Explaining the variation in rebels' violence in civil conflict: a collection of essays on reactive violence, synthetic events, and counterinsurgency practices

A Thesis Submitted to the Degree of

Doctor of Philosophy (Ph.D.)

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2022

To my family, to Nonno Marco and to Zio Sisto.

"Nine-tenths of tactics are certain, and taught in books: but the irrational tenth is like the kingfisher flashing across the pool, and that is the test of generals."

-- Seven Pillars of Wisdom

DECLARATION

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work.

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Summary

This dissertation substantiates in a collection of essays that examine the variation of rebels' and insurgents' violence in civil conflict. Building on the literature on the micro-foundations of civil war, we examine the impact of conflict processes onto said variation. That is, we investigate the reactive patterns of rebels' violence as well as their unfolding in time and space, in response to specific counterinsurgents' and incumbents' tactics on the battlefield. In the three papers we focus on the specific cases of Iraq, Syria, and Lebanon to illustrate the how different 'stimuli' may affect the geo-temporal activities of insurgents. The essays rely on fine-grained geo-referenced conflict data as well as on spatial data describing locations and times where these events occur. To explore the testable implications derived throughout the papers, we rely on multivariate spatial regression and matched wake analysis. The last contribution, a more forecasting oriented piece, employs likelihood-based methods based on generalized linear models for the analysis of count time series. The three papers are preceded by a broader introduction to the substantive field and by an extensive literature review (Chapter 1 and Chapter 2 respectively).

In Chapter 3, we seek to answer the following research question: why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not? In this contribution analyze the sub-national spread of violence proposing that types of violence exerted by different actors influence subsequent instances of conflict at the local level. We show that reactive violence by rebels is linked to the spatial variation of conflict and may be able to trigger horizontal escalations in contiguous or proximal areas. Accordingly, we contribute to the competing theories of deterrence and alienation to population-centric warfare with testable implications on quality and quantity of violence exerted by incumbents and counterinsurgents. We propose that horizontal escalation of rebels' violence is amplified by instances of indiscriminate violence in adjacent spatial units. Conversely, selective violence reduces the incidence of rebels' attacks. Secondly, we propose a link between deterrence and alienation-based explanations relying on the instances of violence against civilians by incumbents. We propose that violence against civilians in contiguous areas from the incumbent increases the instances of rebels' attacks. Yet, when this form of violence surpasses a certain threshold of incidence in contiguous areas, it severely reduces further attacks. We test these hypotheses conducting a dis-aggregated analysis at the sub-national level on a sample of spatial-cell/month observations covering Iraq, Syria and Lebanon from 2011 to 2019.

In Chapter 4, we turn our attention to a more specific form of rebels' violence: indiscriminate 'remote' violence. For this purpose, we use the incidence of Improvised Explosive Devices (IEDs). They have been one of the most common forms of indiscriminate violence employed by insurgents in contemporary asymmetric wars. In Iraq, for instance, they had a devastating effect, yielding more than half of the total coalition casualties between 2016 and 2017. Therefore, we seek to answer the following research question: why do some conflict zones exhibit more IED attacks than others? We

embarked in an enquiry to investigate what drives the variation in the timing of these attacks. The literature has emphasized the role of structural covariates such as geographic features of the contested area, territorial control, strategic locations, and the presence of natural resources. Less attention has been given to the nature of conflict events and reactive behaviors. In this piece, we aim to demonstrate how insurgents' activities on the field are influenced by the quality of counterinsurgents' violence. We draw from the literature on micro-foundations of civil war and on counterinsurgency to illustrate how indiscriminate violence systematically increases subsequent attacks. On the contrary, selective use of force is more efficient in reducing them. We empirically test our hypothesis on the Iraqi insurgency using SIGACT event data from 2016 coded by the US military. We estimate the relative and absolute effect of incumbents' indiscriminate violence. As for the former, we make use of Matched Wake Analysis to compare the post-treatment effect on IED attacks. To estimate the absolute effect of indiscriminate incumbents' violence we propose an approach based on the comparison of such events with synthetic counterfactuals as a simulated baseline. We craft heuristics for these conflict events using road networks and population settlements to help build a set of plausible locations where indiscriminate violence could have occurred but did not. This work makes two substantive and a methodological contribution by (1) evaluating the relative effect of indiscriminate incumbents' violence on IED attacks (2) attempting to offer a tentative framework for utilizing synthetic counterfactuals, and consequently (3) empirically testing the absolute effect of indiscriminate violence on insurgents' violence.

In Chapter 5, we look once more at the variation in IED attacks in an insurgency scenario as a proxy from asymmetric warfare. However, in this piece, we move away from a purely causal inference perspective, and we shift our attention to forecasting. Can we successfully predict waves of these attacks? Improvised explosive devices (IED) have been one of the most common forms of indiscriminate violence employed by insurgents in contemporary asymmetric wars. In Iraq they had a devastating effect, yielding more than half of the total coalition casualties between 2016 and 2017. Can we successfully predict waves of these attacks? This contribution presents a series of models that seek to predict the incidence of IED attacks in Iraq during the Iraqi Insurgency. Building on the literature on the micro-foundations of civil conflict and on counterinsurgency, we predict IED attacks relying on fine-grained daily events drawn from SIGACTs data. We focus, in particular, on types of actions carried out by the US-led coalition to capture the tit-for-tat nature of rebels' violence. Based on previous contributions, we seek to evaluate the predictive performance of belligerents' behaviors on the battlefield. Furthermore, having acknowledged the autocorrelation that characterize rebels' actions, we seek to model the latter to obtain accurate predictions of IED attacks. We test our models on a sample of daily observations based on the Iraqi Insurgency from 2004 to 2009, using likelihood-based methods for count time series. This paper contributes to the literature on conflict forecasting and presents and out-of-sample validation to inferential models based on reactive behaviors.

ACKNOWLEDGEMENTS

This project was made possible only through the generous contribution of the Department of Foreign Affairs and Trade with the Irish Research Council, which founded my research through the Andrew Grene Scholarship in Conflict Resolution under the Government of Ireland Postgraduate Scholarship Programme. Furthermore, I wholeheartedly thank the Grene family.

Many people have shared this journey with me throughout the years. First and foremost, I am grateful for the unwavering academic support of my supervisor, Dr. Thomas Chadefaux. He nurtured my research activity from its wake and guided me towards this final milestone. A special thanks goes to Dr. Constantine Boussalis, Dr. Roman-Gabriel Olar and Dr. Jesse Dillon-Savage. Their support and feedback have been determinant for the full enjoyment of this experience.

Together with Dr. Chadefaux and Dr. Boussalis, I have had the honor to co-author a paper with an incredibly talented young scholar that goes by the name of Dr. Silvia Decadri. Despite our differences, we grew friends from the very first day of the program and we worked together with a singular professional affinity.

A wholehearted and – more personal – thank you goes to my family, to Maria and to and my loved ones (including of course my three dogs: Tristano, Cagnaccio and Pina) who have always been supporting towards my professional goals and expectations. Every one of them, in different ways, gifted me with the chance to move to Ireland and work on my research. A special thought goes out to my grandfathers. Alas, they are not with us anymore, but they were always supportive and caring throughout my professional and academic growth.

I want to extend my appreciation to the whole Department of Political Science and to the whole school of Social Sciences and Philosophy. Thanks to Dr. William Phelan: working as Teaching Assistant for his modules was an extremely formative opportunity. A special thanks goes to Dr. Karsten Donnay and Dr. Sebastian Schutte: aside from being outstanding researchers and mentors, they are fantastic individuals, and I am grateful for the time spent together. Furthermore, I owe my gratitude to Dr. Antonello Maruotti for the continuous and long-lasting support and for all the opportunities he gifted me with (and of course for his singular statistician's patience when dealing with a social scientist). A special thanks undoubtedly goes to Dr. Marchetti Raffaele and Dr. Paolo Spagnoletti from Luiss University: they have always been supportive and offered me plenty of opportunities for professional growth. A wholehearted thank you goes to the guys of '*Codeocean*', who with their amazing platform (and some ad-misericordiam extra computing time) allowed me to run on the bunch of models that compose my dissertation without melting my laptop.

An acknowledgement section would not be complete without mentioning my friends and colleagues at Trinity College Dublin. Nothing cheers you up during a rainy day of Michealmas Term as a few pints (or '*a few scoops*') with such amazing people. Even though I wrote a full Ph.D. dissertation, it is extremely hard to appropriately recount all the reasons why they have been so important to me. Alan, Christian, Dave, Eleonora, Gavin, Giulia, Kevin, Marco, Oguzhan, Raluca, Stefan and Somya (yes, the order is alphabetical!): you really made my time in Trinity an amazing journey! A Ph.D. experience is solely made of research of course, but of plenty of Dungeons and Dragons sessions. Therefore, I want to thank my fellow adventurers Federico, Emanuele, Chiara, Marco and Paolo. Similarly, a special thank you goes to Barra and Oli. A special thanks goes to my ‘tatami comrades’ at Shotokan Ryu Shofukai Karate and to my Irish hosts at St. Paul Karate and Trinity Karate. A huge shout-out wants to reach also “Crossfit Rieti – Forged By Hammer”, Simone’s professionalism helped me a great deal in the final months prior to submission.

My friends at home played a big part in this adventure as well: Francesco, Giacomo, Francesco, Giovanni, Lorenzo, Nicola, Paolo and Valerio: knowing that you have a place to call ‘*home*’ makes one’s journeys more light-hearted.

A unique thanks goes to my beloved ‘*ducklings*’ Francesco and Riccardo: you guys really deserve to be acknowledged for your sincere friendship, long-lasting support. You will always have my appreciation.

Finally, a dissertation on civil conflict and counterinsurgency brought me to spend many days readings accounts from witnesses, bystanders, and special operations veterans. I want to remember all the fallen of the Italian armed forces, in particular the victims of the infamous Nasiriyah bombing. Furthermore, crossing the Atlantic, I want to offer a heartfelt acknowledgement to the brave who returned with a lesson to teach and stories to tell: Will Chesney, Mike Ritland, Jocko Willink, Leif Babin, Marcus Lutrell and “Johnny Walker”. Even more so, a moved thank you goes to the brave who did not return, whose deeds will live on through the survivors: Micheal Monsoor, Marc Lee, Matthew Axelson, Danny Dietz and Micheal Murphy. A special mention goes to Chris Kyle, who lost hist life while lending a helping hand to other veterans. Finally, a

special thank you goes to Cairo, probably the most famous ‘*good boy in tan*’, who saved countless lives with his work on the battlefield.

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1 Introduction

'*Violence can spread and contract in endogenous, self-feeding ways'(Zhukov 2012, 144)*

1.1 Motivation and contribution to the literature

There is a considerable variation in rebels' and insurgents' violence in civil conflict. Attacks vary in quantity and quality, as well in their locations and timing. Furthermore, this variation can be observed at different levels of analysis. As for the spatial variation – from an aggregated perspective – rebels in some cases push their war-effort beyond the borders of a single country (Buhaug and Gleditsch 2008; D. Byman and Pollack 2012), while in others they create strongholds within certain areas - even establishing forms of governance (Arjona, Kasfir, and Mampilly 2015; Kalyvas 2006). At the local level, we can observe similar patterns within regions and provinces (Bormann and Hammond 2016; Kibris 2021; Schutte and Weidmann 2011). Most of the literature on conflict has been focusing on the more aggregate level of analysis, producing mirabilia of the scholarly tradition and seminal contributions (Collier and Hoeffler 2004; Fearon and Laitin 2003; K. Gleditsch and Salehyan 2006). The main causes of conflict, as well as that of its spatial and temporal variations, have been identified in robust national-level indicators that embody the theoretical concepts of *motivation* and *opportunities*. The narrative of '*greed*' and '*grievances'* is in fact well-known by most – if not all – social scientists. In recent years, a new branch of the literature established itself adopting slightly different theoretical lenses. The so-called literature on the micro-foundations of civil war, delves into the heart of conflict zones to explain what Kalyvas (2006) calls '*the logic of violence*'. To put it in Cederman's words, this literature offers '*evidence that civil wars often contain micro-level actions that have little to do with the main conflict dimension of the war in question*'[1]. This outstanding theoretical work has set a prolific research agenda that have been leading scholars to analyze micro-dynamics of war such as the role of violence against civilians, reactive mobilization and local spatial features of the conflict zone (L.-E. Cederman, Weidmann, and Gleditsch 2011; Kalyvas and Kocher 2009; Kocher, Pepinsky, and Kalyvas 2011; Lyall 2009; Raleigh 2012; Raleigh and Hegre 2009; Schutte 2017b). The theoretical and empirical achievements have been impressive, and at the same time, the field is characterized by many exciting unexplored areas.

[1] See the advance praise on (Kalyvas 2006).

This work collocates itself in this branch of the conflict literature and specifically seeks to understand how conflict actions by rebels unfold in space and time. In particular, we investigate the role of incumbents' and counterinsurgents' actions of on the battlefield and their impact on their opposing side. This is in line with many recent work that – thanks to the growing availability of fine-grained data (Raleigh et al. 2010; Sundberg and Melander 2013; Zhukov, Davenport, and Kostyuk 2019) – seek to unravel the interactive processes between belligerents and how past events in conflict areas may influence new instances of violence (Bormann and Hammond 2016; Braithwaite and Johnson 2015; Kibris 2021). Rather than looking at '*why man rebel*'(Gurr 1970), the focus seems to be on '*how men rebel*' and on '*how conflict unfold'*. The great advantage of fine-grained data in this context, resides in the fact that they allow researchers to observe patterns and dynamics *'within'* conflicts. Accordingly, the overarching puzzle that originated this dissertation pertains the effect of indiscriminate violence – and by contrast of selective violence - perpetrated by incumbents and counterinsurgents. Many innovative works have studied whether indiscriminate violence has an escalating or deterrent effect (Kocher, Pepinsky, and Kalyvas 2011; Lyall 2009; Schutte 2017b), and yet many aspects of the relation between quality of incumbents' violence and rebels' reactions remain largely unexplored. In this view, this work aims to contribute to unveil the spatial and temporal reactions of rebels to indiscriminate violence. Each paper deals with a slightly different aspect of this broader puzzle. The choice of these two types of violence rest upon a twofold rationale. Firstly, the literature places a great emphasis on these two strategies that belligerents can adopt. They are often time portrayed as driven by different incentives and conditioned by different factors (e.g., territorial control). Conversely, the study of their effects has received comparatively less attention. While it is true that belligerents have other strategic options[2], indiscriminate and selective violence are the main mediums of 'direct' engagement between warring parties. Furthermore, as the literature and the results show, they seem to be particularly relevant in shaping the geo-temporal evolution of conflict. Secondly, in empirical terms assessing their effect is particularly relevant for counterinsurgents. As detailed in **Chapter 3**, there has been a long tradition of considering indiscriminate violence as the go-to for regular troops fighting an asymmetric war (e.g., the case of Vietnam). Yet, as this dissertation will argue, this choice may yield negative results.

[2] Violence against civilians is a notable example. Further details are presented in **Chapter 3**.

Before delving into a more specific explanation of the three contributions presented here, it is worth clarifying that, while the first research paper (**Chapter 3**) focuses on the broader category of '*civil conflict*'[3], the papers in **Chapter 4** and **Chapter 5** analyze a specific form of civil war: *insurgency*. Based on the seminal contribution of Kilcullen (2010), which in turn resonates the words of the US military field manual (US Army and US Marine Corps 2008) – an insurgency is '*an organized, protracted politico-military struggle designed to weaken the control and legitimacy of an established government, occupying power, or other political authority while increasing insurgent control*' (Kilcullen 2010, 1). To bring it closer to the literature on civil war, it resembles what UCDP (N. P. Gleditsch et al. 2002) defines as an '*incompatibility concerning government*'[4]. This definition slightly narrows the scope of the interaction we analyze in these specific contributions as we mainly consider a single dyad of insurgents and counterinsurgents. Having clarified the domain of analysis, this introduction proceeds to present the single contributions.

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[3] See the extensive literature review in **Chapter 2** whereby we illustrate the definition used in this thesis.

[4] Or 'an incompatibility concerning government and territory' in some cases.

1.2 Unveiling the escalating spatial effect of indiscriminate violence

In the first paper, we investigate how violence in civil war unfolds in space and time. Starting from the observation of the geo-temporal variation of rebels' violence, we proceed to present our puzzle. The spatial dimension of violence is particularly thought-provoking: we know that civil wars tend to break out in a relatively small number of countries. Roughly 60% of civil conflicts from 1946 to 2013 occurred in just 30 countries (Bormann and Hammond 2016), depicting what the literature commonly label as the 'conflict trap' (Collier 2008). A vast host of prominent authors have discussed how part of this variation may be a by-product of a diffusion process. That is, events and happening in conflict zones may exert a considerable influence on the risk of similar events happening elsewhere (K. S. Gleditsch 2007). While for instance the Syrian civil war spilled over into Iraq, Lebanon and Turkey, the conflicts in South Sudan and in the Central African Republic clustered in a relatively limited area. A similar pattern is observable at the local level (Bormann and Hammond 2016): conflict zones can exhibit varying levels of violence with hotspots – whereby violence rages on more fiercely - mostly clustering in proximity of each other.

What we know from the broader literature on spatial diffusion is that ongoing civil wars increase the risk of conflict both in neighboring countries (Buhaug and Gleditsch 2008) and in subnational areas (Bormann and Hammond 2016). Certain structural factors increase the likelihood of this dynamic of contagion, such as refugee flows or geographic characteristics (Forsberg 2014a; K. Gleditsch and Salehyan 2006). However, factors associated to the first strand of literature have several limitations. In first place, they are commonly operationalized as country-level and relatively time invariant indicators. Accordingly, while they can tell us which country experience more risk of diffusion, they do not provide further indications on which subnational areas are experiencing a more concrete risk. Comparatively less attention has been given to '*conflict processes*'. Yet, as shown by the literature on the micro-foundations of civil war (Kalyvas 2008), the latter are crucial determinants that shape the geo-temporal evolution of conflict. That is, types of violence and nature of the actors that perpetrates them influence subsequent instances of conflict (Hegre, Østby, and Raleigh 2009; Kibris 2021; Linke, Witmer, and O'Loughlin 2012; Lyall 2017; Schutte 2017b; Schutte and Weidmann 2011; Townsley, Johnson, and Ratcliffe 2008; Weidmann and Ward 2010). Recently, scholars have been focusing on the explanatory power of rebels' relative capabilities (Holtermann 2016), resources and climate (Carter and Veale 2015; Harari and La Ferrara 2018), road networks and logistics (Salvi, Williamson, and Draper 2020; Zhukov 2012), incapacitating effects on warring sides (Kibris 2021) and retaliatory behaviors (Braithwaite and Johnson 2012, 2015; Linke, Witmer, and O'Loughlin 2012).

