criminal incidents across urban areas.

### Moving Conflict Actors: Relocation Diffusion

The first diffusion pattern is based on the assumption of clear-cut front lines between the zones of control. In conventional wars, we should see a diffusion pattern that has been labeled *relocation* diffusion ([Cohen and Tita 1999](#)). Figure 1 illustrates this pattern.

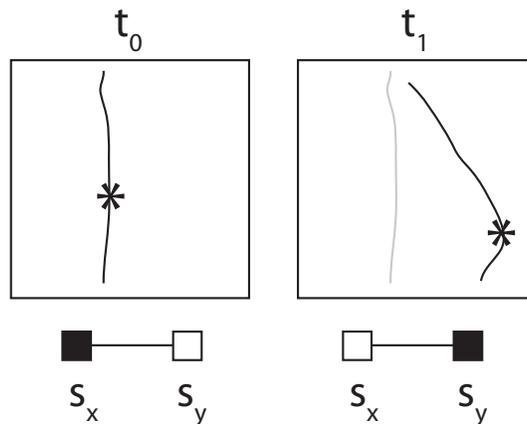


Figure 1: Relocation diffusion. The black lines indicate the boundary between the zones of control. Conflict events (denoted as stars) occur at this boundary. Relocation diffusion is characterized by a shift of conflict activity from location  $s_x$  to a neighboring location  $s_y$ , with  $s_x$  going back to “peace” after the fighting parties have relocated. The boxes below the figures indicate either conflict (black) or peace (white).

Relocation diffusion of conflict is generated by the movement of conflict actors beyond the original control zone boundaries. The left box shows a conflict event occurring at the boundary between the two zones of control ( $s_x$ ) at time  $t_0$ . In the subsequent time period (right box), the left actor is able to extend its control, causing another clash between the

two groups at the nearby location  $s_y$ . If actors are able to retain clear lines of territorial control as in conventional wars, the controlling side should be unchallenged in its zone, and the formerly disputed location  $s_x$  should thus not see violence in  $t_1$ .

Consequently, if civil wars were characterized by clear front lines and areas of control, we should see a frequent occurrence of the pattern outlined at the bottom of Figure 1 when observing pairs of neighboring locations: Conflict (solid boxes) spreads to previously unaffected locations, but the original conflict location goes back to “peace” after the diffusion has taken place.

### Expanding Conflict Areas: Escalation Diffusion

Escalation diffusion is the expansion of the geographic scope of violence to new locations during the course of the conflict. Although we use the term “escalation” following [Cohen and Tita \(1999\)](#), this type of diffusion is more commonly referred to as “expansion” diffusion ([Gould 1988](#)). Figure 2 illustrates this concept.

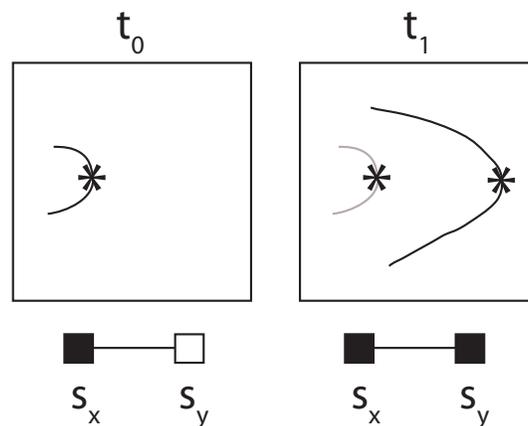


Figure 2: Escalation diffusion. Diffusion of conflict to a new location  $s_y$  does not stop violence at the first location,  $s_x$ . The boxes below the figures indicate either conflict (black) or peace (white).

As for any diffusion process, in our example violence spreads from a previously affected location ( $s_x$ ) to a proximate one ( $s_y$ ). However, rather than shifting violence to a new location, the originating place still experiences conflict. In this sense, the term 'escalation' is justified, since two locations instead of one are exposed to fighting in a subsequent time step. A pattern of this type would be generated if the above assumption of complete control over a conquered territory does not hold: Expanding control beyond  $s_x$  in  $t_1$  leaves the actor still involved in violence at  $s_x$ . The stylized notation at the bottom of 2 shows again the pattern we should frequently observe if escalation diffusion is at work during civil conflict.

### **Violence in Civil Wars: Relocation or Escalation?**

Having established a distinction between relocation and escalation as two different types of diffusion, we return to the core question of this paper: what type of diffusion should we expect in civil wars? Violent confrontations in civil wars occur predominantly between the government, and one or more rebel groups. Different possibilities exist for how these confrontations could diffuse in space and time. First, civil wars may not exhibit any diffusion pattern, or in other words, there is no discernible relationship between events and they occur in isolation from each other. Second, violence in civil wars can be characterized by one particular diffusion pattern, and third, they can exhibit a mix of both patterns. There is ample evidence for spatial autocorrelation in micro-studies of civil war (see e.g. [Buhaug and Rød 2006](#); [Raleigh and Hegre 2009](#); [Weidmann and Ward 2010](#)), so we would expect to see some kind of diffusion. But which one? If civil wars were fought along clear front lines, our findings would correspond to the relocation pattern described above. The front line would essentially mark the border of the control zone of one actor (the rebel group or the government), and a relocation of violence would correspond to a change

in this border. As one actor prevails, its control zone is extended and leads to a new confrontation at the new border of this zone. In this reasoning, the direction of the spread does not matter; the territorial division is a zero-sum game and gains to one actor mean loss to the other.