In the first paper we contribute to this last branch, insisting on the analysis of the tit-for-tat nature of local conflict unfolding. Specifically, we focus on rebels' attacks as an output of specific incumbents' and counterinsurgents' forms of violence. We therefore adopt a dis-aggregated approach towards belligerents' actions and seek to answer the following research question: *Why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not?* We proceed giving particular attention to the supposed escalating effect of indiscriminate violence, that, in turn, may lead to spatial diffusion of violence. We resort to a theoretical framework centered on the role of local adversarial incentives. That is, we expand the current theoretical scenario suggesting that indiscriminate violence is a key element in determining whether the conflict spreads in space or not as a reactive phenomenon. Specifically, we use the theories of deterrence and alienation and derive testable implications on quality and quantity of violence exerted by incumbents. Firstly, we propose that horizontal escalation of rebels' violence is amplified by instances of indiscriminate violence in adjacent spatial units. Conversely, we expect selective violence to reduce subsequent attacks. Furthermore, turning our attention to the interaction with the populace, we propose a link between deterrence and alienation theories. We propose that violence against civilians in contiguous areas perpetrated by incumbents result in increased instances of rebels' attacks. Yet, massive civilians' targeting severely reduces further attacks creating a deterrence mechanism. We test our hypotheses conducting a dis-aggregated spatial analysis at the sub-national level on a dataset of spatial-cell/month observations covering Iraq, Syria, and Lebanon. Our data cover a time-span ranging from 2011 to 2019 and makes use of PRIO-GRID (Tollefsen et al. 2016; Tollefsen, Strand, and Buhaug 2012) as well as integrated events data from the Cross-National Data on Sub-National Violence (Zhukov, Davenport, and Kostyuk 2019). Events from this source, are integrated and disambiguated making use of 'Matching Event Data by Location, Time and Type' (Donnay et al. 2019). The results of the empirical tests are in line with our prior expectation and seem to confirm our hypotheses.

As for the specific contributions of this piece, we foresee three advancements in the conflict research literature. Firstly, we assess the prevalence of reactive rebels' violence and its spatial dimension. Secondly, we tie the concepts of reactive escalations and spatial diffusion of conflict. Finally, this first paper aims to inform decision-makers and practitioners, providing an evaluation of the factors that increase the conflict-proneness of different areas.

1.3 Geo-temporal patterns of Improvised Explosive Devices: a causal analysis of how counterinsurgents indiscriminate violence fuels rebels' attacks.

There is a considerable variation in insurgents' attacks in civil wars both in spatial and temporal terms. A vast majority of these attacks are indiscriminate in nature, particularly against regular troops, and consists in Improvised Explosive Devices (or IEDs). IEDs are made of relatively easily accessible materials and have constituted a prevalent phenomenon in both Iraq and Afghanistan. Prominent academic works (Braithwaite and Johnson 2012, 2015; Kibris 2021) have illustrated their prevalence in war-torn Iraqi cities. And yet, some sub-national areas remained relatively safer from IED attacks. The latter imposed massive costs in human lives to the US-led coalition forces. We know that roughly 65% percent of the coalition casualties have been caused by IEDs between 2006 and 2007 in the wake of the so-called 'surge'. Furthermore, they yielded a tragic number of civilians casualties. In this paper, we investigate this specific form of rebels' violence and formulate the following research question: *why do insurgents carry out IEDs attacks in specific location and at a specific timing*? The specific choice, aside from the dramatic figures presented above, is motivated by the peculiar nature of these attacks. Regular troops normally act in a condition of technological and organizational superiority: IEDs attacks can counter said superiority. That is, these attacks are incarnate the typical nature of asymmetric warfare, whereby insurgents seek to overcome the technological and organizational gap through guerrilla techniques. All in all, we maintain that the choice of IED can serve as a proxy for the broader strategic array of indiscriminate violence.

Scholarly investigations on IEDs have shown their linkages with local infrastructure of various sort, highly populated areas and previous successful attacks (Braithwaite and Johnson 2015). Once more we resort to the nature of interactions between insurgents and counterinsurgents as they may shape subsequent behaviors of warring parties, influencing the time and the location of their strikes. In this second paper we propose that the logic of reactive behaviors is crucial to explain - and eventually predict - where and when IED attacks will be carried out. That is, indiscriminate violence perpetrated by counterinsurgency forces may exhibit a strong causal link with geo-temporal patterns of these attacks. This paper aims to contribute to the prominent body of literature on counterinsurgency strategies by employing a disaggregated approach to isolate the relative and absolute causal of effect of counterinsurgents' indiscriminate violence on insurgents' attacks. Theoretically speaking, indiscriminate violence has been claimed to create '*deterrence*' (Braithwaite and Johnson 2015; Toft and Zhukov 2012) thus discouraging further attacks and disrupting the capabilities of rebels to carry them out respectively (Kibris 2021). Yet, as discussed in the first paper, belligerents actions possess an intrinsic tit-for-tat nature (Braithwaite and Johnson 2015; Kibris 2021; Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017b). In this context, indiscriminate violence by counterinsurgents may trigger reactive behaviors by insurgents that substantiate in more IED attacks. Furthermore, we expect the latter to be carried out in proximity of previous counterinsurgency operations. To verify the causal value of our testable implications, we follow a twofold empirical strategy. Firstly, we test our hypothesis against the exertion of selective violence – i.e. the control - in similar geo-temporal windows resorting to Matched Wake Analysis (Schutte and Donnay 2014). Accordingly, we expect to see an increase in the number of IED attacks after a given geo-temporal window receives the treatment i.e., counterinsurgents' indiscriminate violence. Secondly, we attempt to craft a synthetic baseline based on geographical factors to estimate the absolute effect of indiscriminate violence. For this purpose we create two spatial heuristics based on the presence of primary road networks (Salvi, Williamson, and Draper 2020; Zhukov 2012) and population settlement. We then simulate synthetic events within these buffer areas and use them as controls in Matched Wake Analysis. To build our indicators on indiscriminate and selective violence, as well as for IEDs, we use event data from the Significant Activity (SIGACTS) Reports from 2006 on the Second Iraqi War. The results seem to confirm our hypothesis. However, the absolute effect evaluation – through simulation of synthetic controls – suffers from several limitations and an over-estimation of significant effects.

This study aims to enrich the field of conflict research with a deeper causal understanding of counterinsurgency practices and their results on the battlefield. On the more societal edge, it constitutes a potentially clarifying benchmark for strategies adopted by military organizations.

1.4 Predicting the incidence of IED attacks in Iraq: forecasting conflict-related count time series

In this paper, our attention is focused once more onto the variation of IED attacks. Rather than taking on a causal-oriented quest, this time we seek to provide accurate country-wide predictions on the incidence of those actions. As mentioned above, IEDs have been a dominant strategy in contemporary insurgencies. The widespread usage of those weapons both in Iraq and Afghanistan substantiated in an unprecedented number of attacks in the form of vehicle-born explosives, rigged bunkers and 'pseudo-mines'. The coalition forces have attempted to mitigate the risk stemming from these weapons, but without ever succeeding in eradicating them. Counterinsurgents cannot de-facto out-armor or out-engineer the problem of IEDs (Moulton 2009). This is extremely problematic given that one of the key advantages of regular troops in insurgencies is the technological superiority: IED attacks almost nullify this strategic vantage point and forces counterinsurgents to adopt more complex strategies to counter opposing forces.

Accordingly, this paper seeks the answer the following research question: *can we successfully predict the incidence of IED attacks?*

We therefore present a series of models to predict the number of IED attacks in Iraq during the Iraqi Insurgency (2004-2010). In line with the overarching puzzle, we focus two main categories of predictors. Firstly, we seek to model the dependency between insurgents and counterinsurgents actions. In particular IEDs seem to cluster temporally and spatially around counterinsurgency operations (Braithwaite and Johnson 2012, 2015). In this paper, we aim to test the predictive power of our previous findings developing forecasting models that include counts of disaggregated conflict events classified by types of actions and types of actors. Particular attention is once more given to the role of indiscriminate violence as we expect the latter to be a strong predictor of IED attacks. Secondly, we know from previous works that insurgents attack tend to cluster in time and space (Braithwaite and Johnson 2012; Brandt, Freeman, and Schrodt 2011; Townsley, Johnson, and Ratcliffe 2008). In this paper we want to account for their temporal serial correlation and make use of the latter to obtain better predictions. In simple terms, we posit that past incidence of IED attacks, as well as their past trends over longer periods of time, can be strong predictors of future incidents.

In practice, we test a novel technique to forecast the incidence of IED attacks at the daily and weekly level. Once more we make use of SIGACTs data to obtain countrywide counts of these incident that will serve as our dependent variable. Furthermore, we aggregate event data to obtain counts of other relevant conflict processes depicting counterinsurgents' actions. As for the modeling, we employ a likelihood-based estimation for count time series that follows generalized linear models. These methods are provided in the *tscount* R-package (Liboschik, Fokianos, and Fried 2017) and provide an efficient modeling option for serial correlation of the response variable. Furthermore, they allow us to account for the conditional mean of the process which in turn is related to its past values, past observations and to covariates (Liboschik, Fokianos, and Fried 2017, 1). Our paper succeeds in providing relatively accurate forecasts of IEDs incidence in a counterinsurgency scenario.

As for the contributions of this third paper, we seek to expand our knowledge in the literature on micro-foundations of civil war and in the literature on counterinsurgency. Most importantly, we assess the predictive power of reactive explanations to rebels' attacks that constitute the theoretical pillar of this dissertation. In methodological terms, we test a novel approach to model count time series and apply it to conflict data.

2 LITERATURE REVIEW

2.1 Introduction

Why do civil conflicts arise? There is a considerable variation in civil war onsets and unfolding patterns. Since 1945, their occurrence has been increasing almost linearly (Fearon and Laitin 2003). Just in 2019 they yielded almost 100.000 fatalities (See **Errore. L'origine riferimento non è stata trovata.**) and resulted in severe spill overs that harmed the social, political, and economic fabric of political systems. As Gleditsch noted (2007), the majority of extant studies has focused on the variation of civil war occurrence framing it as a purely intrastate. That is, scholars have identified the main determinants for civil conflicts in a handful of domestic structural features. By extension, until recently they have been regarded as relatively self-contained and unitary events.

However, the geographic distribution of these conflict – and of the events that they encompass - may lead to an intuition regarding their interconnectedness. In other words, their spatial clustering suggests that seemingly distinct clusters of violence and conflict are in reality linked. That is, events and happening beyond the borders of a country or beyond a certain administrative units might exert a considerable influence on the risk of new events (K. S. Gleditsch 2007). Accordingly, it is worth wondering why some civil wars – or even forms of violence - spread into neighboring areas while others remain clutched to their zone of origin where the spark was ignited.

In terms of countries for instance, while the Syrian civil war has spilled over into Iraq Lebanon and Turkey, the conflicts in South Sudan, the Central African Republic and Ukraine have remained largely contained. Similarly, the war in Rwanda spread into Zaire whilst, the Balkans' conflict, against practitioners' expectations, did not reverberate in Eastern Europe (Black 2013).

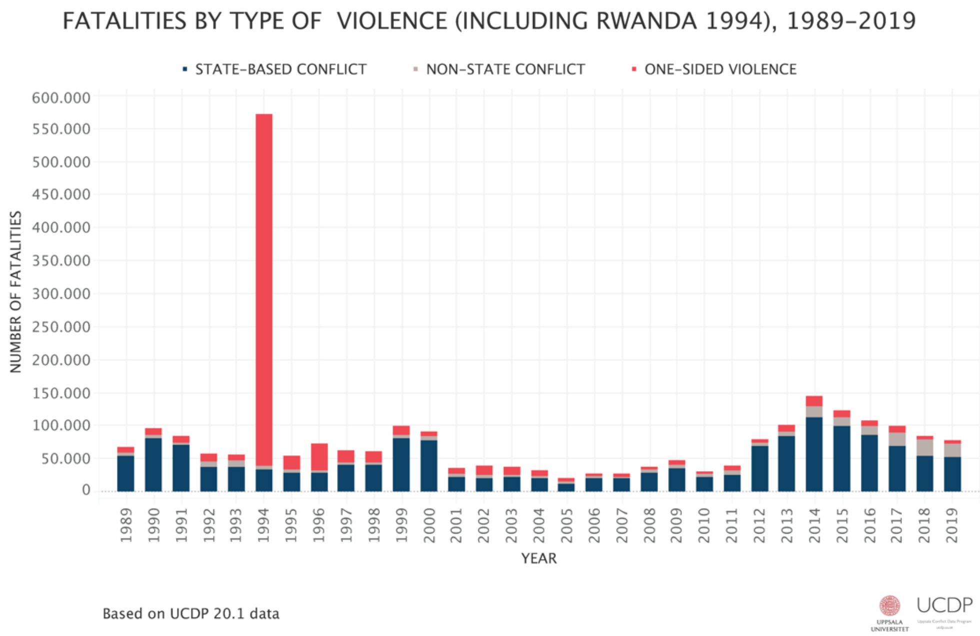

Figure 1: Fatalities by Type of Violence 1989-2019 – UCDP 20.1 (N. P. Gleditsch et al. 2002; Pettersson and Öberg 2020)

What we know from the growing literature on geographically contiguous outbreaks is that civil wars and violence do propagate transnationally and sub-nationally (Bormann and Hammond 2016; Buhaug and Gleditsch 2008). The literature has shown as certain structural factors increase the likelihood of this dynamic of contagion: such as refugee flows or geographic characteristics (L.-E. Cederman et al. 2013; K. Gleditsch and Salehyan 2006; Turkoglu and Chadefaux 2019).

The purpose of this first chapter is that of providing a review of the main works that analyse the spatial variation of civil conflict. The resulting observations and gaps will highlight the main areas of contribution provided by the dissertation. Firstly, we will provide a brief overview on civil wars highlighting the main features of this type of armed conflict and discussing its principal determinants. Secondly, we will present several alternative explanations for the outbreak of civil wars delving into the debate over Greed and Grievances. We will then build on a more recent strand of literature to assess the transnational – and transregional - dimensions of civil war and, consequently, to define the process of 'diffusion' and its main determinants, both at the 'macro-level' and at the 'micro-level'. Lastly, this piece will offer a brief review on the ever-growing literature of conflict forecasting discussing how a disaggregated approach to civil conflict studies may contribute to that strand of research.

2.2 Civil wars: prevalence, recurrence, and accumulation

Civil wars - broadly defined as a contested incompatibility over government and/or territory between two parties (N. P. Gleditsch et al. 2002) - are the indeed the most prevalent type of conflicts in the contemporary times. Accordingly, there is a considerable temporal variation in intrastate wars outbreak. Approximately 225 civil conflicts erupted from 1946 to 2001, with more than 110 emerging after 1989. In 2001, 34 were being active in 28 countries (N. P. Gleditsch et al. 2002). Among those, in January 2001, the National Liberation Army started a fierce rebellion for constitutional concessions in Macedonia while in May a branch of the military attempted to seize power in the Central African Republic (N. P. Gleditsch et al. 2002). This trend of new onsets has been increasing linearly since the end of the Cold War leading to a naive 'conventional wisdom' over their origin. In fact, these conflicts were largely considered as a direct heritage of the bipolar order's collapse. That is, intrastate armed conflicts were considered a spawn of the newly established international system that allowed the exacerbation of pre-existing clashes of ethnic and religious nature (Fearon and Laitin 2003). In their seminal contribution Fearon and Laitin (2003) demonstrated that the prevalence of intrastate wars is however product of a progressive accumulation of unresolved conflicts originated in the 1950s and 1960s, thus originating well before the end of the Cold War.

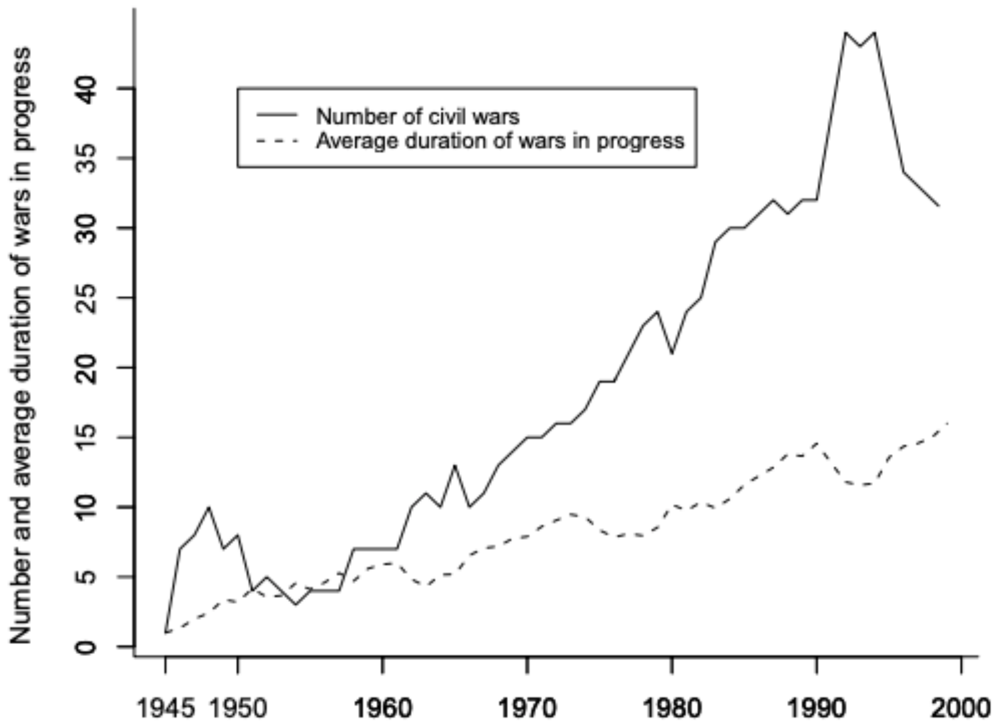

Figure 2: Number and average duration of civil wars in progress (1945-1999) (Fearon 2004, 276)

More specifically, civil wars between 1945 and 1999 had an onset rate of 2.3 per year and a settlement rate of 1.85 per year. Moreover, their average duration has been progressively increasing (See Errore. L'origine riferimento non è stata trovata.)(Fearon 2004; Fearon and Laitin 2003).

On the other hand, structural international factors, such as drops in prices of exports and third-party interventions seems to exert a palliative effect (Collier and Hoeffler 2004). Moreover, (Fearon 2004) has identified co-variates related on the type of conflict creating five conflict classes. In particular, *'sons of the soil wars'* (Fearon 2004, 275) and conflicts whereby rebel groups fund themselves from contraband tend to be more persistent than others. Their effect therefore reverberates for longer timespans both at the country level and at the very local level. Conversely, conflicts stemming from coups appears to be relatively short, together with anti-colonial-wars and post-USSR break up conflicts. Having described the main features of these kind of conflict - and before delving in their supposedly infectious natures - we will know consider a handful of alternative explanations for new onsets.