However, we argue that civil wars should primarily show episodes of escalation diffusion. In particular, we believe that there are two reasons why combatants in civil wars experience violence within their zone of control, which would lead to escalation diffusion as defined above. First, as McColl (1969) argues, insurgents aim to secure territory by planting a set of initial, small bases mostly in the countryside, and then try to expand these further. This corresponds to tactics of unconventional warfare used in civil wars (Kalyvas 2007). If control of the original base is constantly challenged by government forces, attempts to expand these bases will be characterized by the escalation diffusion pattern described above. Second, having pushed their zone of control further, combatants typically cannot rely on well-established support lines. Rather, violent attempts to extract resources *within* their controlled territory leads to the occurrence of violence behind front lines and thus to a pattern of escalation diffusion. Although to a lesser extent, this pattern should also apply to an expansion of the government's zone of control. If government troops try to regain control over rebel terrain, the high fragmentation of rebel troops can lead to attacks behind their current lines, and thus to an escalation diffusion pattern as introduced above. Such guerrilla tactics have been described in the literature; see for example Greiner (2009:36) or Kalyvas (2006:66).

In sum, our reasoning suggests that violence in civil wars should exhibit patterns of diffusion, and that due to the nature of irregular warfare, this violence should be predominantly of the escalation type. In the following sections, we present an approach to test for the occurrence of different diffusion patterns and apply this approach to recent civil wars.

## **DETECTING DIFFUSION: DATA AND METHOD**

A suitable approach for answering our research question must have the following characteristics: First and most importantly, accurate data on single conflict events is required for the investigation. Moreover, a statistical method for testing diffusion effects against a null hypothesis is necessary. This section provides a detailed overview of both the data and the method employed.

### **The ACLED Data Set**

Conflict research has come a long way from its early data collections on wars and casualties (such as Richardson’s (1948) list of “Fatal Quarrels”) to today’s high resolution data on single conflict events ([Camilo et al. 2009](#)). With increasing technological sophistication and computational power, various data collection efforts are underway to provide researchers with increasingly detailed information about civil conflict. One of these projects, the “Armed Conflict Location and Event Dataset” (ACLED, see [Raleigh et al. 2010](#)), has a wide coverage and is thus especially suited for our analysis. ACLED provides information on single conflict events with regard to the political actors involved, the exact timing, and the location of the confrontation. Changes in territorial control, casualties, and violence against civilians are also reported, but only for a subset of all events in the dataset. Even though ACLED eventually aims to provide global coverage for all civil wars of the post World War II era, current coding efforts focus on conflicts in Sub-Saharan Africa. Moreover, the Bosnian War in the early 1990s is included together with a few conflicts from the Far- and Middle East. For a complete overview of coded countries and the data see the ACLED web site at <http://www.acleddata.com>.

The geographic coordinates provided for each conflict event usually refer to the nearest settlement to the actual fighting. In conjunction with the timing information in ACLED,

this spatial information is essential for our analysis. One limitation of the dataset is the abstraction from “severity” in terms of casualties caused by a conflict event. Although information on battle-related deaths is provided for some cases, there is no systematic and comprehensive coding of severity. Moreover, a wide variety of scenarios qualify as conflict events, ranging from small skirmishes to major attacks on strategic targets. As a result of these limitations, our analysis does not take the severity of conflict events into account. Moreover, we have to accept that only a fraction of all violent events that occurred are reported in ACLED, since this data collection relies on media sources exclusively (but see O’Loughlin et al. (2010) who find high correlations between ACLED and event counts based on military records). Interpreting the data most conservatively, we assume violence to be present if one or more ACLED events fall within a particular location. With these limitations in mind, the provided location-day accuracy in the data allows for a wide variety of techniques in spatial statistics to be used, including the approach we propose in the following section.

## **Analyzing Diffusion in Space and Time**

The assumption that fighting in civil wars follows endogenous dynamics requires an empirical test that explicitly takes space and time into account. In the following, we first describe methods to analyze static spatial clustering, and then discuss how these methods can be extended to incorporate dynamic diffusion processes over time.

### **Measuring spatial clustering**

Geographers have developed a variety of tools and techniques to analyze spatial clustering, and we can distinguish between two general approaches. First, in point pattern analysis (see e.g. O’Sullivan and Unwin 2003) the task is to find spatial clusters of points (representing,

for instance, locations of a particular animal species), and to assess the degree and the scale of clustering. Here, points can be located anywhere in a two-dimensional space, and the focus of analysis are the features of this pattern. For example, Ripley's  $K$  function ([Ripley 1977](#)) is a frequently-used distance based quantification of the degree of clustering. A second type of spatial clustering departs from a set of fixed spatial entities or units, each of which displays a particular value of a variable of interest, and assesses the extent to which proximate units are similar to each other. For example, when measuring the degree of spatial clustering of democracy in the world ([Gleditsch 2002](#)), countries constitute the basic units of analysis, and our measure of interest is an indicator for democracy. For our analysis of diffusion, we observe fixed locations over different periods of time, so this second approach applies to our problem at hand.

One of the most important statistics for assessing spatial autocorrelation in a set of fixed spatial units is Moran's  $I$  ([Moran 1950](#)). Moran's  $I$  measures the degree of similarity in the variable of interest between neighboring units, essentially by computing the correlation between a unit and each of its neighbors. In order to find out whether a given value of Moran's  $I$  is significant (i.e. indicating spatial correlation in the variable of interest), we need to compare it against its expected value under the absence of spatial correlation. This value is the correlation we would observe if the measurements of our variable of interest were *distributed randomly* across the units of observation ([Ward and Gleditsch 2008:23](#)). Moran's  $I$  applies to variables with continuous values, but alternatives exist. For binary variables as the one in our study (conflict/peace), joint count statistics are appropriate ([Lee and Wong 2005:353](#)). Joint count statistics are simple counts of pairwise occurrences of values in neighboring units. Significance testing can be performed as described for Moran's  $I$ , by comparing the observed count to the one obtained from randomly distributed values across the set of spatial units.

One important feature of spatial autocorrelation measures such as Moran’s  $I$  that makes them inapplicable to the study of diffusion processes is the lack of a temporal dimension. Essentially, these indicators tell us whether a given variable displays spatial autocorrelation at a given point in time, but it cannot detect the unfolding of diffusion processes as we described above. However, there are two main ideas we retain when developing our spatial-temporal framework below: First, we focus on local neighborhood pairs, i.e. all pairs of adjacent units. Keeping things simple, we only include first-order neighbors in the analysis and not higher-order ones. In contrast to static autocorrelation measures, we do not observe these pairs at a single point in time only, but over subsequent time steps. Second, we develop a significance test for our diffusion indicator that follows the typical approach, essentially comparing the observed outcome to a simulated random allocation of our dependent variable —conflict— across the spatial units. The next section describes our method.

### **Detecting diffusion**

Extending static indicators of clustering to incorporate time can be done in a variety of ways. One contribution to this problem is Kulldorff’s SaTScan statistic ([Kulldorff 1997](#)). Developed for epidemiological analysis, SaTScan checks for clusters of point events in both space and time, using sliding space-time windows. The method allows for a fast assessment of event-clusters that are unlikely to be brought about by chance. Nevertheless, the introduced diffusion scenarios of relocation and escalation are not accounted for in this method. Therefore, it cannot be applied to our task, while being suitable for related studies (e.g. O’Loughlin and Witmer 2011). Since our research goal is the identification of spatio-temporal patterns that can be linked to different types of warfare, extending the existing methodology was mandatory.

The basic motivation for our approach stems from a criminological study on the diffusion of homicide across neighborhoods in Pittsburgh ([Cohen and Tita 1999](#)) using local indicators of correlation ([Anselin 1995](#)). While static autocorrelation coefficients rely on pairwise comparisons of neighboring units for one given point in time, Cohen and Tita (1999) observed these pairs of spatial units (in their example, urban neighborhoods) repeatedly over many time steps. This extension is critical for the assessment of different diffusion effects, as described above. However, their method deals with continuous variables, so we modified their basic approach to incorporate binary outcomes, similar to a joint count statistic as described above. Using the notation introduced above, we look at pairs of neighboring units  $(s_x, s_y)$ . At a given point in time, a unit can either experience conflict ( $C$ ) or peace ( $P$ ). As mentioned above, this study does not take the severity of conflict events into account. Focusing on arguably the simplest measurement, conflict activity ( $C$ ) is defined as the presence of at least one ACLED event within a spatial unit at a given time, and peace ( $P$ ) as the absence of ACLED events. We denote one of these pairwise observations by the respective outcome, for example  $CC$  if both units are affected by violence. In order to trace the temporal unfolding of the diffusion process, following Cohen and Tita (1999) we observe these pairs over two subsequent time steps  $t_1$  and  $t_2$ . For example, if in a pair of units one is affected by conflict at  $t_1$  and the other at  $t_2$ , we denote this as  $CP \rightarrow PC$ .

In total, there are 16 possible transitions for any particular pair of units (two units, each either in conflict or peace, observed over two time steps). Many of these 16 possible transitions are not of particular interest to us: For example, there will be many instances of absence of conflict, corresponding to  $PP \rightarrow PP$ . Also, isolated conflict events as in  $CP \rightarrow PP$  and  $PC \rightarrow PP$  are not related to our question. In our first scenario, relocation diffusion, conflict activity moves away from the originating unit to the next. Since we

ignore direction of spread, this corresponds to the following two transitions:

- $CP \rightarrow PC$
- $PC \rightarrow CP$

The second mechanism, escalation diffusion, is characterized by the expansion of conflict to a neighboring location, while the originating location remains affected. In our simplified framework, this corresponds to

- $CP \rightarrow CC$
- $PC \rightarrow CC$

This simple inclusion of time in the static joint count statistic allows for the detection of diffusion effects. In the next two sections, we proceed by defining our unit of analysis and devising a significance test for these measures.

### **The unit of analysis**

A further design choice has to be made to for answering our research question. So far, we have referred to locations of units without mentioning their spatial extent. In many empirical studies, sound theoretical arguments can be made to define the unit of analysis. A study on the diffusion of democracy, for example, might focus on the state as the elementary unit. However, the diffusion of conflict events within civil wars does not lend itself to such considerations. Administrative units such as provinces or districts, considered in many other studies as meaningful subdivisions of countries, would also be a less than optimal choice: First, by aggregating conflict activity up to the level of these units we lose information of the fine-grained dynamics in conflict provided in ACLED. Second, administrative boundaries may have little relevance in civil wars, since they can be crossed

easily by armed forces. Third, administrative units vary greatly between countries. In our cross-national comparison, we would be comparing areas of vastly different sizes, which would limit the generalizability of our findings.