2.3 Why Men Rebel? Explanations for the outbreak of Civil Wars

2.3.1 A story of Greed and Grievances

"In the end, the wars resembled the movies images of the American Wild West or of gangland Chicago, and they often had less to do with nationalism than with criminal opportunism and sadistic cruelty, very commonly enhanced with liquor." (J. Mueller 2000, 92)

At the theoretical level, the first contemporary explanations for civil conflict onsets have highlighted the role of grievances. Defining the latter has been an undertaking for many scholars as framing their scope - and finding a suitable operationalization - has been an extremely controversial and non-trivial task. As Cederman, Weidmann, and Gleditsch (2011, 478) noted, *"most of the contemporary* *literature regards explanations rooted in political and economic grievances with suspicion"*. Classical contributions (e.g. (Davies 1962)) have insisted on the role of frustrations resulting from asymmetries in aspirations and actual conditions. Such an approach provided the literature with an impulse to move towards a series of more psychological analyses. That branch of literature ultimately coalesced in the 'relative deprivation theory' (Gurr 1970). This dissatisfaction-based explanation was challenged by Tilly and Snyder (1972) and the scholarship progressively moved towards an explanation for conflict onsets based on opportunities. That is, 'discontent and frustrations' are not sufficient causes for 'mobilization and revolution', as upheavals are ultimately determined by resources and by the organization of the contenders (Tilly 1978). Hence, mobilization and conflict were framed as a collective action problem and the literature started to place a particular emphasis on the incentives that prompted mobilization taking into account its imposed costs.

Much later, vis-a-vis the hardships and hurdles faced in quantifying and localizing grievances the literature was pervaded by an open and declared 'grievance-skepticism' (L.-E. Cederman et al. 2013; L.-E. Cederman, Gleditsch, and Buhaug 2013). Collier, in particular, claimed that "*rebel movements themselves justify their actions in terms of a catalogue of grievances: repression, exploitation, exclusion*"(2008, 18) and openly deemed the discourse on grievances as 'self-serving'. Accordingly, Collier and Hoeffler (2004) proposed a different portrait for rebels. Instead of being depicted as patriotic heroes fighting against grievances, they turned into 'rent-seekers'. Making use of a global dataset and extensive data on structural characteristics, Collier and Hoeffler proposed that while "*according to popular perceptions grievances are often seen as the main causes of rebellion [...] those factors which determine the financial and military viability of a rebellion are more important than objective grounds for grievance*" (2004, 563). Estimating two competing models of 'greed' and 'grievance', they tested and confirmed the pre-eminence of the former over the latter thus adopting a 'labour market' stance towards civil conflicts (L.-E. Cederman, Gleditsch, and Buhaug 2013). In a nutshell, looking at the 'finance of civil war' they claimed that the likelihood of conflict is higher whereby the opportunity cost of engaging in a war is low (Collier and Hoeffler 2004). Furthermore, they have shown how the concept of 'opportunity' is further reinforced by the presence of local characteristics of the environment: in this context natural resources constitute another relevant determinant. Fearon and Laitin (Fearon and Laitin 2003), adopting a similar stance towards ethnic grievances, maintained that we have "*little evidence that one can predict where a civil war will break out by looking for where ethnic or other broad political grievances are strongest*" (2003, 75). In particular, they framed the discourse on opportunities – as opposed to motivations - proposing a theory encompassing the role of the incumbent state and the role of peripheries.

As for the empirical support, a large body of literature have created a strong consensus around country-level indicators that covaries with the occurrence of intra-state conflicts and local violence. Among others poverty[5] and the presence of natural resources seems

[5] In the authors' words poverty "[…] marks financially and bureaucratically weak states and also favours rebel recruitment political stability"(Fearon and Laitin 2003, 75).

to play a major role in shaping the instances between war and peace and more specifically in influencing the opportunity cost of taking up arms (Collier 2008; Collier and Hoeffler 2004; Fearon and Laitin 2003; Hegre 2001). However, whether scholars and practitioners should look at ethnicity and ethnographic cleavages or not is still a debated issue. While some argues that these features are the essential cradle of civil conflicts and local violence (L. Cederman, Girardin, and Gleditsch 2009), others provided evidence that "*after controlling for per capita income, more ethnically or religiously diverse countries have been no more likely to experience significant civil violence*" (Fearon and Laitin 2003, 75).

To conclude, the main issues in the Greed and Grievances debate - their merits notwithstanding - pertains the blurred line between them. While in conceptual terms the division between the two dimensions is relatively stark and straightforward to grasp, in the empirical domain their measurement as mutually exclusive concepts is extremely difficult.

2.3.2 Civil Wars as self-contained and domestic phenomena

Are civil wars purely domestic phenomena? Can we look at them as unitary blocks or 'standalone' instances of violence? As Gleditsch (2007) argued, the majority of works have ascribed civil conflicts to a purely domestic – and by extension self-contained - dimension. More succinctly, while looking solely at country-specific structural characteristics, Large-N studies have been roosted onto a 'close polity assumption'(K. S. Gleditsch 2007). That is, scholars have often underestimated - or even ignored - the role of transnational, transregional and 'trans-provincial' traits and linkages among actors (K. S. Gleditsch 2007) that latter are most commonly considered in works on mediation and interventions (Regan 2002). Conversely, many works on specific cases have acknowledged how third parties might exert a considerable influence on the onsets of civil war.

Yet, a strand of the literature has contributed to challenge this strict assumption of 'leakproof' spatial units. Weiner (1997) for instance studied the transnational effects of civil conflicts with regards to refugee flows and acknowledging the role of 'Bad Neighbors and Bad Neighborhoods'. Furthering the argument, Ward and Gleditsch (2002) have studied the effect of regional interdependence on conflict, finding evidence that that the risk of conflict increases when neighbors are in conflict. Similarly, Sambanis (2001) empirically demonstrated that '*that living in a bad neighborhood, with undemocratic neighbors or neighbors at war, significantly increases a country's risk of experiencing ethnic civil war*'(Sambanis 2001, 259). These results seem to particularly accurate as they have been proved robust in different specifications of the models and on different cases. Hegre and Sambanis (2006), for instance, in their Sensitivity Analysis, confirmed '*a strong neighborhood effects of civil war*'(Hegre and Sambanis 2006, 533). In sum, treating civil conflicts as purely domestic[6] phenomena omits the crucial observation that '*spatial proximity increases the opportunity for conflictual and cooperative interactions between states'* - or other collective actors - *'as well as the*

[6] Domestic, here, refers not only to a State perspective but is meant to encompass different spatial units.

willingness of leaders to engage in particular types of behavior'(K. S. Gleditsch 2007, 295).

Building on the previous section, an alternative explanation over the origins of civil violence implies a certain degree of connection between distinct conflicts. As Forsberg (2014a) noted, virtually every internal conflict has consequences that reverberate well beyond its original perimeter: i.e. the colonial wars in Africa and, on the more mundane scale, civil wars in West Africa, the Great Lakes region, and the Caucasus (Forsberg 2014b, 188). The spatial clustering of violence intuitively suggests that seemingly distinct civil wars are in reality linked - particularly within regions. That is, events and happening beyond the borders of a country might exert a considerable influence on the risk of new onsets(K. S. Gleditsch 2007).

Specifically, ongoing conflicts produce enormous and costly spillovers such as refugee flows or arms flows (K. Gleditsch and Salehyan 2006; Turkoglu and Chadefaux 2019) that reverberate on the risk further violence. This mechanism, commonly labelled as diffusion, contagion or horizontal escalation (Forsberg 2014a), has found flourishing grounds in the scholarly debate on interstate conflicts and protests (Most and Starr 1990). Broadly speaking, it has been described as a process whereby an event happening in a place i at time t affects the probability of a similar event taking place at time $t + 1$ in place j (Elkins and Simmons 2005; Strang 1991). A specific definition in the domain of intrastate conflicts has been given by Most and Starr (1990). In particular, they referred to spatial diffusion as a process whereby events of a given type in a given polity are influenced by similar - and posterior - events in other polities.

As Forsberg (Forsberg 2014a) acknowledged, such an explanation for conflict onsets posits several difficulties due to the unobservable nature of the process. That is, while we are able to observe the actual outcome of the variation - namely the outbreak of violence close to another hotspot - we cannot assess whether it occurred due to contagion or, alternatively, due to purely independent features. Moreover, even acknowledging a particular relevance of the neighborhood in shaping the risk of violence, said pre-eminence might have different rationales. On the one hand, observable spatial groupings of civil violence might be a result of matching clusters of conflict-associated characteristics (Elkins and Simmons 2005). On the other hand, an explanation of the aforementioned clustering may be that of diffusion. Buhaug and Gleditsch (2008) showed that conflict occurs in neighboring countries not only because of clustering of similar structural features in the area, but specifically - in some instances - because of a diffusion process. Vis-a-vis their seminal contribution, the latter has been largely accepted as the most consistent and empirically supported explanation for outbreaks in conflict-prevalent neighborhoods.

2.4 Diffusion and its determinants

Having acknowledged that conflict and violence do diffuse (Buhaug and Gleditsch 2008), the study of the mechanism of diffusion has followed two main approaches (Forsberg 2014a). In particular, some authors emphasized the covariates that make a country more vulnerable to new onsets vis-a-vis a conflict in a bordering country or spatial unit (K. S. Gleditsch 2007; K. Gleditsch and Salehyan 2006) whilst others proposed determinants revolving around 'infectious cases' (Black 2012; Forsberg 2014b) that might prompt new outbreak in the neighborhood. Thus, the scholarly debate encompassed the source-country, the target-country, and the dyad as a whole. Even though these different scopes originated different branches of research, the resulting determinants enjoy from a widespread consensus and are accounted as '*mediums*' that can either prompt or hamper diffusion.

Factors associated to '*infectious cases*' have been analyzed by Buhaug and Gleditsch (2008). Firstly, they tested if exposure to proximate conflicts influences the risk of contagion and – quite surprisingly - it turned out not to be the case. Rather, they found that the presence of separatist movements works as a catalyst for onsets in neighbouring areas. Separatists groups, in fact, are often uneven distributed with regards to the borders and might mobilize transnationally due to demonstration effects (Forsberg 2014b). The same authors proposed that higher death tolls might favor the diffusion process due to increased spillovers across borders. As Forsberg (Forsberg 2014a, 2014b) noted, however, the empirical support for this second claim is not as strong. Accordingly, the author suggests that high intensity conflicts might work as deterrent to discourage emulation. Furthermore, rebel success, particularly when it comes to territorial concessions, has been theorized to be a strong predictor for the mechanism of contagion. It has been argued that successful deeds may 'inspire' other rebel groups providing them with motives - or chances - to seize the momentum (S. Hill and Rothchild 1986; S. Hill, Rothchild, and Cameron 1998). Yet, Forsberg (2014b) tested this '*domino effect*' on a global scale and find no evidence supporting it. Conversely, peacekeeping and peace-enforcement operations have a strong negative association with onsets in neighboring countries (Beardsley 2011) .In this view, it is not a case that behind third-party interventions, there are often times motives roosted on the will to prevent spill overs and contain instances of violence (Fortna 2004).

As for '*target countries*', we know that pre-existing grievances constitute flourishing grounds for new hotspots of violence (Forsberg 2014a; Lake and Rothchild 1998). For such reason '*stability, control, protection from predation, the extraction of resources, and the ability to adapt and respond to unexpected crises*' (Maves and Braithwaite 2013, 313) constitute an effective aegis against onsets via contagion. In particular, stronger states are able to tame rebels relegating them to a more institutionalized form of dissent (e.g., legal actions). Consequently, an high state-capacity implies higher capabilities to face externalities and to rebound from spill overs and. Braithwaite and Maves (2013) further their enquiry finding that autocratic states that have elected chambers are more likely to experience onsets via diffusion. As for the ethnic composition, the fierce scholarly debate notwithstanding, there is a considerable consensus around the fact that ethnic polarization might favor contagion and escalations (Bhavnani and Miodownik 2009; L.-E. Cederman et al. 2013).

As mentioned above, some factors influence the dyad: while proximity might seem an obvious correlate, Forsberg (2014a) points how it is most commonly used as a mere selection criteria largely overlooking its significance. Moreover, religious and ethnic ties across borders seems to be strong predictors for onsets via diffusion (Forsberg 2014b; Fox 2004).

Source	Dyad	Target
Separatism (+)	Proximity (+)	State capacity (−)
High-intensity conflict (+)	Ethnic ties (+)	Repressive capacity (−)
Rebel success (+)	Religious ties (+)	Border control (−)
Peacekeeping (−)	Refugee flows (+)	Authoritarian regime with elected legislature (+)
Arms flows (+)	Ethnic polarization (+)	
Mountainous border (−)		
Long border (+)		

Table 1: Determinants of Civil War Outbreaks in Neighboring Countries (Forsberg 2014a, 192)

Refugees (K. Gleditsch and Salehyan 2006) and geographic features of the borders might influence the border control capacity of the two states, thus having a considerable influence on a new onset. On the same line, arms flows may ‘decrease the price of weapons and increase their availability, thereby making it relatively less expensive for aggrieved groups to mobilize insurgencies’(K. S. Gleditsch 2007, 295). Lastly, Gleditsch and Buhaug found that '*conflict is more likely when there are ethnic ties to groups in a neighboring conflict and that contagion is primarily a feature of separatist conflicts*' (Buhaug and Gleditsch 2008, 215). This result, ties to the idea that transnational and transregional ethnic linkages constitute a central mechanism of conflict contagion.

Even though scholars have successfully accounted for good part of the variation at stake, the aforementioned determinants are often context specific. Furthermore, they cannot explain conclusively why violence diffuses in some cases but not in others with similar structural conditions. These pitfalls, we argue, may stem from the scope of the analysis most studies on diffusion have adopted. The country-level perspective most often relies on relatively static indicators for both conflict processes and covariates: while successful many instances, this method of analysis focuses solely on the broader outcome. That is, most work focuses on identifying whether some structural characteristics – or ongoing conflict – of a neighbor play a role originating a conflict in the country of focus or not. Furthermore, by looking at countries, many contributions have been missing the dynamics and patterns of events that make conflict escalates or diffuse spatially. In this work, we want to look at how violence and conflict move in space in a more disaggregated and granular fashion. Firstly, horizontal escalations may happen virtually everywhere if certain conditions are met: the presence of a border – particularly in war-torn areas - may be largely overestimated. Moreover, using common taxonomies for civil conflict[7], we may miss '*minor spillovers*' in close spatial units that are hardly irrelevant for that country, region, or province. Secondly, diffusion may happen through several medium, directly, or indirectly and does necessarily requires spatial contiguity. The next section will review the main works that addressed these gaps as well as those tied to the broader branch on the micro-foundations of civil war.

2.4.1 Direct and Indirect Diffusion

As seen above, diffusion might happen through several channels such as refugees flows or other transnational externalities. However, as suggested by Forsberg (2014a), it can occur in a more implicit - and stealthy - form. The same spillovers originated from a country in conflict, for instance, can affect not only the immediate neighbors but also other states, in or outside the region where the country is clutched. That is, spillovers may run through lines of trade, ethnicity, and diplomatic contacts. On this, authors have found '*evidence of significant collateral damage on economic growth in neighboring*

[7] Most often thresholds of inclusion based on Battle Related Deaths (henceforth BRDs).

nations [...] In addition, this damage is attributed to country-specific influences rather than to migration, human capital, or investment factors' (Murdoch and Sandler 2002, 91). In turn – as in a vicious circle - the worsened economic conditions are expected to increase the risk of conflict in the country – or area - suffering from the spillovers.

Even more intangibly, a conflict – even more so when it takes the form of an insurgency - might inform other actors that shares similar features and provide them with motives or chances for mobilizing. Bakke (2010) for instance proposes that insurgents might be able to "*copy and learn*" from outsiders. Specifically, building on the literatures on intrastate conflicts, social movements, and transnationalism, Bakke suggest that transnational insurgents might impact the choices of domestic movements and qualitatively test such hypothesis on the Chechen Wars. Apart from this form of strategic learning based on tactical information, others have suggested that insurgencies in an area might increase the perceived likelihood of success of other rebel groups in other – not necessarily contiguous – areas (S. Hill, Rothchild, and Cameron 1998; Lake and Rothchild 1998). The same logic can be extended to rebel successes and favourable outcomes from negotiations.

In sum, as Forsberg (2014) argues on the lines of Byman and Pollack (D. L. Byman and Pollack 2008), conflicts can actively increase the demands of specific groups and trigger a '*replication effect*' elsewhere. Despite its thought-provoking nature and the abundance of anecdotal recounts, this kind of approach has never been systematically implemented in Large-N studies due to the lack of actual data. In this view, recent advancement in data on perceived risks and in tensions (Chadefaux 2014, 2015, 2016) may constitute an invaluable assess to proxy the determinant of indirect diffusion.

2.4.2 Micro-diffusion

"Political violence is not always necessarily political identities and actions cannot be reduced to decisions taken by the belligerent organizations, to the discourses produced at the centre, and to the ideologies derived from the war's master cleavage"(Kalyvas 2003, 487)

While the aggregated scholarship has been the dominant one for many years – mainly due to the lack of fine-grained data - in more recent times a strand of literature has highlighted the importance of the 'microlevel'. That is, many scholars have been progressively focusing on a 'radical disaggregation'(L.-E. Cederman, Gleditsch, and Buhaug 2013) as a new way of conducting causal inference on the logic of violence at its roots and in its more local manifestations. As Kalyvas explains, the research program on the micro-dynamics of civil wars '*calls for the systematic collection of data at the subnational level and its sophisticated analysis. Compared to the macro level, a subnational focus offers the possibility of improving data quality, testing micro-foundations and causal mechanisms, maximizing the fit between concepts and data, and controlling for many*' (Kalyvas 2008, 397).

This new strand is particularly promising for studies on horizontal escalations or diffusion. A closer scope of analysis may enable researchers to zoom in onto the mechanisms the belie the '*broader output*' observed in country-level or aggregated studies. Many scholars have applied such perspective. In this view, Schutte and Weidmann (2011), studied how violence temporally and spatially diffuses within states making use of highly fine-grained geo-coded data from The Armed Conflict Location & Event Data Project (henceforth ACLED). They proposed that what scholars commonly call diffusion may occur through two inherently different mechanisms.