We therefore follow existing studies on civil war and use artificial spatial cells as the unit of analysis ([Buhaug and Rød 2006](#); [Hegre et al. 2009](#)). These studies divide the entire study area into equal-sized cells of a given size (e.g. 100 km x 100 km). The common approach is to fix the size of these cells for the entire study, and few if any robustness checks are conducted for variations in the cell size. Yet, for our application there is no reason to home in on any particular size, since we have no prior expectation about the precise scale at which conflict diffusion should occur. Moreover, the selection of one arbitrary size for the spatial cells can have significant effects on any statistical analysis. This is known as the “modifiable areal unit problem” ([Openshaw and Taylor 1979](#)) and has received extensive treatment in the geographic literature. In order to exclude the possibility that any effects we find are the result of choosing a particular grid resolution, we perform our analysis for different cell sizes, starting with a minimal resolution of 3 km. We increase this resolution stepwise up to 21 km. A similar consideration applies to the choice of the temporal resolution. Typically, quantitative analyses on conflict resort to calendar units such as years or months. Again, for our study this could result in temporal over-aggregation, while at the same time lacking a justification for a particular temporal resolution. For these reasons, we again apply our analysis for different sizes of the time intervals, from 3 to 31 days. Together with the spatial resolution described previously, this results in a “spatial-temporal window” for which we conduct our analysis.

For a given parameter setting (i.e. a spatial-temporal window of a given size), we obtain our observed count of diffusion instances by allocating the conflict events to the given cells and time periods, and then counting the number of cases that satisfy the relocation or

escalation pattern as defined above. For example, a pair of two adjacent cells observed over two time periods counts as an instance of relocation if one cell contains at least one conflict event in the first time period, and its neighbor contains an event in the subsequent time step. Similarly, an instance of escalation diffusion is a pair of cells where one cell is affected by conflict in one time step, and both cells are affected in the subsequent time step. The neighborhood of a cell is defined as the Moore neighborhood, i.e. the eight cells surrounding it along the x- and y-axis and the diagonals.

### **Statistical test**

As described above, our approach to test for the presence of the two diffusion types follows the procedure employed for static measure of autocorrelation, such as Moran's  $I$  or the joint count statistic. Essentially, the approach is to establish the expected value and the variance of the spatial correlation coefficient using Monte Carlo simulation. For each run of the simulation, the observed values of the variable of interest are distributed randomly across all units, and the correlation coefficient is computed. Repeating this procedure for multiple simulation runs gives the variance of the correlations under the null hypothesis of random spatial distribution, and thus a way to test whether an observed correlation is significantly higher.

We adapted this Monte Carlo approach for our purpose. As described above, we count the *observed* number of escalation and relocation transitions over the entire duration of a conflict, after fixing a spatial-temporal window size. We compute the *expected* number of escalation and relocation transitions for this given window size by populating our set of cells randomly for each time step, but using the same number of conflict outcomes we observed. Repeating this procedure many times in a Monte Carlo experiment gives us the expected number of transitions and its variance for the given window size, and we can

test whether the observed count is significantly higher. In summary, our method works as follows:

1. Choose one spatio-temporal window as the unit of analysis.
2. Allocate the observed conflict events to the spatial-temporal units of the given size.
3. Count all the instances of relocation and escalation diffusion (e.g. the occurrence of the transitions defined above).
4. Simulate a null model by randomly allocating the observed number of conflict events to spatial units for every time step. In our Monte Carlo simulation, this step was repeated 250 times to get an estimate of the distribution of transition counts under the null hypothesis.
5. For each type of diffusion (relocation and escalation), we test whether the observed count is larger than the 95th percentile of the simulated distribution. If so, we conclude that the observed count is significant, i.e. that the respective conflict exhibits diffusion patterns of the given type.

Essentially, this procedure is a spatial-temporal joint count statistic, adapted to different types of diffusion and applied to different spatial-temporal windows. Simply counting the number of instances consistent with relocation or escalation ignores the direction of spread, i.e. whether rebels or government gain or lose territory. As we have argued above, however, for relocation diffusion this direction does not matter; if violence marks territorial changes in the zones of control, these changes can benefit either side. Similarly, in the case of escalation diffusion, irregular warfare can be associated with violence within the rebel or government control zone. Thus, ignoring the direction of spread is a good approximation, but further refinement of our methodology—though not considered here—is possible.

## RESULTS

Since the presented space-time joint count statistic is computationally expensive, we apply it to four selected conflict cases from ACLED. This selection is guided by two considerations. First, we want to explore both differences between, but also similarities within, world regions, and thus select two cases each from Africa and Europe. Second, our method requires the specification of a conflict zone, which is then used to create the sample of spatial cells for a given resolution. Large countries with a relatively limited conflict zone are thus not suited for our simulations, since the large number of empty cells will artificially bias our simulations towards fewer simulated diffusion transitions. We therefore selected three small countries and one clearly delimited region that experienced violence almost anywhere in their territory. The sample includes the cases of Rwanda, Burundi, Bosnia, and Kosovo, described in detail below. Clearly, however, this selection is insufficient to provide a widely generalizable test of diffusion patterns in civil wars. Moreover, data availability restricts the temporal scope of our analysis, and oftentimes excludes periods of escalation and de-escalation short of full-fledged war. Thus, the results presented here constitute a proof of concept of our proposed method, and should be taken with the necessary grain of salt. Still, as we will see below, even the limited number of cases is sufficient to generate some interesting insights into the spatial-temporal dynamics of violence, which can hopefully spur further work on this topic.

For each of the four conflicts, we test different spatial-temporal resolutions as described above. The Monte Carlo simulation was run 250 times for all space-time resolutions with different random number sequences to establish the null model. In the following, we present the results of our analysis visually, by plotting the spatial-temporal resolutions that generate significantly higher numbers of relocation and escalation diffusion instances. This outcome is shown in a two-dimensional plot, with the spatial resolution shown along x-

axis, and the temporal resolution along the y-axis. Black patches indicate the combinations of spatial and temporal resolution for which we find evidence of (relocation or escalation) diffusion in the respective conflict.

## **Bosnia**

The first case in our analysis is the Bosnian War during the early 1990s. We included 87 conflict events from the entire country for a timespan of more than three years (April 1992 through October 1995). Figure 3 (left) shows the areas of the parameter space for which we found significant numbers of escalation diffusion instances. For a large portion of the parameter space, a significant number of escalation diffusion transitions can be found in the empirical data. For a spatial cell size ranging from 3 km to about 19 km, significant effects can be found for almost the entire temporal dimension. Figure 3 (right) shows a different pattern of relocation diffusion effects. Fewer instances of relocation diffusion can be observed, and they occur for small temporal resolutions.

As explained above, we associate a high number of escalation events with the absence of clear front lines and repeated challenges for territorial control or attacks following guerrilla style tactics, whereas relocation diffusion corresponds to more or less clearly delineated zones of control. The literature has portrayed the Bosnian civil war as a mixed case. Kalyvas and Sambanis (2005) label it as “symmetric nonconventional war”, which was “characterized by a mix of regular and irregular forces fighting in a territory defined by clear front lines [..]” (p. 212). This observation explains the occurrence of (few) instances of relocation diffusion in Figure 3 (right), but goes counter to the predominance of escalation diffusion we find. However, Kalyvas and Sambanis (2005) also point to the importance of ethnic settlement patterns in determining where violence was applied during the war. Intermingled settlements of Bosniaks, Serbs and Croats provided incentives

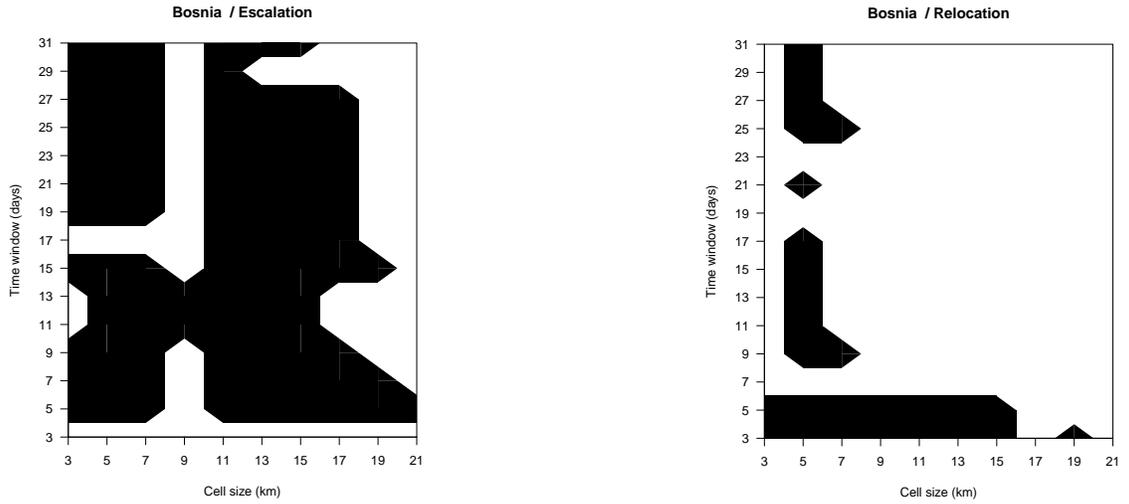


Figure 3: Diffusion effects for the civil war in Bosnia. Significant results are shown in black. Left: Parameter configurations for which the observed number of *escalation* instances is significant. Right: Parameter configurations for which the observed number of *relocation* instances is significant.

for ethnic cleansing, which was oftentimes carried out by regular forces against irregular “self-defense” units. Much of this violence seems to have been carried out by centrally organized forces and militias, who “imported” violence to particular locations because of their ethnic composition (Gagnon 2004, but see Ó Tuathail 2010 for a critical discussion). As a result, what determined violence during this “pursuit of security through separation” (Dahlman and Ó Tuathail 2005:574), were ethno-territorial incentives. Since violence was perpetrated by irregular units and small militias (Mueller 2000), they are not likely to have followed clear-cut front lines, where fighting was shifting back and forth over a period of time. Instead, the diffusion pattern generated by these isolated incidents is closer to what we label as escalation diffusion, using guerilla-style tactics. In sum, both ethno-territorial aims and the nature of the war actors in Bosnia would provide explanations for the results shown in Figure 3 (left).