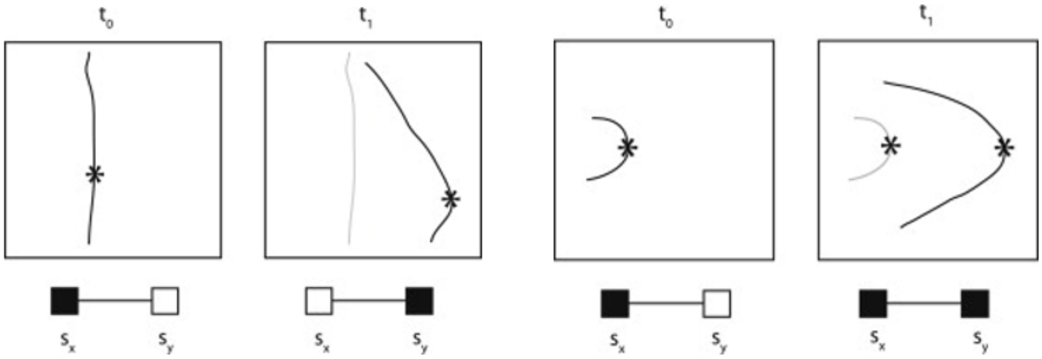

Figure 3: Relocation and Escalation Diffusion (Schutte and Weidmann 2011, 145)

Building on a study on the spread of criminal violence (Cohen and Tita 1999) they conceptualized and validated the patterns of *relocation* and *escalation*. As shown in **Figure 3**, they show that *relocation* essentially correspond to a shift of conflict activity in space. In the first figure we observe how the instance of violence that occurs in location s_x at time t_0, moves spatially to another location s_y at time t_1. The whole conflict activity shifts towards the new location with s_x [8]. As for escalation, the unfolding in space starts from a location s_x at time t_0 and *'infects'* location s_y at time t_1. That is, looking at the situation in t_1 we will observe two instances of violence. As

[8] The black and white squares below the spatial identifier s_x and s_y denotes whether the area is in conflict or not respectively at any given time.

we know from previous literature as well as from the observation of contemporary military campaigns, most of civil conflicts are characterized by unconventional warfare. Therefore, the authors expected these conflicts to largely exhibit an '*escalation pattern*'. The significance of the findings has been assessed with a Monte Carlo simulation that ultimately confirmed the main hypotheses.

Zhukov (2012) in its seminal contribution tested with an explanation based on logistics and road networks. This paper offers a glimpse of one of the most fundamental of these mechanisms: logistics. That is, the author placed emphasis on the transportation of personnel and equipment over a road network. As pointed out in the paper, diffusion cannot fall short of three main elements: a location experiencing violence, susceptible target location, and a channel of communication. In essence, "*strategy decides where to act; logistics brings the troops to this point*" (Jomini 1862, 69). Resorting to fine-grained data, Zhukov demonstrated that networks of transportation influence the cost of operations '*which facilitates the transmission of violence to new locations, but can also intensify competition for limited military resources between nearby battlefronts*' (2012, 144). He found that '*relocation*' is more common when dealing with insurgents' violence.

It is important to mention that both Schutte and Weidman (2011) and Zhukov (2012) based their study on a specific observation, namely that '*violence can spread and contract in endogenous, self-feeding ways*' (Zhukov 2012, 144). Yet, we do not know much about the mechanisms by which violence and conflict diffuse. That is, the influence of conflict processes on the unfolding of further violence has been comparatively understudied. Recent contributions have taken into account the role of these processes looking at the variation of indiscriminate violence determined by post-battle shifts in territorial control (Oswald et al. 2020), at the variation of violence against civilians in high-risk locations (Salvi, Williamson, and Draper 2020), and at the evolution of conflicts as influenced by incapacitating of previous violent events (Kibris 2021). Furthermore, starting from observations of armed groups compositions(Burg and Shoup 1999) authors have applied this micro-level analysis to violence diffusing through ethnic channels within the same country (Bormann and Hammond 2016). Having completed a review of the main works pertaining the spatial evolution of conflict, we now turn our attention to another crucial element that is intimately tied to the use of such models: forecasting of these events.

2.5 Explaining and predicting conflict: the importance of forecasting and the of disaggregated indicators

The value of predicting where conflict may struck have been growing throughout the year, despite an initial skepticism. Here, we argue that forecasting possesses an intrinsic value. Firstly, at the more societal level, it constitutes a bridge between scholars and policymaking. Officials of international organizations[9],

[9] This claim is based on consulting experiences of the author with institutional actors and stakeholders in the field of conflict prevention and mitigation.

governments and private organizations are growing more and more interested into the promises of quantitative methods for predicting events and crises – that often goes by the name of 'early warnings' or 'threat intelligence'(Baskerville, Spagnoletti, and Kim 2014; Moynihan 2009). These models are commonly implemented as full-fledged systems that can help organizations to take strategic level decisions as well as guide their more tactical and operational aspects, even in boots-on-the-ground scenarios, augmenting the situational awareness and the perception of risk of the operators (Chevli et al. 2006; Fraher, Branicki, and Grint 2017; Franke and Brynielsson 2014; Salvi and Spagnoletti 2021a).

As for the discipline of Political Science, conflict forecasting has been '*on the mind of many*'(Ward et al. 2013) however scholars had often veered to an accentuated emphasis on causal interpretation and statistical significance (Chadefaux 2017). Nevertheless, '*causal theories are considerably harder to verify than forecasts, and forecasts have the advantage of being observable implications of the same theories as the causal hypotheses*' (Beck, King, and Zeng 2000, 21). That is, by verifying and improving the accuracy of a predictive model we can obtain potentially illuminating insights that stems directly from casual theories. Furthermore, we can actively contribute to the work of practitioner: identifying strong predictors and better modelling strategies. Contemporaneously – on the more academic pitch - predictions can be used as a tool for validation and for robustness tests in order to reinforce models and – most importantly – preventing overfitting.

In a recent article Weidmann and Ward (Weidmann and Ward 2010) explored the possibility of using geography to obtain more accurate predictions. In particular, making use of geo-located event-data for the case of Bosnia, they estimated a temporally autoregressive model. The latter was then tested out-of-sample and compared to a standard regression with lagged variables obtaining more precise forecasts. More recently, Schutte (2016) designed a method to forecast hotspots of violence in civil wars using point process models. Several theory-driven determinants from the micro-foundation literature were tested as predictors for conflict areas on ten Sub-Saharan countries. The same author, used forecasting techniques to estimate local wealth – a strong predictor of conflict – through nightlight emissions (Weidmann and Schutte 2016). This shows how forecasting can be used to create valuable indicators that can be used to proxy for unobservable – or hardly available – data. On the same line recent works have extracted information from texts (Boussalis et al. 2021; H. Mueller and Rauh 2017) and then used them to forecast violent crises or upcoming violence.

2.6 Conclusion

Based on the previous analysis, we concluded that the study of diffusion poses several challenges for scholars and practitioners alike. In particular, the seemingly unobservable nature constitutes the gordian knot behind the full understanding of this process.

Is there such a thing as diffusion of violence – and more broadly of conflict? We do know that contagion happens at times, however how can we distinct between the latter and the clustering of similar structural features that generated the new hotspot of violence? The growing literature on the micro-foundations of civil conflict provides us solid theoretical foundations to explore the dynamics and the determinants that make violence escalate, relocate, and move through space. Much has been done – as detailed above – and yet the role of endogenous conflict events and reactive violence has received comparatively less attention. This is also due to the fact that while the intuition behind diffusion has a long theoretical tradition, its empirical assessment is extremely difficult due to the lack of specific measurable data.

The recent advancement in conflict-related data, in this context, may provide considerable room for improvement. Being able to observe, measure and use the '*endogenous and self-feeding ways*' by which violence spreads and contracts, we may be able to test and expand micro-level theories even further (Zhukov 2012, 144).

3 EXPLAINING THE SPATIAL VARIATION IN REBELS' VIOLENCE: REACTIVE ATTACKS BETWEEN DETERRENCE AND ALIENATION

ABSTRACT

Why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not? What we know from the broader literature on contagion is that diffusion does occur, and that certain structural factors affect it, such as refugee flows or geographic characteristics. Nonetheless, previous research has mainly focused on transnational instances of diffusion and few studies have analyzed the sub-national dimension of this phenomenon. Furthermore, while many scholars have studied the role of exogenous and structural covariates, conflict processes have been comparatively under researched. Moreover, most of these studies focuses on single countries rather than on broader – transnational - conflict spaces. Yet, as shown by the literature on the micro-foundations of civil war, conflict processes are pivotal determinants that shape the unfolding of wars. That is, types of violence, nature of the actors and tactical considerations have an effect on subsequent instances of conflict at the local level. Here, we show that reactive violence by rebels is linked to the spatial variation of conflict and may be able to trigger horizontal escalations in contiguous or proximal areas. Accordingly, we contribute to the competing theories of deterrence and alienation to population-centric warfare with testable implications on quality and quantity of violence exerted by incumbents and counterinsurgents. In first place, we propose horizontal escalation of rebels' violence is amplified by instances of indiscriminate violence in adjacent spatial units. Conversely, targeted violence, even in surrounding areas reduces the incidence of rebels' attacks. Secondly, we propose a link between deterrence and alienation-based explanations relying on the instances of violence against civilians by the incumbents. We propose that violence against civilians in contiguous areas from the incumbent increases the instances of rebels' attacks. Yet, when this form of violence surpasses a certain threshold of incidence in contiguous areas, it severely reduces further attacks. We test these hypotheses conducting a dis-aggregated analysis at the sub-national level on a sample of spatial-cell/month observations covering Iraq, Syria, and Lebanon from 2011 to 2019.

3.1 Introduction

How does violence in civil war unfolds in space and time? Civil conflict – and violent events that composes them - exhibits a considerable temporal and spatial variation. As recounted in **Chapter 2**, the salience of these political phenomena has been increasing in the aftermath of World War Two, and even more so after the end of the Cold War (Fearon and Laitin 2003). In 2019 alone, these type of conflict yielded almost 80.000 deaths and resulted in severe negative spillovers (N. P. Gleditsch et al. 2002; Pettersson and Öberg 2020).

The spatial dimension of violence is equally puzzling: civil wars tend to break out in a relatively small number of countries. Roughly 60% of civil conflicts from 1946 to 2013 occurred in just 30 countries (Bormann and Hammond 2016), leading to the so-called ‘conflict trap’ theory (Collier 2008). However, observing the geographic distribution of these conflicts, may lead to an intuition regarding their interconnected nature. In other words, their relatively close spatial clustering suggests that seemingly distinct hotspots of violence are linked - particularly within regions. That is, events happening in conflict zones may exert a considerable influence on the risk of similar events happening elsewhere (K. S. Gleditsch 2007). While the Syrian civil war exhibits a notable spatial variation, and has even spilled over into Iraq, Lebanon and Turkey, the conflicts in South Sudan, the Central African Republic and Ukraine have remained largely contained and clutched to specific areas. At the sub-national level, we can observe a similar pattern: a qualitative assessment of mapped conflict locations in Syria, Iraq and Lebabon (2011-2019) (See Figure 4) shows an evident clustering of armed conflict in certain areas but not in others – depicted as grey cells. Similarly, even conflict zones exhibit different levels of violence with hotspots mostly clustering in proximity of each other. As mentioned above, the spillover in other countries in the specific case of the Syrian civil conflict has been thoroughly documented. That allowed researchers and practitioners to observe the granular processes that drove the conflict to evolve in space and to expand – first locally and then transnationally (D. Byman and Pollack 2012; Salloukh 2017; Young et al. 2014).

Figure 4: Spatial variation of violence ($log10$ count of events) in Syria, Iraq and Lebanon (2011-2019) depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any violent event.

Introducing the temporal dimension into the broader picture, we can observe how some conflict tend to escalate over time and flood certain areas, whereby violence - particularly in '*irregular warfare*' - exhibits specific patterns (Schutte and Weidmann 2011). For example, in 1994 the province of Sud-Kivu (Democratic Republic Of Congo, henceforth DRC) witnessed a surge in insurgents' violence that subsequently spread in the adjacent regions and had severe spillovers in the whole country. Conversely, in western areas of the DRC, conflict events remained firmly clutched to their local origin showing a rather sparse distribution[10].

What we know from the broader literature on spatial diffusion is that ongoing civil wars increase the risk of conflict both in neighboring countries (Buhaug and Gleditsch 2008) and in subnational areas (Bormann and Hammond 2016). Certain structural factors increase the likelihood of this dynamic of contagion or horizontal escalation[11], such as refugee flows or geographic characteristics (Forsberg 2014a; K. Gleditsch and Salehyan 2006).

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[10] For further discussion see (Salvi, Williamson, and Draper 2020).

[11] For the sake of this paper, 'contagion', 'diffusion' and 'horizontal escalation' will be used interchangeably.

However, factors associated to the first strand of literature have several limitations. In first place, they are commonly operationalized as country-level and relatively time invariant indicators. Accordingly, while they can tell us which country experience more risk of diffusion, they do not provide further indications on which areas – of that same country - are more likely to experience diffusion. In other words, is the whole country experiencing the same risk? How do we define the '*neighbors at risk*'? Furthermore, spatially dis-aggregated approaches have often emphasized the marginal effect of territorial or demographic features (Raleigh and Hegre 2009) and the role of violence mostly dealt with controlling for spatial auto-correlation. Therefore, until recently, comparatively less attention has been given to conflict features or '*conflict processes*'. Yet, as shown by the literature on the Micro-Foundations of civil war (Kalyvas 2008), the latter are pivotal determinants that shape the unfolding of wars. That is, types of violence, nature of the actors and strategic considerations influence subsequent instances of conflict.

Several existing studies have explored the empirical domain of this research strand and have found evidence of interconnections between violent events (Hegre, Østby, and Raleigh 2009; Kibris 2021; Linke, Witmer, and O'Loughlin 2012; Lyall 2017; Schutte 2017b; Schutte and Weidmann 2011; Townsley, Johnson, and Ratcliffe 2008; Weidmann and Ward 2010). Factors that may drive the changes in space and time at the micro-level includes relative capabilities of rebels (Holtermann 2016), resources and climate (Carter and Veale 2015; Harari and La Ferrara 2018), road networks and logistics (Salvi, Williamson, and Draper 2020; Zhukov 2012), incapacitating effects on warring sides (Kibris 2021) and retaliatory behaviors (Braithwaite and Johnson 2012, 2015; Linke, Witmer, and O'Loughlin 2012). In this study we contribute to this last branch furthering the analysis of the tit-for-tat – or reactive - nature of local conflict unfolding. Specifically, we focus on rebels' attacks and actions as an output of specific incumbents' and counterinsurgents' behaviors on the battlefield.

We therefore build on this branch of conflict scholarship to answer the following research question and - more broadly - to investigate how and why conflict evolves in space adopting a dis-aggregated approach towards belligerents' actions.

RQ: Why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not?

We aim to show that the nature of exerted violence and the targets of violence by the incumbent and counterinsurgents have a considerable effect in shaping the subsequent actions of rebels. To do so, we resort to theoretical framework centered on the role of local – conflict-driven - incentives as the main motivations for diffusion of violence. That is, we argue that the patterns of rebels' violence may have an important reactive component. We expand the current theoretical scenario suggesting that reactive violence is a key element in determining whether the conflict spreads in space or not. Retaliatory behaviors have in fact been receiving growing attention to explain conflict escalations: plethora of qualitative studies and interviews have highlighted how these psychological/reactive motives play a major role in informing and shaping fighters' decisions (Balcells 2010, 2017; Boyle 2010; R. Hill, Gwendolyn, and Temin 2008; S. Hill, Rothchild, and Cameron 1998).

Accordingly, we contribute to the competing theories of deterrence and alienation to population-centric warfare with testable implications on quality and quantity of violence exerted by incumbents and counterinsurgents. In first place, we propose horizontal escalation of rebels' violence to be amplified by instances of indiscriminate violence perpetrated by the incumbent in adjacent spatial units. Conversely, targeted actions – or 'surgical attacks' against rebels, reduce the subsequent numbers of rebels' attacks. Moreover, we propose a link between deterrence and alienation theories of violence relying on the instances of violence against civilians. We propose that violence against civilians – perpetrated by incumbents - in contiguous areas results in increased numbers of rebels' attacks. Yet, large numbers of civilians' targeting events severely reduces further attacks creating a deterrence mechanism. We test our hypotheses conducting a dis-aggregated spatial analysis at the sub-national level on a dataset of spatial-cell/month observations covering Iraq, Syria, and Lebanon. Since reactive violence is most likely to happen in short time horizons, we adopt very granular scope of analysis for which this data are excellent candidates. The data cover a time-span ranging from 2011 to 2019 and makes use of PRIO-GRID (Tollefsen et al. 2016; Tollefsen, Strand, and Buhaug 2012) as well as integrated events data from the Cross-National Data on Sub-National Violence (henceforth xSub) (Zhukov, Davenport, and Kostyuk 2019). The repository allows to draw fine-grained event-data from 22 widely recognized data sources. Furthermore, events are integrated and disambiguated making use of 'Matching Event Data by Location, Time and Type' (henceforth MELTT) (Donnay et al. 2019). The results of empirical tests are in line with the propositions and largely confirmed the hypotheses.

This work makes three main scholarly contribution to the conflict research literature. In first place - in terms of substantive knowledge - we assess the prevalence of reactive rebels' violence and its spatial dimension. Secondly, we show the link between the concepts of reactive escalations and spatial diffusion of conflict. This stance is key for the methodological contribution to the study of sub-national variations in armed conflict dynamics. In fact, identifying which '*stimuli*' from the other warring side result in spatial spillovers may enable further – more detailed analysis – on the causal mechanism behind each of these determinants. Finally, this study aims to inform decision-makers and practitioners alike in evaluating what are the factors that increase the conflict-proneness of different areas and in identifying what are the least rewarding counterinsurgency strategies.

The paper is structured as follows: firstly, we will present the main concepts and the relevant taxonomy of conflict. Secondly, we present a brief literature review of the main contributions that analyze patterns of spatial diffusion: from there, we will present the theoretical fulcrum of this paper. Thirdly, we will delve into the specific case of the Syrian Civil War. Then, we will introduce the data, the models as well as the main results. Finally, we will present the conclusions and discuss the main findings as well as the limits of this contribution.

3.2 Concepts and taxonomy

Given the sub-national and dis-aggregated nature of the study, it is important to clarify the main concepts that will be presented throughout the paper. There are many definitions for civil conflict and wars, but they are broadly defined by the literature as a contested incompatibility over government and/or territory between two parties (N. P. Gleditsch et al. 2002) with one of them being a government. Normally, different datasets provide a minimum-threshold for inclusion of conflicts based on Battle-Related Deaths (henceforth BRDs). These thresholds may vary depending on the scope of analysis, but UCDP definition has found a widespread consensus in most recent literature. An armed conflict must yield at least 25 BRDs per year, while a civil war has a threshold of 1000 BRDs. Therefore, they are differentiated by severity. Conversely, this paper will use '*war*' and '*conflict*' interchangeably as we do not aim to focus on the different intensities but rather to focus on the micro-dynamics the trigger broader spatial escalations. Since we decided to focus on the '*local*' aspects of armed conflict, we adopt no threshold of inclusion in accordance with most recent studies and datasets in this branch of literature. As postulated by we define a civil conflict as '*armed combat within the boundaries of a recognized sovereign entity between parties subject to a common authority at the outset of the hostilities'* (Kalyvas 2006, 17). In our specific case, we make use of a three-countries collection of data whereby a variety of belligerent parties interacted within and across international borders.