## Kosovo

We applied our method to the Kosovo conflict, using 559 ACLED events from March 1998 through October 1999. The results differ from the Bosnia example. Figure 4 (left) shows instances of escalation diffusion for the entire time axis, but with a spatial extent of only 3 km to 7 km. Overall, the escalation diffusion pattern is time invariant and occurs at small spatial scales. Figure 4 (right) shows only few instances of relocation diffusion. The two scattered “islands” of significant relocation effects can be safely ignored in the interpretation which is concerned with more robust patterns. Virtually no relocation effects can be observed in the Kosovo case for the tested parameter space. How do these findings relate to the Kosovo case?

A short summary of the events might illustrate the relationship. The fighting in Kosovo before the 1999 NATO intervention took place predominantly between the “Kosovo Liberation Army” (KLA) and Serbian police and military. A previously less influential political actor, the KLA acquired much of its arms during the uprisings in Albania in 1997. In its attempt to remove Belgrade’s rule in the contested Kosovo province, the KLA waged a successful guerrilla campaign against Serbian forces in much of 1998. Repeated attacks on Serbian police forces and retaliation attacks on Albanian paramilitaries marked an escalating spiral of violence in the region. Examples for this development in early March 1998 can be found in the literature. Judah (2000:138ff) describes a KLA attack on a police patrol in the small village Likošane. This attack left several policemen dead and supposedly led to increasingly brutal actions by the Serb dominated police against suspected paramilitaries, such as an attack on several compounds in Donji Prekaz by heavily armed police forces which led to several civilian casualties on March 5. The KLA forces mainly drew on targeted killings and guerrilla tactics during this phase of the conflict (FCO 1999:6-10). Describing the style of fighting employed by the KLA, Judah concludes:

“It was guerrilla war of a type unseen so far in the wars of the former Yugoslavia and it resembled nothing so much as the ultimate Serbian nightmare: its very own Vietnam” (Judah 2000:156).

For in the first half of 1998, the conventional Serbian military was not strongly involved in combat in the region. This changed in August when a Serbian counter-offensive drawing on heavy arms such as tanks and artillery drove the KLA from some of their secured positions, encountering little resistance by the lightly armed KLA (IISS 1998; Judah 2000:150,169). While being unable to challenge the military forces, ambushes and scattered attacks by the KLA, as well as violence against civilians on both sides, continued on. With regard to the irregular tactics employed by the KLA, the case seems to be typical for a wider range of civil conflicts. However, Kosovo is very small, with area of only about 11,000 km<sup>2</sup>. Therefore, the resulting pattern of escalation diffusion is also limited to small spatial resolutions. The empirical record still shows the predominance of escalation over relocation, therefore being in line with our expectations.

### **Burundi**

We also performed our analysis on 396 conflict events from the civil war in Burundi for November 1993 through the end of 2003. Figure 5 (left) shows a pattern that is slightly weaker than escalation diffusion in the Bosnian case. For the entire time axis starting with 8 day intervals and cell sizes from 3 km to 14 km, a significant number of escalation diffusion instances can be observed. For the left-hand side of the plot, a more robust pattern of escalation than relocation diffusion emerges, thereby confirming our expectation. Figure 5 (right) shows a somewhat scattered pattern of relocation diffusion. Cell sizes up to 8 km also lead to a jagged pattern of significantly increased relocation diffusion along the time axis. This finding seems surprising at first. However, in direct comparison to the escalation

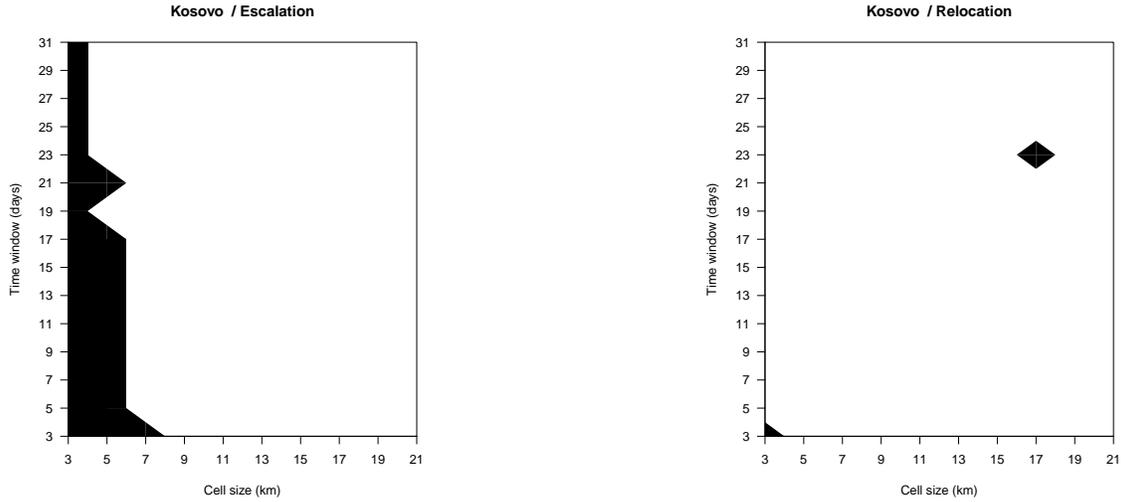


Figure 4: Diffusion effects for the civil war in Kosovo. Significant results are shown in black. Left: Parameter configurations for which the observed number of *escalation* instances is significant. Right: Parameter configurations for which the observed number of *relocation* instances is significant

effects, instances of relocation diffusion are less spread out across the parameter space and occur closer to the axes where the simulated baseline is necessarily low. How does this pattern relate to the history of the conflict?