Another key concept worth clarifying is that of '*diffusion*'. We adopt a rather shallow definition of this phenomenon. That is, diffusion is a process whereby an event happening in a spatial unit i at time t affects the probability of a similar event taking place at time $t + 1$ in a spatial unit j (Elkins and Simmons 2005; Forsberg 2014a; Strang 1991). For the sake of our argument, however we need to specify the meaning of '*similar*'. As discussed above, we aim to explain how specific form of violence by incumbents and counterinsurgents may trigger escalations of rebels' violence in their neighborhood. These '*categories of events*' are profoundly different as they are driven by different strategies, incentives and even doctrines. However, they have been commonly aggregated in the country level literature controlling for the presence of a neighboring spatial unit in conflict. Thus, we further refine the concept of diffusion as a process whereby specific dynamics of conflict occurring in a spatial unit i at time t at time t, affect the probability of reactive dynamics taking place at time $t + 1$ in a spatial unit j. This seemingly minor specification is key to show how only some conflict dynamics make violence spatially infectious.

3.3 Related Works

Civil conflict and violence have long been ascribed to a purely domestic dimension building on the so-called ‘*close-polity assumption*’(K. S. Gleditsch 2007). By extension, conflict themselves have been often looked at as self-contained political phenomena. However, empirical works have shown how some transnational and transregional factors (e.g., refugee flows, transnational linkages and bad-neighbours) can influence the risk of conflict (K. S. Gleditsch 2007; Sambanis 2001; Weiner 1997). Accordingly, neighborhood effects led some researchers to propose an alternative origin for the spatial clustering of wars and violent events. That is, events happening in a given spatial unit may exert a considerable influence on the risk of new outbreaks of violence. The scholarly work on conflict diffusion have been growing in recent years through a two-fold scope. An impressive number of prominent works have been analysing transnational and international contagions looking at the spillovers created by mediums of diffusion. The latter are generated by characteristics that make the origin country more ‘*infectious*’, the target country more ‘*vulnerable*’ or due to specific linkages between the two[12]. **Figure 5** shows a schematic portrait of the variation observed in

[12] For an extensive discussion see Chapter 2.

these studies. Such approach implies adopting a cross-country perspective and mainly focuses on conflict onsets using a threshold of 25 BRDs per year to code a binary dependent variable.

As recounted in Chapter 2, the prolific scholarly work in this branch have been able to identify a vast host of '*transborder carriers of conflict*' (Kibris 2021). These carriers funnel – or hamper – the spatial evolution of conflict into neighboring countries through several mechanisms. Among others, we mention refugee and arm flows (K. S. Gleditsch 2007; K. Gleditsch and Salehyan 2006), circulation of combatants and foreign fighters (Braithwaite and Chu 2018), low state capacity (Braithwaite 2010), religious and ethnic ties across borders (L.-E. Cederman et al. 2013; Forsberg 2014b; Fox 2004).

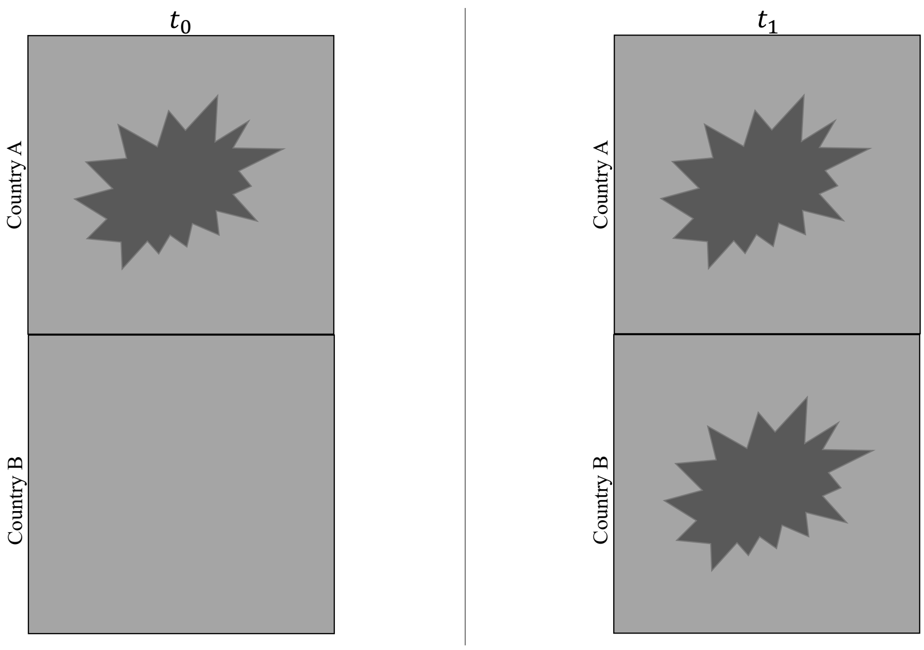

Figure 5: Conceptual model of transnational diffusion of civil war. It shows two neighboring countries, A and B respectively depicted at t_0 and t_1. At time t_0, only country A is experiencing conflict. Through mediums of diffusion and spillovers, conflict propagates to Country B at time t_1.

In general, shared grievances constitute fertile terrain for new hotspots of violence (Forsberg 2014a; Lake and Rothchild 1998) as well as victories or concessions that may foster emulation (Buhaug and Gleditsch 2008; Forsberg 2014b; S. Hill and Rothchild 1986; S. Hill, Rothchild, and Cameron 1998; Maves and Braithwaite 2013). On the contrary, peacekeeping have a strong deterrence effect with onsets in neighboring countries (Beardsley 2011) while external support to rebels on ethnic or political basis have an exacerbating effect on the risk of war (L. Cederman, Girardin, and Gleditsch 2009).

In the last decade, the findings of the transnational literature together with the theoretical and technical advancements have laid the foundations for '*micro-level*' analyses. While the other strand mainly focuses on '*extra-conflict*' factors - or covariates of instability – the new-born scholarly effort has been looking into those conflict processes that create interdependencies between seemingly unrelated eruptions of violence. This follows the intuition that civil wars may follow a peculiar logic that is shaped by violence itself (Kalyvas 2006). **Figure 6** shows a schematic portrait of the variation analyzed in micro-level studies. In this case, the scope of analyses is that of understanding the '*within-conflict variation*' (Kibris 2021) looking into the granular evolution of violence in space and time.

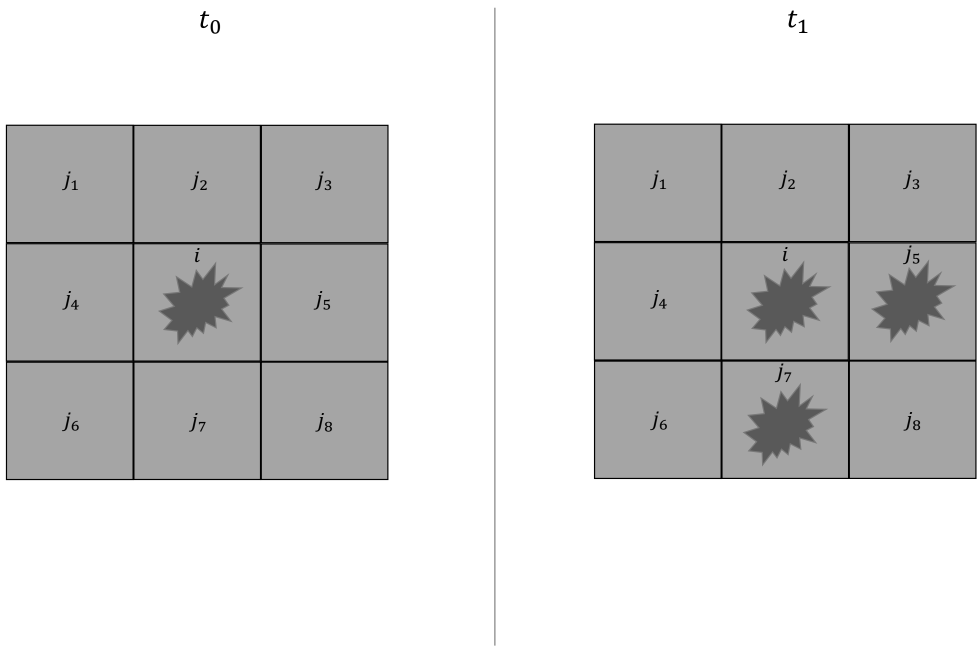

Figure 6: Conceptual model of subnational diffusion of civil war and violence. It shows a set of 9 subnational units, i and $j_{1\ldots8}$ respectively depicted at t_0 and t_1. At time t_0, only spatial unit i is experiencing conflict. Through local mediums of diffusion and spillovers conflict propagates to adjacent spatial units.

What has been previously defined as '*conflict*' has been disaggregated into events and processes, both at the theoretical and at the empirical level. This approach allowed to look more closely to the interdependencies between conflict events that are profoundly different in nature from each other. Several studies have looked at the patterns exhibited by civil conflict and observed the linkages between different types of violence, different types of targeting as well as different types of combat strategies (Hegre, Østby, and Raleigh 2009; Kalyvas and Kocher 2009; Kocher, Pepinsky, and Kalyvas 2011; Lyall 2014; Raleigh and Hegre 2009; Schutte, Ruhe, and Linke 2020; Schutte and Weidmann 2011; Weidmann and Ward 2010). This strand of research have further looked into the determinants that may contribute to the clustering of violence in specific locations and in specific times by looking for instance at the variation of indiscriminate violence determined by post-battle shifts in territorial control (Oswald et al. 2020) and at the variation of violence against civilians in high-risk locations (Salvi, Williamson, and Draper 2020). Other studies have shown how the incapacitating effect of previous violent events influences the spatial evolution of further violence (Kibris 2021) and the role of ethnic channels within the same country in creating clusters of violence (Bormann and Hammond 2016). More structural factors such as accessibility (Zhukov 2012) and presence of internally displace people (Bohnet, Cottier, and Hug 2018) seem to have a notable effect on within-conflict diffusion. Other works have investigated how '*violence can spread and contract in endogenous, self-feeding ways*' (Zhukov 2012, 144). These scholarly contributions introduce the role of retaliatory or reactive behaviors (Braithwaite and Johnson 2012, 2015; Kocher, Pepinsky, and Kalyvas 2011; Linke, Witmer, and O'Loughlin 2012; Schutte and Donnay 2014) for explaining spatial and temporal spillovers. This '*tit-for-tat*' approach creates a link between the quality and quantity of violence exerted by belligerents onto each other or onto civilians postulating that such actions will generate specific conflict responses.

In this paper, we contribute to this strand of literature focusing on systematizing the interactions between belligerents and estimate their influence on the spatial evolution of conflict. Specifically, we frame rebels' attacks and actions as an output of specific incumbents' and counterinsurgents' behaviors on the battlefield. That is, we show that the nature of exerted violence – defined as indiscriminate or selective - and the targets of violence by the incumbent and counterinsurgents have a considerable effect in shaping local conflict-driven incentive. Those in turn, will instantiate in shaping the subsequent actions of rebels as increases or reductions in attacks. Furthermore, we build on the theories of deterrence and alienation to expand the understanding of within-conflict diffusion. While most of previous studies focused on a single country analysis, we decided to offer an illustrative case based on a transnational scenario to account for broader patterns of violence in a conflict zone.

3.4 Between Alienation and Deterrence: can violence fuel itself?

As mentioned above, we argue that locally formed incentives – driven by the self-fueling of violence - play a major role in making an area conflict-prone or not. That is, the way incumbents and counterinsurgents engage with their foes generates different responses. Therefore, reactive violence may be a core mechanism that contributes to instances of spatial diffusion and incidence. Protracted contact with conflict environment may play a considerable role in producing motivations and opportunities to '*strike back*' or even for joining a rebellion. Types of violence exerted in a given area may therefore be strongly linked with the actions of combatants. Similarly, civilians play a preeminent role as one of the main '*conflict resources'*.

Civil wars are population-centered conflicts that place a high emphasis on the populace. The asymmetric nature of warfare pushes the rebels to try to exert influence on the population and the same is true for the incumbents or counterinsurgents. The latter may not be able to engage in direct combat with rebels and must fight for the control – or benevolence - of civilians. '*Winning hearts and minds*' is key both for thwarting an insurgency and for making it succeed. In this view, parties may resort to violence to influence civilians' choices and loyalties.

The literature has offered two alternative explanations on how rebels and civilians react to violence. A branch of scholars and policymakers proposes *Deterrence-based Explanations*. The latter suggest the existence of negative effect of indiscriminate violence and deliberated violence against civilians on rebels' mobilization and persistence of violence (Kalyvas 2006; Schutte 2017b). That is, the use of indiscriminate violence – which usually comes with severe collateral damages onto the populace – create deterrence both in other belligerents and discourage civilians from supporting rebels. This type of violence when exerted by governments or counterinsurgents commonly take the form of airstrikes, drone-strikes, bombings, artillery strikes and the like. Such an approach has found common application in the form of a doctrine of ‘absolute firepower’ in several military campaigns (e.g., Vietnam War (Kocher, Pepinsky, and Kalyvas 2011)) and has been regarded as one of the pillars of Counter-Insurgency doctrines (Kilcullen 2010). The first effect of such exertion is maintained to be direct and directly address the enemies: the attacks thwart the foes’ capacity to carry on their offensive activities by reducing their operational capabilities[13]. Secondly, there is also an indirect effect. The logic of deterrence towards non-combatants is based on the idea that they would face a collective-action problem - both with the rebels and with the incumbents’ forces - and will adjust their risk-reward considerations accordingly (Schutte 2017b). As a result, the risk of taking up arms and joining the rebellion - or that of collaborating with the incumbent - would be too high to make it a viable course of action. **Figure 7** shows a conceptual illustration of the *Deterrence-based Explanations*.

[13] Both damaging the logistic resources and causing casualties.

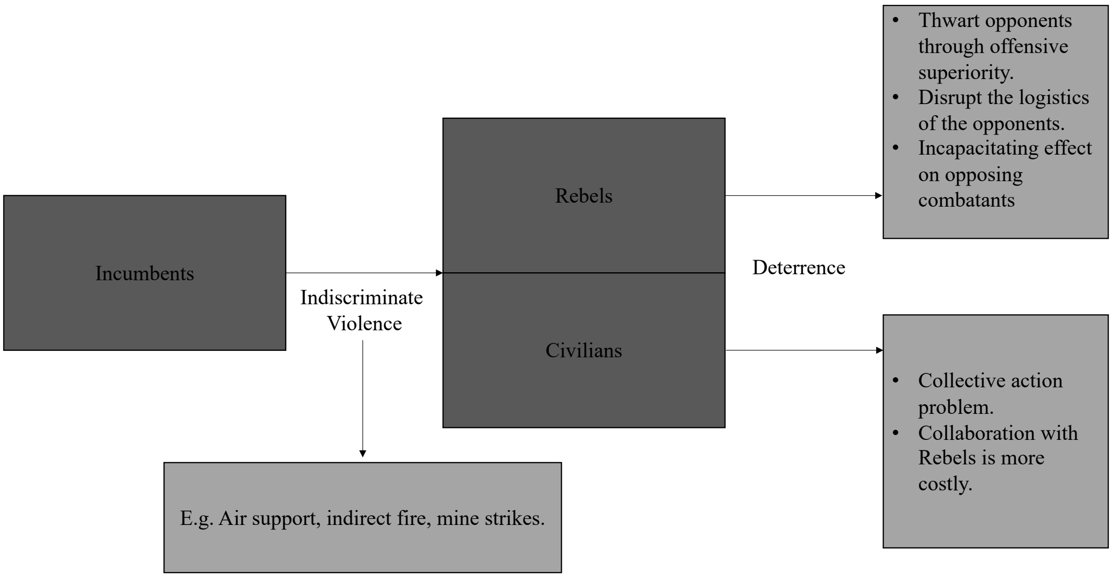

Figure 7: Conceptual illustration of the direct and indirect effect of Indiscriminate Violence exerted by Incumbents under Deterrence-based explanations.

If this theory is correct, we should observe a dramatic reduction in rebels' attacks after surges of indiscriminate violence by incumbents and counterinsurgents. Similarly, this would prevent civilians from allegiance with rebels and force them into compliance with the government or counterinsurgents. By extension, direct violence against civilians should generated a similar effect decluttering rebels' support-base in the populace. In short, indiscriminate violence would be a highly rewarding strategies for counterinsurgents.

On the opposite theoretical end, the *Alienation-Based Explanation* has found flourishing grounds in more recent theoretical and empirical studies (Kocher, Pepinsky, and Kalyvas 2011; Lyall 2014; Schutte 2017b). That is, '*indiscriminate violence*' has positive effect onto further attacks: instead of reducing them, it triggers a reactive behavior in a tit-for-tat fashion and provide civilians with incentive to collaborate with rebels. Even in this case, we have a direct effect onto rebels and indirect effect onto the populace. As shown in **Figure 8**, exerting indiscriminate violence onto rebels may generate swift retaliatory responses. Furthermore, these responses will act as reputational assets as they are used to signal the insurgents' presence both to the adversaries and to civilians despite the attacks carried out against them. The indirect effect pertains civilians and non-combatants.

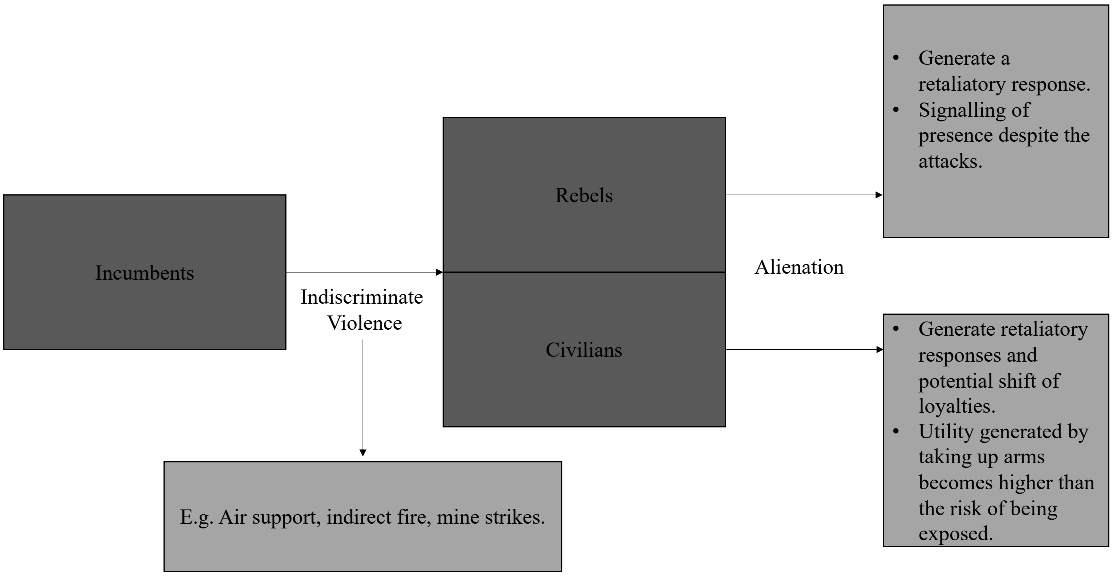

Figure 8: Conceptual illustration of the direct and indirect effect of Indiscriminate Violence exerted by Incumbents under Alienation-based explanations.

This explanation maintains that civilians and non-combatants adopt adaptive behaviors when victimized with indiscriminate violence or, by extension, when violence is directly exerted on them or on their peers in close areas. Such adaptation results in reactive mobilization or potential shifts in loyalties and collaboration with rebels. In this context reactive siding or even mobilization constitute a solution to the collective action problem. In short, when civilians are targeted or witness violence against other non-combatants, either with deliberated violence or as collateral victims from aerial strikes and bombings, the utility generated by taking up arms, or by adopting retaliatory behaviors, or even by siding with the adversaries of the perpetrator will be higher than the risk of being exposed. If this explanation is correct, we should observe an increase in rebels' activities in the aftermath of exertion of indiscriminate violence by incumbents or counterinsurgents. Such attacks would be further favored by the reactive involvement of the populace alienated by indiscriminate violence or victimization. Scholarly work mentioned above as well as historical accounts (Ricks 2007) and counterinsurgency field manuals (Kilcullen 2010, 2015; US Army and US Marine Corps 2008) seem to confirm that alienation is a well-documented effect of indiscriminate violence. The latter seem not to be a highly rewarding counterinsurgency strategies in most cases. We build on this explanation for rebellions suggesting that reactive retaliatory behaviors are a key element in determining whether violence expand or contract in space and time in a given conflict. Targets and 'close spectators' of indiscriminate violence and of unilateral violence against civilians are on average more prone react due to '*within-conflict incentives*' that push them to do so. This claim is confirmed by several empirical cases and field-interviews. For instance, interviews with several combatants from the Liberian conflict reported that to have engaged in combat or have actively collaborated with insurgents due to reactive material reward. More than 60% of the respondents that expected such gains detailed them as '*revenge for previous violence*' (R. Hill, Gwendolyn, and Temin 2008). This process share many similarities with that of radicalization (Quantum 2015), however reactive violence in civil wars has a shorter horizon both in time and space. Rebels, civilian targets, and bystanders of violence in conflict areas are more likely to react in a relative short time and in proximate spatial areas due to evident constraints in choices and strategies (Kocher, Pepinsky, and Kalyvas 2011). In this context, we claim that retaliatory and reactive behaviours driven by alienation are at the core of the geo-temporal horizontal escalation of conflict. Specifically, we aim to establish how this process unfolding in proximate areas, influences the risk of further rebels' attacks in a given spatial unit. **Figure 9** offers a simplified conceptual illustration of the hypothesized relationship.

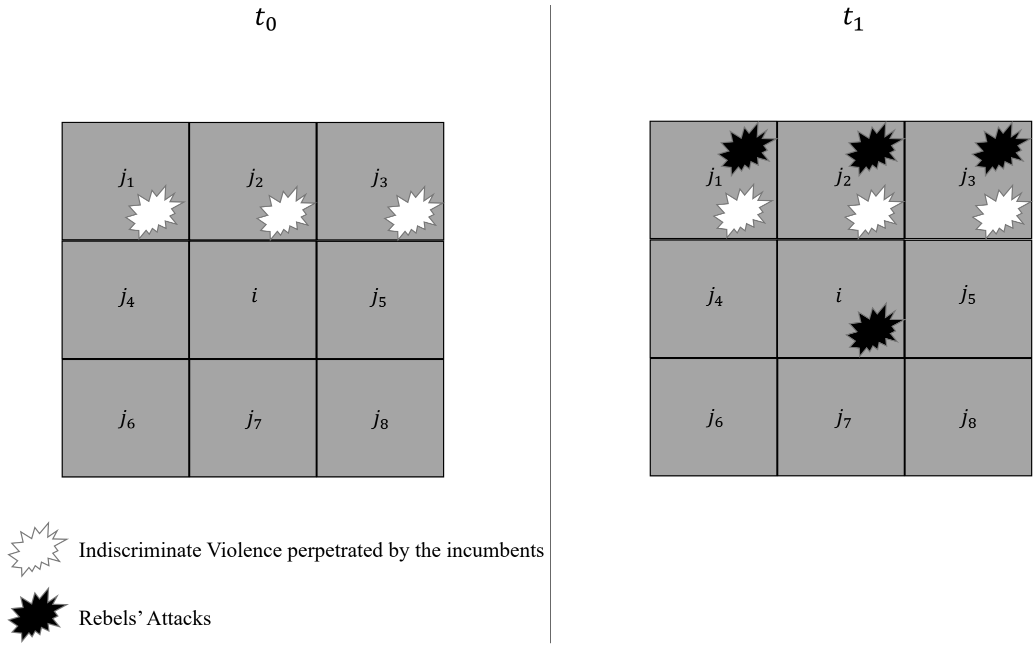

Figure 9: Conceptual illustration of the hypothesized effect of indiscriminate violence onto rebel attacks in proximate subnational spatial units.

As shown in the figure, the exertion of Indiscriminate Violence by incumbents in subnational units $j_{1..3}$ at t_0 will result in an increased occurrence of Rebels' attacks at t_1 not only in subnational units $j_{1..3}$ – as previous works would suggest - but also in i. This conceptualization, allow us to model in a simple way the implications of the '*direct effects*' of alienation discussed above. From that, we derive our first testable implication:

[H1] Consider adjacent sub-national spatial units i *and* $\mathrm{j}_{1..8}$*, the exertion of indiscriminate violence by incumbents in* $\mathrm{j}_{1...8}$ *at time* t_0 *increases the occurrence of rebels' attacks in unit* i *at time* t_1.

Conversely, the use of selective violence by incumbents - such as surgical strikes, direct fire, and targeted raids should not yield such effect. Quite on the contrary, targeted actions of the government and counterinsurgents should yield positive results in thwarting the further insurgents' actions by focusing on diminishing their numbers or on hampering their operational capabilities (e.g., dismantling IEDs laboratories and targeting safehouses). We postulate that when this strategy is chosen, alienation is not triggered neither in its direct effects nor in its indirect effects. Furthermore, for the scope of our study, we propose that the '*stabilizing effect*' of selective violence should influence adjacent spatial units. Accordingly, we derive our second testable implication.

[H2] Consider adjacent sub-national spatial units i *and* $\mathrm{j}_{1..8}$*, the exertion of selective violence by incumbents in* $\mathrm{j}_{1\ldots8}$ *at time* t_0 *decreases the occurrence of rebels' attacks in unit* i *at time* t_1.

As a third step, we turn our attention towards deliberate violence against civilians to assess its effect in fueling further rebel's attacks. In this case, we derive a twofold implication that aims to bridge deterrence and alienation explanations. Most likely, these two theoretical concepts are not mutually exclusive, and we propose that their balance is conceptually linked to the '*quantity*' of violence. Building on the mechanisms detailed above, we postulate that violence against civilians perpetrated by incumbents generates alienation. Once again, we witness to an equalization of the probability of victimization for participants and nonparticipants. That is, civilians' payoffs for rebelling or supporting the insurgency in these scenarios are equal - or larger - than those for not taking parts. Yet, we propose a U-curve relationship between the two variables. If in fact, occurrences of violence against civilians become prevalent, we expect a deterrence effect. In theoretical terms, repeated, frequent and localized instances of civilian victimization make support for rebels – or direct engagement - extremely costly and risky. In turn, rebels will be able to carry out fewer attacks in the area. Therefore, we derive two testable implications to verify the non-linear relationship:

[H3.1] Consider adjacent sub-national spatial units i *and* $j_{1..8}$*, the exertion of violence against civilians by incumbents below a certain threshold in* $j_{1...8}$ *at time* t_0 *increases the occurrence of rebels' attacks in unit* i *at time* t_1.

[H3.2] Consider adjacent sub-national spatial units i *and* $j_{1..8}$*, the exertion of violence against civilians by incumbents above a certain threshold in* $j_{1...8}$ *at time* t_0 *increases the occurrence of rebels' attacks in unit* i *at time* t_1.

We test our hypotheses on a disaggregated dataset on the Syrian War. It is based on spatial-cell/month observations covering Iraq, Syria and Lebanon. A grid is overlaid to the countries of interest with spatial cells of 0.5 x 0.5 decimal degrees constituting the unit of analysis at each month in a timespan ranging from 2011 to 2019. Since reactive violence is most likely to occur in short time horizons and it is a relatively swift process, we adopt very granular scope for which this data are excellent candidates and should be able to capture the tit-for-tat nature of the interactions. The data are based on the use of PRIO-GRID (Tollefsen et al. 2016; Tollefsen, Strand, and Buhaug 2012) as well as integrated events data from the Cross-National Data on Sub-National Violence (henceforth xSub) (Zhukov, Davenport, and Kostyuk 2019). This innovative repository allows to draw fine-grained event-data from 22 widely recognized data sources for geo-referenced event data including the Armed Conflict Location and Event Data Project (ACLED), the Empirical Studies of Conflict Project (henceforth ESOC), the Political Instability Task Force, the Social Conflict Analysis Database (henceforth SCAD) and the UCDP Georeferenced Event Dataset (henceforth UCDP GED)(Berman, Shapiro, and Felter 2011; Croicu and Sundberg 2015; Raleigh et al. 2010; Salehyan et al. 2012; Schrodt and Ulfelder 2016; Sundberg and Melander 2013; Wigle 2010; Zhukov, Davenport, and Kostyuk 2019). Furthermore, the events are integrated and disambiguated making use of 'Matching Event Data by Location, Time and Type' (henceforth MELTT) (Donnay et al. 2019). MELTT has been proven an invaluable tool that allows to avoid redundancies in the data that may inflate models' results and to improve comprehensiveness and completeness (Oswald et al. 2020). Maximizing these two parameters, as argued by Kibris (2021), is key to avoid systematic selection biases as well as to miss crucial parts of the event chain that leads to conflict unfolding. Contemporaneously, we veered to a multi-country subnational analysis to further improve the comprehensiveness towards conflict processes. As we will show in the next section, the Syrian Civil War have spilled over in several other countries and border areas were crucial for rebels' operations. That perspective would have been lost adopting a single-country perspective under a closed-polity assumption. As detailed in the next section, the Syrian case is an ideal candidate for the analysis of this paper. The reason for that belie the multidimensional nature of the conflict. In fact, several conflicts coexist in a relatively contained territory that spans across three states. Similarly, the Syrian case is characterized by a vast host of actors broadly classifiable as government forces, challengers, civilians, and other militias (see below) and yet with precise motives, strategies and group compositions in each case. Such plurality of territories and actors – as well as the multi-state setting – allow to dilute the specificities that a single-country scenario may have and – at the same time – allow to capture the interconnections between the groups. The latter would not have been possible analyzing a mixed sample of country in-conflict without territorial continuity. All in all, the case should on the hand allow us to capture the dynamics of reactive violence at the subnational and transnational level. On the other hand, it should allow us to represent typical civil conflict dynamics that can be generalized to a broader population. It is entirely plausible, we recognize, that we may be capturing idiosyncrasies pertaining the broader Syrian case – or even of the MENA region but this seem to be unlikely possibility due to the variance in actors, territorial features and behaviors. Further details on the variation to be explained are provided in the next section.

3.5 Case Description

Since March 2011, Syria has been experiencing a multi-sided conflict tha broadly speaking involves the Syrian Arab Republic against several domestic and international groups. Furthermore, it has drawn the attention and direct involvement of other countries. The Syrian Observatory of Human Rights (henceforth SOHR) estimates that the conflicted yielded over 594,000 deaths from the March 2011 to March 2021 (SOHR 2021). Over 110,000 of the victims were civilians. The conflict stemmed from protests and uprising in the aftermath of the so-called 'Arab-Spring' in March 2011 and turned into a full-fledged insurgency in July of the same year. The conflict quickly escalated and witnessed the involvement of Islamists groups as well as that of Russia and the United States between 2014 and 2016. In terms of spillovers, the Syrian civil war directly impacted Iraq, Lebanon, Turkey, and Jordan. Furthermore, it reverberated throughout several countries in the Arab World and beyond, particularly after the involvement of the Islamic State of Iraq and the Levant (henceforth ISIL). As for Iraq, there had been a constant presence of militias at the border with Syria and the delicate balance was further exacerbated when ISIL '*unified*' their effort in both countries. Similarly, the north of Lebanon witnessed several incidents fueled by Syrian conflict. Further spillovers included Hezbollah's cross-border activities as well as the territorial claims of ISIL and al-Nusra[14].

Such a multi-layered and multi-dyadic picture requires some coding decision to be made when characterizing the different actors for the sake of this study. In our hypotheses we discussed the role of '*Rebels*' and '*Incumbents*' – or '*counterinsurgents*'. To cluster the variety of actors that took part in the Syrian Conflict as well as in the Iraqi and Lebanese one we rely on the xSub classification (Zhukov, Davenport, and Kostyuk 2019). The latter is in line with the most common definitions in the literature and are helpful in integrating different dataset under the same taxonomy. Accordingly, **Table 2** presents this classification providing a description of the actors included in each cluster. For the sake of this study, we make use of the '*government*', '*challenger*' and '*civilian*' clusters. The right column of **Table 2** presents the paper nomenclature used for each category in order to match the hypotheses. A detailed description of the specific actors included in each cluster for each country under analysis is included in **Appendix 1** due to space limitations.

[14] As a notable example see, the Battle of Arsal.

Cluster	Actors	Paper Nomenclature
Government	Incumbent government, pro-government militia, third party acting on incumbent's behalf.	Incumbents/Counterinsurgents
Challenger	Rebels, anti-government militia, third party acting on rebels' behalf, and other armed groups directly challenging the government.	Rebels
Civilians	Civilians	Civilians
Other	Local militia, tribe, other non-state actors not directly challenging the government.	Not applicable

Table 2: xSub coding rules by actors involved in conflict. It divides conflict actors in four clusters listed in the left column (Zhukov, Davenport, and Kostyuk 2019).

Following this classification, we know present some quantitative evidence of the variation to be explained in the specific case of Iraq, Lebanon, and Syria. **Figure 10** presents the temporal variation of violent actions initiated by rebels in the three countries in the time window of the sample (2011-2019). It shows not only the temporal evolution in the three areas, but also the relative prevalence of events' occurrence. Iraq for instance witnessed comparatively starker spikes of rebels' violence from 2014 to 2018 when the ISIL activity peaked. Furthermore, we can see a peak of violence by the end of 2019 in Lebanon that visually seems to match the one in Syria in the same period.

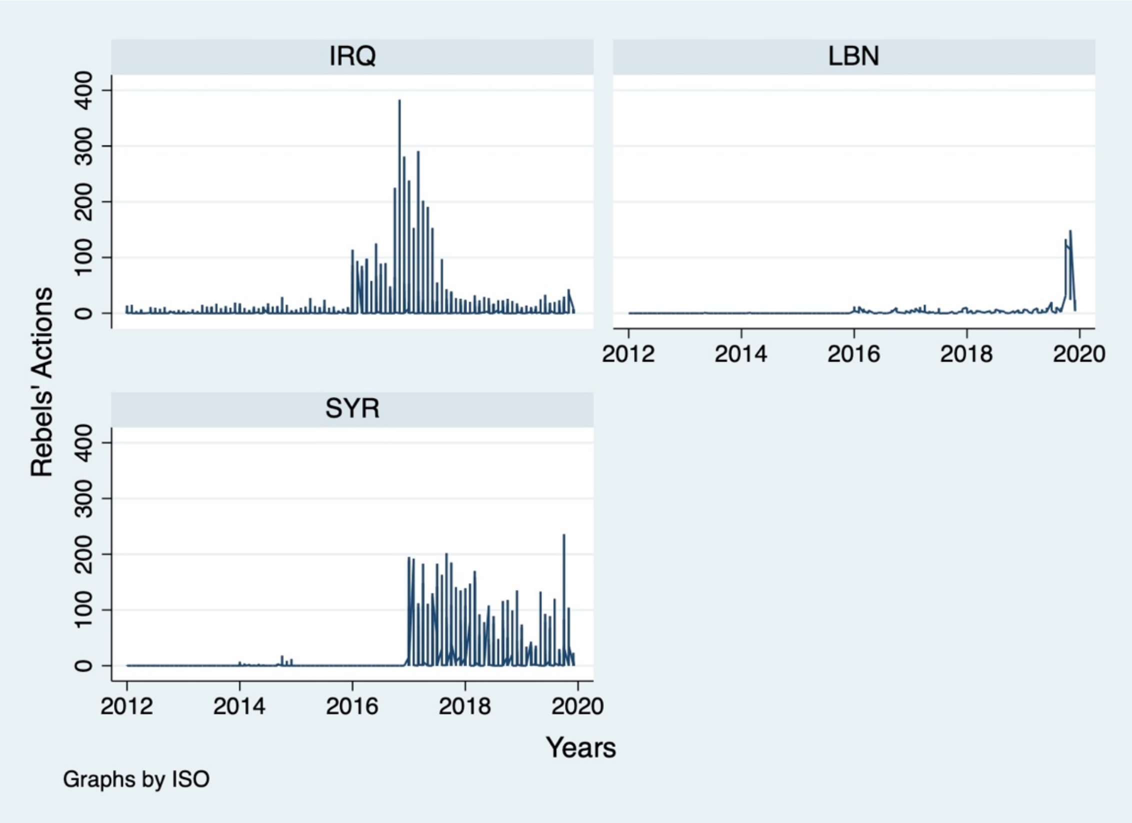

Figure 10: Time Series of actions initiated by Rebels in Iraq (IRQ), Lebanon (LBN) and Syria (SYR) from 2011 to 2019.

Figure 11 portrays the 299 grid cells analyzed in our dataset portraying the spatial variation of violence initiated by rebels and incumbents respectively. The figure includes the aggregated $log10$ count of events throughout the full time-window. Similarly, **Figure 12** the spatial variation of selective and indiscriminate violence respectively initiated both by incumbents and rebels. Once again, the figure portrays the aggregated $log10$ count of events throughout the full time-window. We can see some overlapping between cells that experienced the different types of violence. This is most likely due to the fact that these cells generally experienced more violence and corresponds to crucial strategic hotspots – mainly in Syria and Iraq.