Burundi slipped into civil war following the assassination of its President, Melchior Ndadaye, in October 1993 and the subsequent death of his successor, Cyprien Ntaryamira. Fueled by long standing ethnic tensions between Hutu and Tutsi, the resulting conflict proved to be extended and destructive. It lasted for a full decade and left about 300,000 dead (Notholt 2008:2.26). The war gained an international dimension in 1996, when government forces engaged in fighting in neighboring Democratic Republic of the Congo. Politically, the operation aimed at improving the security situation in the eastern part of the country, denying rebels safe havens for preparing cross border attacks: “Rebel movements from Uganda (ADF), Rwanda (former government army FAR and *interahamwe* militia),

and Burundi (CNDD-FDD) used Congolese territory as bases for assault and retreat” (Reyntjens 1999:242). This type of mobile warfare has been described as the predominant tactic employed in the field. “As already mentioned, one specific feature of the Burundian civil war was that the Hutu rebels never seized a larger territory inside the country, but followed a guerrilla strategy of moving in and out” (Vorrath 2010:101). The ACLED record for Burundi also shows that violence was not executed homogeneously across the country. Instead, much of the fighting occurred its most western part. Unlike the fighting in Kosovo that mainly consisted of ambushes and surprise attacks, Burundi saw more large scale and movements across the border to neighboring Democratic Republic of the Congo. These movements might resemble the advancing conventional front-lines and thereby yield more relocation dynamics than fighting that breaks out between ethnic groups in intermingled settlement patterns.

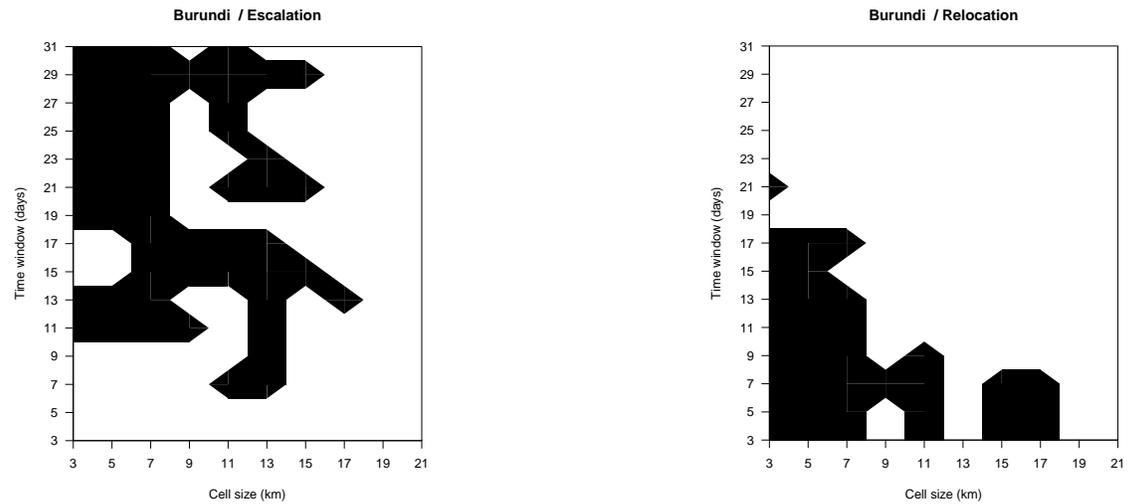


Figure 5: Diffusion effects for the civil war in Burundi. Significant results are shown in black. Left: Parameter configurations for which the observed number of *escalation* instances is significant. Right: Parameter configurations for which the observed number of *relocation* instances is significant

## Rwanda

Another 264 conflict events that occurred in the Rwandan civil after 1994 war were included in the analysis. Figure 6 shows the results. While there is an almost complete absence of instances of relocation diffusion, for spatial scales between 3 km and 8 km we find a significant number of escalation diffusion instances on the entire time axis. In and after 1994, two conflicts unfolded in Rwanda: (i) the military confrontation between the Rwandan Patriotic Front (RPF) and the Hutu government of the country, and (ii), the civil war of the Hutu militia groups against the Kagame government after the Hutu government was ousted from power. The RPF war started in April 1994 after the onset of the Hutu genocide against the Tutsi. The genocide itself caused an estimated 800,000 casualties, but due to ACLED's focus on confrontations between military units the corresponding events are not included in this analysis.