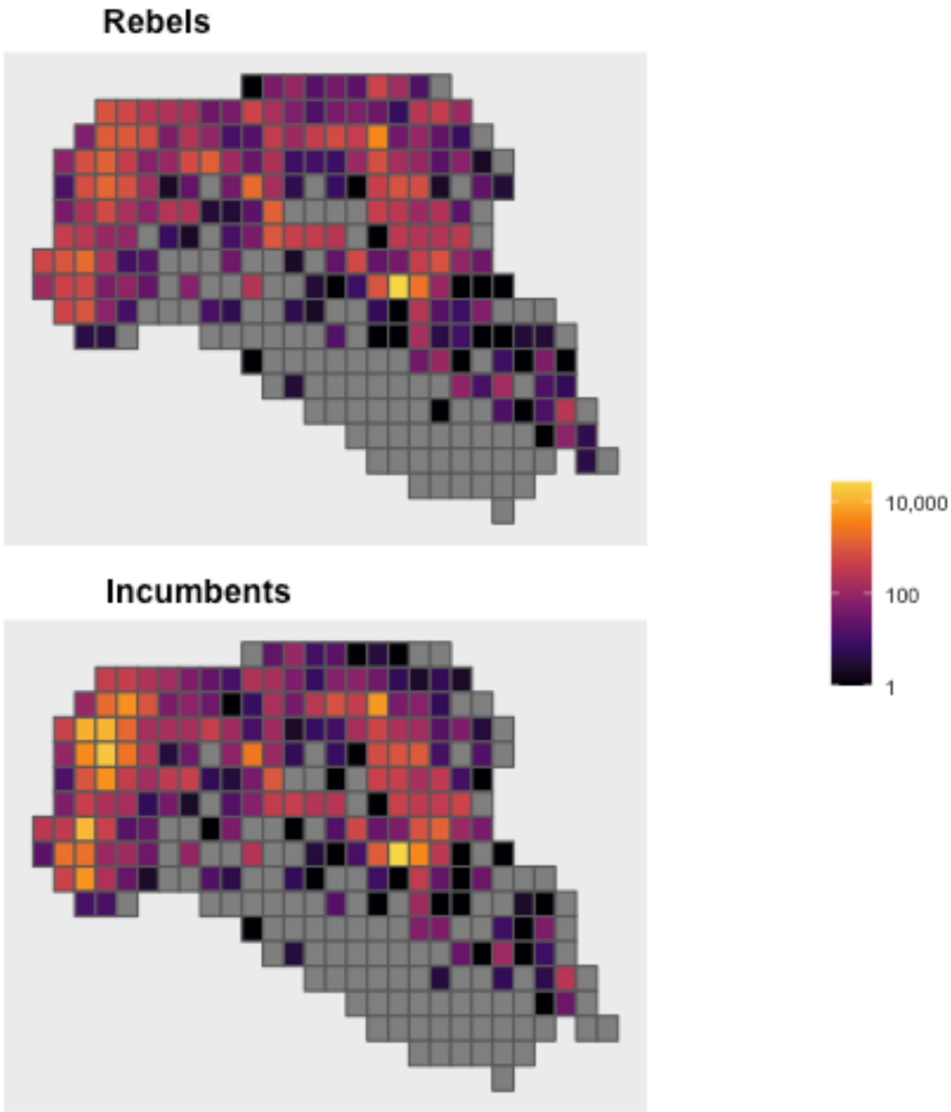

Figure 11: Spatial variation of violence ($log10$ count of events) initiated by Rebels and Incumbents respectively. xSub Data from Syria, Iraq, and Lebanon (2011-2019 depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any violent event.

In the next section, we present the data in more detail providing indications of the classification by type of violence, providing an overview of the sample, and presenting the models as well as the results.

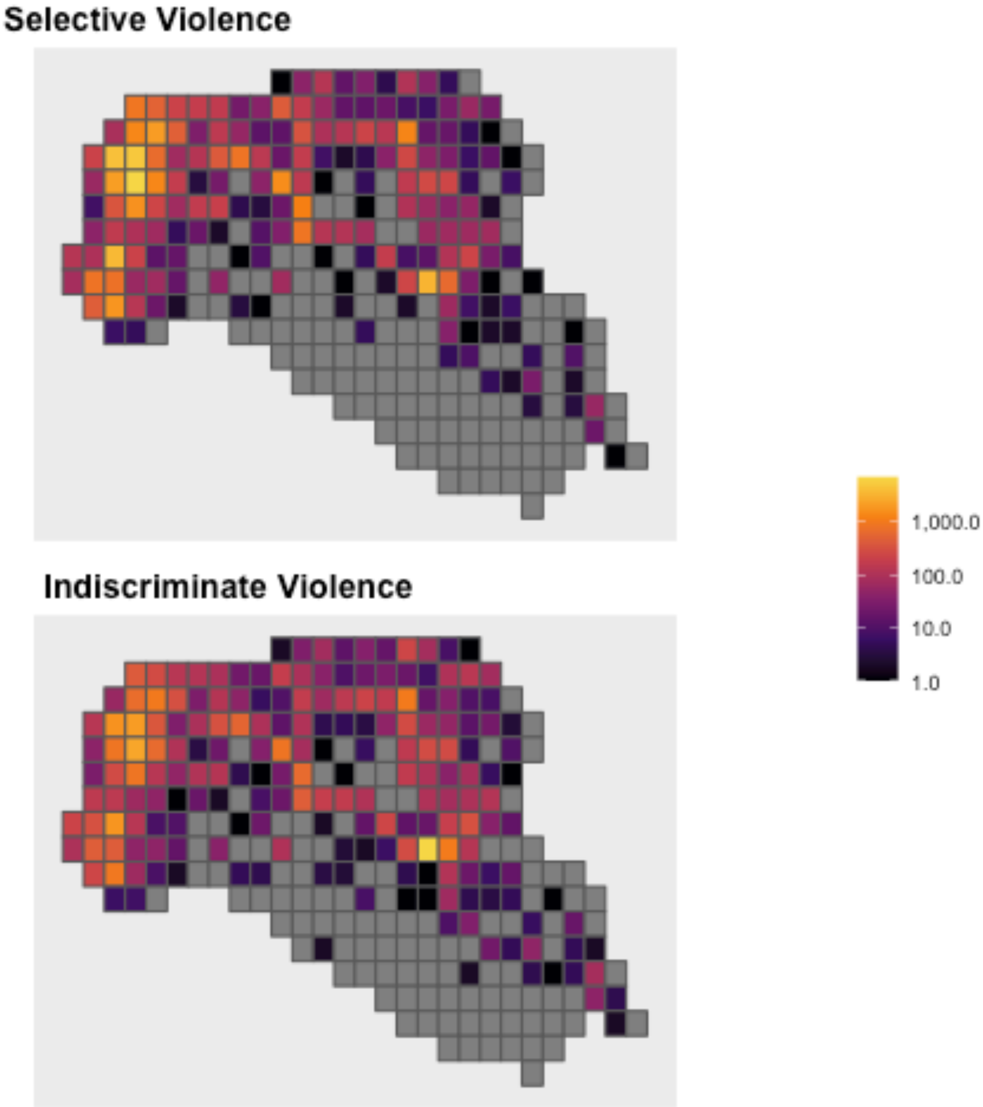

Figure 12: Spatial variation of violence ($log10$ count of events) by type. xSub Data from Syria, Iraq, and Lebanon (2011-2019 depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any violent event.

3.6 Analysis

3.6.1 Data

As recounted above, hypotheses are tested using a fine-grained grid-cells dataset based on PRIO-GRID as unified spatial structure and xSub (Tollefsen et al. 2016; Tollefsen, Strand, and Buhaug 2012; Zhukov, Davenport, and Kostyuk 2019). The first provide an ideal grid structure able to provide synthetic cell units for sub-national spatial analysis that have found widespread use in conflict research. A grid composed of spatial cells of 0.5 x 0.5 decimal degrees is overlaid on all terrestrial areas of the world. In this specific case, Syria, Iraq and Lebanon are composed by 299 cells. The dataset covers 8 years, from 2011 to 2019, in monthly intervals. We therefore have 28,704 observations. As for conflict data, we make use of xSub (Zhukov, Davenport, and Kostyuk 2019), a recent and innovative repository of micro-level event data on conflict and political violence. The repository conveniently harmonizes over 22 eminent data sources into common units of analysis by spatial units and time. These unique features translate in a rich set of events that are ideal candidates for disaggregated studies that requires high-resolution data, comprehensiveness, and completeness. Datasets are further integrated making use of the MELTT methodology (Donnay et al. 2019). The latter easily allows to integrate multiple sources avoiding redundancies, duplicates and overcounting stemming from simple integration (Hendrix and Salehyan 2015). Specifically, events can be 'co-located' (Zhukov, Davenport, and Kostyuk 2019) querying xSub based on spatial and temporal filter. To construct our dataset, we relied on a restrictive filtering. That is, events of the same category occurring at the same time within 1 km of radius from one-another are aggregated as a single data point. Similarly, for the temporal aggregation, we chose a threshold of 1 day. That is, geographically co-located events reported within 1 day of each other are aggregated as a single data point

(Donnay et al. 2019; Zhukov, Davenport, and Kostyuk 2019). We chose such conservative criteria among those available to minimize the chances of over-aggregation[15]. As for the event sources, currently integrable datasets in xSub that cover our geo-temporal window of interests include: the Armed Conflict Location and Event Data Project (ACLED), the Empirical Studies of Conflict Project[16] (ESOC), the Political Instability Task Force, the Social Conflict Analysis Database (SCAD) and the UCDP Georeferenced Event Dataset (UCDP GED)(Berman, Shapiro, and Felter 2011; Croicu and Sundberg 2015; Raleigh et al. 2010; Salehyan et al. 2012; Schrodt and Ulfelder 2016; Sundberg and Melander 2013; Wigle 2010; Zhukov, Davenport, and Kostyuk 2019). Such process allowed to obtain counts of conflict events disaggregated by type, initiator, and target for each of the 28,704 observations.

The variables used in this study will be further discussed in the next section, however it is worth clarifying the classification of event counts offered in xSub. As shown in **Table 3** the taxonomy is based on three main types of actions based on '*quality*' of violence that are further disaggregated by perpetrators and targets. An aggregated mapping as

[15] In the Robustness section we recount the results of different time and space aggregations.

[16] Including both SIGACT data and Worldwide Incidents Tracking System (WITS) on Iraq (Berman, Shapiro, and Felter 2011; Wigle 2010).

well as time-series analysis of conflict related counts is provided in **Appendix 1**. For the sake of this study, we used three main count variables of conflict events: Rebels' Actions, Incumbents' Indiscriminate Violence, Incumbents' Selective Violence, Incumbents' Violence against Civilians[17] (henceforth VAC).

Types of actions	Description
Any	Any use of force
Indiscriminate	Indiscriminate force such as indirect fire, shelling, air-strikes, chemical weapons
Selective	Selective force such as direct fire, arrest, assassination

Table 3: Classification of relevant actions in xSub. There are three main types for which both the initiator and the target is indicated according to the taxonomy presented in Table 2. The original classification includes a fourth categories that include protests. Such events are not taken into consideration in this study.

As for variables on geography, demographics and other commonly used structural determinant of civil violence, xSub conveniently allow to integrate them with each pertinent cell at each given time. In particular, we included population per square kilometer (2000)(SEDAC 2005), average elevation in meters (ETOPO05),

[17] Defined as violent events by incumbents targeting civilians, despite the quality of the violence exerted.

proportion of land covered by open terrain (GLCC), proportion of land covered by forests (GLCC), proportion of land covered by farmlands (GLCC) , number of local ethnic groups (GREG)(Weidmann, Rød, and Cederman 2010), number of built-up areas (GGIS), number of petroleum fields (PRIO)(Lujala, Ketil Rod, and Thieme 2007), distance to province capital in km (GGIS), road density in kilometers over squared kilometers (DCW), and mean of calibrated nightlights from DMSP OLS Night-time Lights adapted in PRIO-GRID. **Table 4** contains the descriptive statistics of the dataset used in this study. It is worth noting that most of these variables are time-invariant (e.g., land variables) or yearly (e.g., night lights) in nature.

	N	Std. Dev.	min	max	Mean	skewness	kurtosis
Rebels' Actions	28704	9.2223	0	383	1.5163	14.9931	335.9386
Incumbents' Indiscr.	28704	15.9826	0	551	1.7204	17.1424	362.8959
Incumbents' Selective	28704	13.2177	0	416	1.2971	17.6441	371.7235
Incumbents' VAC	28704	0.2403	0	12	0.0210	20.4787	608.4309
Average Elevation	28704	398.7701	-1048.0833	2117.0556	415.4730	1.0714	6.6376
Open Terrain	28704	0.3130	0.0019	1	0.5526	-0.3069	1.8196
N of Ethnic Groups	28704	0.8251	1	5	1.6321	1.3073	4.5060
N Built-up Areas	28704	0.8602	0	4	0.3913	2.3407	7.8916
N Petroleum Fields	28704	0.7444	0	3	0.6923	0.8566	3.2590
Distance Prov. Cap.	28704	93.2390	4.1469	513.4854	122.7101	1.3693	4.9674
Road Density	28704	0.0466	0	0.4269	0.0621	1.9395	15.0959
Calibrated Night Lights	28704	0.0623	0.0612	0.5470	0.1029	2.9252	14.3183
Forest	28704	0.1615	0	0.7767	0.0934	2.0508	6.6839
Farmland	28704	0.0079	0	0.0786	0.0014	7.8521	68.8657
Wetland	28704	0.0067	0	0.0778	0.0010	9.5057	101.1299
Population (2000)	28704	149.1936	1.3746	1570.7295	76.6184	5.9493	48.8341

Table 4: Descriptive statistics of the main variables in the dataset. It comprises 28704 observations of cell/month units from January 2011 to December 2019.

3.6.2 Modelling

Having derived testable implications and discussed the structure of the data we define our model as follows:

$$Rebels'Actions_{i,t} = x'_{i,t}\beta + \mathrm{w}'v_{it-1}\rho + u_i + \gamma_y + \varepsilon_{it}$$

Here $Rebels'Actions_{i,t}$ indicates the total number of rebels' attacks occurring in cell i at year-month t. x'_{it} is a vector of *K* variables for cell i at year-month t. w is a vector of spatial weights for each of the cells in our sample based on contiguity using the Queen criterion. v_{it-1} is a matrix of *M* counts of violence in neighboring cells. u_i and γ_y and are cell random effects with $y \in [2011,2019]$. β is a vector of *K* coefficient to be estimated, whereas ρ is a vector of *M* spatial coefficients.

As recounted above, and as shown in **Table 4**, our dependent variable (henceforth DV) is the count of rebels' actions occurring in cell i at time t. Being a count variable that takes only non-negative integer values, we chose to model the relationship resorting to a negative binomial model. While a Poisson distribution is often well suited for count data, in this case the over-dispersion of our DV made us veer towards the negative binomial.

To model the spatial relationship proposed by our hypotheses, in our main model we defined a matrix of spatial weights based on the Queen criterion of contiguity. As shown in **Figure 13**, given a spatial unit $\boldsymbol{i}$, its neighbours are those spatial units – say $j_{1\ldots8}$ if i is fully surrounded by other cells - sharing a common edge or a common vertex.

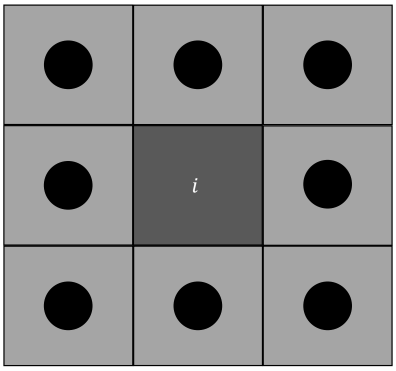

Figure 13: Queen criterion of contiguity. Given a spatial unit i, its neighbours are those spatial units sharing a common edge or a common vertex. Neighbours are denoted by a black circle.

The main independent variables are represented by v_{it-1} that represent the time and spatially lagged counts of Incumbents' Selective Violence, Incumbents' Indiscriminate Violence and Incumbents' VAC taking place at $t-1$ in i and in its neighbouring cells. For each of these variables therefore we obtained a weighted version of it defined as $w_{i,t-1}Incumbents'Indiscriminate$, $w_{i,t-1}Incumbents'Selective$ and $w_{i,t-1}Incumbents'VAC.$ Concerning Hypothesis 3.1 and Hypothesis 3.2, in order to test for the proposed non-linear relationship, we included a quadratic term expressed as $w_{i,t-1}IncumbentsVAC^2$.

As for the control variables included in vector x'_{it}, we included demographic, geographical and ethnic indicators that are commonly used in conflict research. In fact, they have been identified as factors affecting conflict-proneness of a certain spatial unit.

We added dummy variables for each year in our sample to account for the broader time component. Finally, assuming cell-specific effects to be uncorrelated with the independent variables in our equation, we included cells random effects to account for their specificity. This choice seems particularly well suited to capture the peculiarities of each fine-grained location which are hardly captured by other indicators. For the sake of completeness, should our assumption be too naive, we ran a variation of the model including cells fixed effects.

3.6.3 Results

We present the results of various specifications of our model in **Table 5**. The dependent variable, as mentioned above is the number of rebels' actions in cell i at time t. The different configurations of the models are specified below the observations row. **Model 1** includes only the main explanatory variables referring to cell i at time $t-1$ (i.e., *Lag Incumbents' Indiscr.*, *Lag Incumbents' Selective*, *Lag Incumbents VAC* and the quadratic term of the latter) both those including the spatial weights (identified by the term *w*). Furthermore, it includes cell random effects to control for unobserved heterogeneity. **Model 2** includes control variables related to demographical, geographical, and structural determinants of violence as well. **Model 3** year-dummies to account for between-year variation. **Model 4** has the same specification of the previous one but include bootstrapped standard errors on cells to account for non-independent observations. Finally, **Model 5** substitute cell random effects with cell fixed effect as discussed in the previous section and – once more – includes bootstrapped standard errors.

In line with our previous propositions, we find a substantial neighborhood effect of the different types of violence exerted by incumbents and counterinsurgents. It appears that the quality and quantity of prior violence have a significant impact on the number of rebels' attacks in each cell of the grid. The direction of the effect is also compatible with our hypotheses.