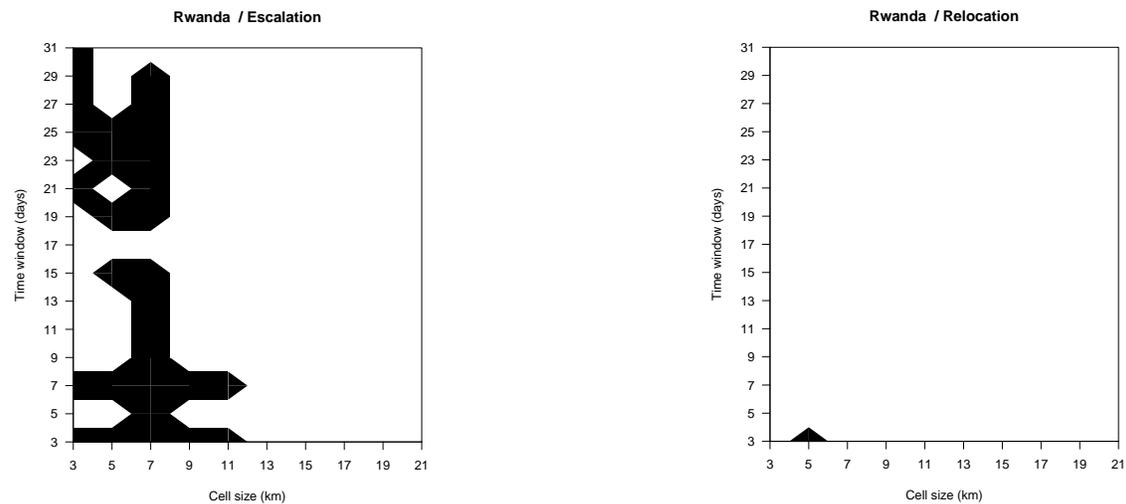


Figure 6: Diffusion effects for the civil war in Rwanda. Significant results are shown in black. Left: Parameter configurations for which the observed number of *escalation* instances is significant. Right: Parameter configurations for which the observed number of *relocation* instances is significant

When the RPF resumed their military campaign in 1994 following the 1992 Arusha accords, they did so by relaunching their efforts in the north of the country. Progress was quick, and they reached the capital only a few days later. While this campaign was likely fought using conventional warfare and should thus exhibit the relocation pattern, due to the fast progress and the resulting concentrated fighting in the capital Kigali, the data may simply not be sufficient to allow for a robust detection of this type of diffusion. However, in parallel with the quick conquest of Kigali, the RPF also tried to bring the rest of the country under their control, and in doing so extended its campaign towards the countryside. This part of the campaign was fought as a guerilla-style war, but more as a result of the different (comparatively weak) Hutu militias fighting them, rather than their own military tactics (Human Rights Watch 1999). Because the majority of the events included in our analysis belongs to the rural RPF campaign, this may partly explain the occurrence of the escalation pattern we find. The second conflict included in our data is the violence between the new Tutsi government under Kagame, and the former Hutu militias, which after the genocide had formed a new rebel group, now mostly operating from eastern Congo. As we have discussed above, however, this type of cross-border attack is unlikely to generate a pattern with changing territorial zones of control.

## **Discussion**

The four conflicts included in our analysis display a picture that is largely consistent with our expectations. For three out of the four cases, we observe a pattern of escalation diffusion that matches our predictions. In short, violence in civil wars seems to diffuse with a distinct pattern that is comparable across cases. Once violence has occurred at a particular location, it is likely to expand in scope. On the contrary, there is an almost complete absence of relocation diffusion in our cases, with the only exception being the Burundi

conflict. Here, we observe a robust pattern of relocation diffusion, which nevertheless still occurs in fewer places of the parameter space than the escalation effects. Subsequent work could shed more light on our basic findings. For example, if there are typical ranges of relocation and escalation diffusion, these could be established on the basis of more cases and better data. This would also allow for a finer specification of the actors and processes of violence production that generate the observable patterns. For now, our analysis provides preliminary evidence for the escalation diffusion pattern across cases, which is generally in line with our theoretical expectations and fits the stylized model of irregular warfare without demarcated areas of control.

## CONCLUSION

Existing research on the diffusion of conflict has had a tendency to infer diffusion processes from the observation of contemporaneous spatial correlation. However, diffusion itself is a dynamic process, where the “contagion” of proximate units is temporally subsequent to observing conflict in the originating unit. Thus, a proper way to deal with diffusion processes needs to incorporate this temporal element. In this paper, we have presented a simple approach that applies this reasoning to the micro-diffusion of violence in civil wars. We employ a methodology from the geospatial criminology literature and adapt it for our purpose. This method allows us to distinguish among, and test for, two types of diffusion: relocation diffusion, where violence “travels” from one location to a proximate one, and escalation diffusion, where violence expands in scope. We argue that whereas relocation should be associated with conflicts that have clear front lines, these are mostly absent in civil wars, and violent confrontations should follow primarily the escalation diffusion pattern. We apply our method to four cases of civil war, using micro-level data on conflict events drawn from the ACLED dataset. Our results show that consistent with our

expectations, violence in civil wars follow the escalation pattern, with isolated islands of violence that dynamically expand in scope.

Our analysis is a first step toward analyzing the endogenous micro-patterns of violence. Whereas the predominant approach is to explain micro-variation in violence by exogenous factors (such as population density, poverty or ethnic mix), this typically ignores that violence itself can cause violence. Prior confrontations determine to a large extent what is going to happen in the immediate the future, and where violence is going to take place. However, quantitative studies rarely go beyond the inclusion of spatial and temporal lags, treating this dependence as a nuisance. Extending the static measurements of spatial autocorrelation towards a spatio-temporal statistic is the first step towards a better understanding of wartime violence.

Despite these contributions, our analysis is only a proof of concept for the study of diffusion patterns in civil wars, and more research is necessary to explain the patterns we find. On the one hand, one could think of more comparative research that explores systematic differences in spatial patterns, depending on the technology of warfare. For example, following recent work by [Kalyvas and Balcells \(2010\)](#), one could test whether civil wars relying on conventional warfare exhibit predominantly relocation diffusion. On the other hand, there is need for more micro-research. We can show that our subset of civil wars exhibits characteristic diffusion patterns, but we do not know precisely what actors and conditions generate them. As more and better data is being collected on violence in civil wars, future research will shed more light on these issues.

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