DV: Rebels' Actions	(1)	(2)	(3)	(4)	(5)
Neigh. Incumbents' Indiscr.	.056***	.0579***	.0366***	.0366***	.0366***
	(.0034)	(.0036)	(.0042)	(.0079)	(.0073)
Incumbents' Indiscr.	.0083***	.0095***	.0074***	.0074**	.0074***
	(.0014)	(.0015)	(.0013)	(.0034)	(.0024)
Neigh. Incumbents' Selective	-.0482***	-.0474***	-.0308***	-.0308***	-.0308***
	(.0041)	(.0042)	(.005)	(.0093)	(.0089)
Incumbents' Selective	-.0049***	-.0063***	-.0024	-.0024	-.0024
	(.0018)	(.0019)	(.0017)	(.0039)	(.0027)
Neigh Incumbents' VAC	2.8121***	2.7489***	.0776	.0776	.0658
	(.2136)	(.2164)	(.1819)	(.3178)	(.2642)
Neigh Incumbents' VAC^2	-2.4383***	-2.3773***	-.334**	-.334	-.3249
	(.2245)	(.2277)	(.1664)	(.23)	(.2329)
Incumbents' VAC	.4322***	.4686***	.1768***	.1768**	.1736**
		(.0526)	(.0484)	(.07)	(.0674)
	(.0498)				
Incumbents' VAC^2	-.0504***	-.0564***	-.0221***	-.0221**	-.0216**
	(.0087)	(.0096)	(.0083)	(.0104)	(.0089)
Constant	-1.8059***	-2.799***	-4.5743***	-4.5743***	-4.4938***
	(.0222)	(.1307)	(.379)	(.6609)	(.7398)
Ln(r)	-.8166***	-.7856***	-.6901***	-.6901***	
	(.0888)	(.0886)	(.0907)	(.0601)	
Ln(s)	-1.4015***	-1.293***	-1.3312***	-1.3312***	
	(.0983)	(.1032)	(.1003)	(.1249)	
Observations	28405	28405	28405	28405	18145
Control Variables	No	Yes	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes	Yes
Cell RE	Yes	Yes	Yes	Yes	No
Cell FE	No	No	No	No	Yes
Bootstrapped SE	No	No	No	Yes	Yes

Standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1

Table 5: Models' estimation with different specification of the Negative Binomial Regression. DV: Rebels' Actions.

Specifically, we can see how the coefficient of the spatially weighted variable on indiscriminate violence *Neigh Incumbents' Indiscriminate* is consistently positive and significant across different specifications. That is, increases in the use of indiscriminate violence by incumbents seem to encourage rebels' attacks. Conversely the coefficient of *Neigh. Incumbents' Selective,* the variable portraying the use of selective violence, is significant and negative across all models. That suggests that the use of selective violence by incumbents seem to reduce further rebels' attacks. As for violence against civilians*,* we can see the value of introducing a quadratic term given the different sign of the coefficient of *Neigh Incumbents' VAC and Neigh Incumbents'* VAC^2. The latter would suggest that while relatively low levels of VAC cause an increase of rebels' actions, higher levels of VAC reduce them. This strongly support our hypotheses on the creation of deterrence after a peak in VAC. Unfortunately, the estimates for *Neigh Incumbents' VAC and Neigh. Incumbents'* VAC^2 are not significant in **Model 4** and **5** and thus we cannot confirm a substantial neighborhood effect for VAC.

Interestingly, the local levels of VAC – represented by *Incumbents' VAC and Incumbents'* VAC^2- have a similar behavior as far as the sign is concerned, but they are significant across all specifications. As for other local predictors, we can see that our hypotheses are largely confirmed by *Incumbents' Indiscriminate* but not by *Incumbents' Selective.* The significance of the latter is not robust in **Model 4** and **5**.

For the sake of clarity, we provide a plot of the coefficients from **Model 3** in **Figure 14**.

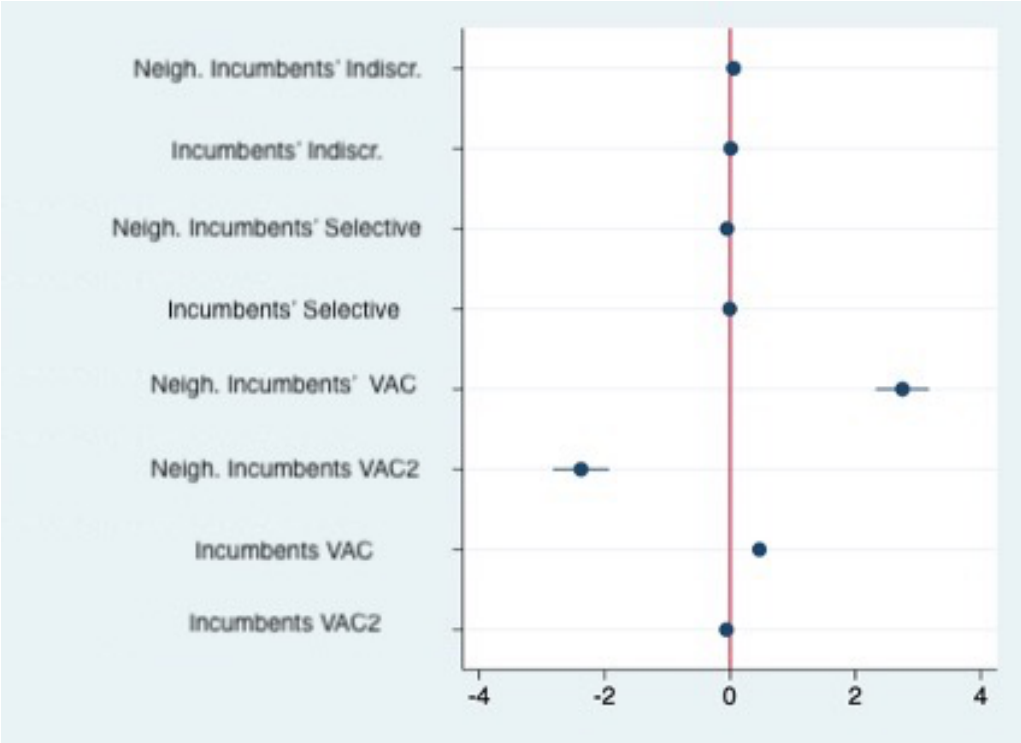

Figure 14: Coefficient Plot portraying the expected change in the count of rebels' actions for unitary changes of the explanatory variables. Coefficients are derived from Model 3. Coefficients on the right side of the plot represent positive changes, while coefficients on the left side represent negative changes.

For example, we can see that a unit change in *Neigh Lag Incumbents' VAC* the expected count of rebels' actions changes by roughly 3, holding other covariates constant. Similarly, a unit change in the quadratic term pertaining VAC changes the expected count of rebels' actions by roughly -2.2 holding other covariates constant. The absolute values of other expected changes are all smaller than the one presented as an example and are therefore closer to the vertical line representing a lack in changes. Nonetheless all the estimated confidence intervals at the 95% level – as represented by the horizontal bars – shows that they are significantly different from 0.

3.6.4 Robustness

To the test the robustness of our findings, we specified further models and introduced variations to the dataset used. As mentioned above, our first step was changing the threshold of MELTT events aggregation. As for spatial aggregation, we tested our models on a 5 kilometers threshold instead of 1 day. As for temporal aggregation we selected a time window of 4 days instead of 1 day. Despite these changes in the data, the results are consistent and – therefore – the estimated coefficient are not dependent on the aggregation parameters.

Furthermore, our results are robust to alternative estimation methods including OLS with spatial weights, Poisson models and Spatial Autoregressive Models (SAR)[18]. As for the latter - despite not being included in the main specifications it includes spatially lagged errors ε_{it}. The latter are defined as follow: $\varepsilon = \lambda(w)\varepsilon + u$. In this case w represent the spatial weights' matrix used above and ε a vector of spatially autocorrelated errors terms. As for u, it represents a vector of independent identically

[18] The latter are particularly well suited for auto-regressive dependent variables, yet they are ideal for continuous variables and not as accurate for counts.

distributed errors. This variation of the errors has been tested to account for autocorrelation in the errors with the weights' matrix of choice.

We also varied the estimation of the spatial weights' matrix selecting different criteria (e.g., Rook's criterion that excludes spatial units which share a common vertex with the cell under analysis). Despite these changes, the results proved robust.

Finally, we recoded our dependent variable as a binary indicator that takes value of 1 in case of occurrence of rebels' attacks and 0 otherwise. With that, we estimated a logistic regression with spatial weights. Despite the changes on the magnitude of the effects, the direction and significance of our predictors has proven to be robust.

An instrumental variable approach has been considered for this contribution. The reason behind the lack of such implementation resides in the fact that independent variable and the dependent variable are deeply interconnected in their own nature. That is, they are influenced by similar factors. A typical example of instrumental variables are rainfalls (Harari and La Ferrara 2018). In this specific context, they influence both rebels' actions and incumbents' actions in their logistics and in their operational aspects. A similar consideration can be formulated for more conflict specific variables such as areas controlled by rebels/incumbents (Kalyvas 2006) . Some contributions highlight that indiscriminate violence by incumbents is more likely when the incumbent itself 'can't tell friends from foes' (Costalli and Moro 2011; Costalli, Moro, and Ruggeri 2020) thus using relative territorial control. Even this case, such instruments have a considerable effect on rebels actions and is reflected by the strategic nature of guerrilla. Other contributions based on local cases, make use more specific variables (e.g. distance from a certain border). The latter however are not applicable to a multi country setting like the one presented here. The reason resides in the fact that these variables would not have the same "value" as instruments neither statistically and theoretically.

We recognize that, while in principle there could be some aspects that may influence the rebels' actions uniquely through incumbents, most of them are almost impossible to capture at the current stage. For example, for counterinsurgents we may need detailed information that describe instructions from the hierarchy or tactical considerations. In short, after long consideration the author decided to veer to the approach presented here. Given the plausibly reactive interconnection between my rebels' actions and indiscriminate violence by counterinsurgents and given that they coexist in the same geo-temporal clusters, most used variables would affect both.

3.7 Conclusion

This paper analyses why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not. It shows that the nature of exerted violence and the targets of violence by incumbents have a considerable effect on the incidence of rebels' attacks. Secondly, it shows a neighborhood effect of alienation. That is, indiscriminate violence exerted in neighboring areas have an impact on the local rebels' responses. We argued that rebels' violence may have an important reactive component and expanded the current theoretical scenario suggesting that reactive violence is a key element in determining whether the conflict spreads in space or not.

To do so, we proposed that escalation and the spatial diffusion of rebels' actions is favored by instances of indiscriminate violence by incumbents in the neighborhood. On the other hand, targeted actions, reduce further incidence of rebels' attacks and are perhaps more efficient counterinsurgency measures. Moreover, we bridged the empirical implications of deterrence and alienation theories of violence against civilians. We showed that violence against civilians perpetrated by incumbents in contiguous areas results in more instances of rebels' attacks. Nonetheless, numerous instances of violence against civilians seems to create deterrence by reducing subsequent attacks. The results fit into the broader scholarly debate on the effects of indiscriminate violence confirming its escalating effect, not only in terms of intensity, but also in terms of geographical escalation. Therefore, it seems that deterrence cannot be created through exertion of this form of violence. Quite on the contrary, the findings suggest that a retaliation mechanism is more likely. On the other hand, selective violence seems to be more efficient in thwarting further attacks. As for violence against civilians we contribute to the literature on its effect finding a U-curve relationship. In case of prevalence of violence against civilians, we find what seems a deterrence effect.

There are of course several limitations that affect this work. In first place, in terms of causal inference, it does not fully clarify the mechanisms that trigger a reaction by rebels. Secondly, it may suffer from methodological limitations given the hurdle of modelling conflict-processes data. While the temporal and spatial lags – as well as other modelling techniques – tries to address endogeneity to a certain degree, genuine and rigorous skepticism should prevent us from fully embracing the results. However, given the theoretical support onto which the paper builds, said problem should not invalidate our empirical effort. We believe that this may constitute a first step towards further subnational-level studies that analyze the role of conflict processes and events – assessing their quality and quantity – to explain broader phenomena in conflict research.

All in all, the paper makes a three-fold contribution. In first place we want to clarify the role of reactive violence in influencing spatial patterns of civil war. It does so offer a first systematic analysis of subnational patterns of violence between belligerents and of civilians targeting. Secondly, we link the literature on escalation – encompassing the role of alienation and deterrence - with that of spatial diffusion providing a unified perspective that may help understanding which sub-national areas are more conflict-prone. Thirdly, this paper hopes to contribute in terms of informing policymaking by analyzing and showing the effects of incumbents' strategies and counterinsurgency doctrines. We show how certain strategies can punish the incumbents and severely hinder conflict alleviation efforts.

4 EXPLAINING THE VARIATION IN TIMING AND LOCATION IED ATTACKS: EVIDENCE FROM IRAQ USING A SIMULATED BASELINE APPROACH

ABSTRACT

Why do some conflict zones exhibit more IED attacks than others? What drives the variation in the timing of these attacks? The literature has emphasized the role of structural covariates such as geographic features of the contested area, territorial control, strategic locations, and the presence of natural resources. Comparatively less attention has been given to the nature of conflict events and reactive behaviors. Here, we aim to demonstrate how insurgents' activities on the field are influenced by the quality of counterinsurgents' violence. We draw from the literature on micro-foundations of civil war and on counterinsurgency to illustrate how indiscriminate violence systematically increases subsequent attacks. On the contrary, selective use of force is more efficient in reducing subsequent IED attacks. We empirically test our hypothesis on the Iraqi insurgency using SIGACT event data from 2016 coded by the US military. We estimate the relative and absolute effect of incumbents' indiscriminate violence. As for the former, we make use of Matched Wake Analysis to compare the post-treatment effect on IED attacks. To estimate the absolute effect of indiscriminate incumbents' violence we propose an approach based on the comparison of such events with synthetic counterfactuals as a simulated baseline. We craft heuristics for these conflict events using road networks and population settlements to help build a set of plausible locations where indiscriminate violence could have occurred but did not. This work makes two substantive and a methodological contribution by (1) evaluating the relative effect of indiscriminate incumbents' violence on IED attacks (2) attempting to offer a tentative framework for utilizing synthetic counterfactuals, and consequently (3) empirically testing the absolute effect of indiscriminate violence on insurgents' violence.

4.1 Introduction

There is a considerable variation in insurgents' attacks in civil wars both in spatial and temporal terms. Some areas tend to exhibit more attacks than other becoming real hot spots for the warring parties. A vast majority of these attacks, particularly against regular troops of foreign counterinsurgents, consists of Improvised Explosive Devices (henceforth IEDs). The latter are made of relatively easily accessible materials and have constituted a prevalent phenomenon in both Iraq and Afghanistan. Academic works (Braithwaite and Johnson 2012, 2015; Kibris 2021) - as well as anecdotal evidence from war diaries and media - have described the war-torn scenarios of the Iraqi cities of Mosul, Ramadi, Fallujah and some districts of Baghdad (e.g. Sadr City)(Braithwaite and Johnson 2015). Conversely, some areas - even within the same capital - remained relatively safer from IED attacks although extremely close to the clusters of violence. To date, despite the prevalence, few studies in the domain of conflict research has focused on IED attacks carried out against counterinsurgents (Braithwaite and Johnson 2012, 2015; Townsley, Johnson, and Ratcliffe 2008). Yet, they resulted in many casualties for the US-led coalition forces (formally "Killed in Action", henceforth KIAs). Over 65% percent of the coalition casualties have been caused by IEDs between 2006 and 2007. Similarly, their toll in terms of civilian casualties has been severe. Vis-à-vis these considerations, we develop the following research question.

RQ: Why do insurgents carry out IEDs attacks in specific location and at a specific timing?

What we know from the broader literature on civil war is that rebels lead more sorties out of opportunities, to seek resources and depending on the infrastructures at their disposal (Fearon and Laitin 2003; Tilly 1978; Zhukov 2012). Similarly, other specific hypotheses on IEDs have linked them local infrastructure of various sort, highly populated areas and previous successful attacks (Braithwaite and Johnson 2015). Yet comparatively less attention has been given to the so-called conflict dynamics. These events are part of the conflict itself and are now available to analyze in the form of event-data. In this context, the nature of interactions between insurgents and counterinsurgents may shape subsequent behaviors in the warring parties, influencing the time and the location of their strikes. In this work we will propose that reactive behavior is key to explain - and eventually predict - where and when IED attacks will be carried out. We argue that indiscriminate violence perpetrated by the incumbent or by counterinsurgency forces is a key explanatory factor in this context. Several scholars argued how the extensive use of indiscriminate violence is counterproductive to incumbents' goals (Kalyvas 2006; Kalyvas and Kocher 2009; Lyall 2017; Maoz 2007). This theoretical claim is puzzling given the widespread application of specific forms of this kind in the history of counterinsurgency. Bombing and airstrikes are a prime example of that, and it has been a relatively common tactic executed with the aim to thwart insurgents' efforts through air superiority and '*absolute firepower*'. This paper aims to contribute to this body of literature by using a disaggregated approach to isolate the relative and absolute causal of effect of counterinsurgents' indiscriminate violence on insurgents' attacks. Theoretically speaking, indiscriminate violence has been claimed to create '*deterrence*' (Braithwaite and Johnson 2015; Toft and Zhukov 2012) thus discouraging further attacks and disrupting the capabilities of rebels to carry them out respectively (Kibris 2021).

Other studies have shown that activities of the warring parties possess an intrinsic tit-for-tat nature (Braithwaite and Johnson 2015; Kibris 2021; Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017b). That is, the interactions on the battlefield contribute to create geo-temporal interdependence between subsequent events. In this context, indiscriminate violence by counterinsurgents may trigger reactive behaviors by insurgents. Furthermore, we expect IED attacks to be carried out in proximity of previous counterinsurgency operations. Building on the previous theoretical and empirical contribution we make use of a novel empirical method for testing the proposed relation. To verify our testable implications, we follow a twofold empirical strategy. Firstly, we test our hypothesis against the exertion of selective violence – i.e. the control - in similar geo-temporal windows resorting to Matched Wake Analysis (Schutte and Donnay 2014). Accordingly, we expect to see an increase in the number of IED attacks after a given geo-temporal window receives the treatment i.e., counterinsurgents' indiscriminate violence. Secondly, in this paper we attempt to craft a synthetic baseline based on geographical factors (Salvi, Williamson, and Draper 2020). That is, we claim that some areas are more prone to experience instances of indiscriminate violence. We craft this spatial heuristics based on the presence of primary road networks (Salvi, Williamson, and Draper 2020; Zhukov 2012) and population settlement. We therefore simulate synthetic events within these areas and use them as synthetic controls in Matched Wake Analysis.

Firstly, we will discuss related works in the field and present an overview of the theoretical framework we build upon. Secondly, we will derive a testable implication assess its explanatory power. Thirdly, we will discuss our baseline approach to simulate counterfactuals. Thereafter, we will detail our approach towards the heuristic making use of spatial data on road networks and settlements to identify locations where the occurrence of a treatment event would have been likely but did not take place. This will result a '*buffer*' where to simulate plausible control events representing the baseline risk of a given area/time. Finally, making use of fine-grained event data from the Significant Activity (SIGACTS) Reports from 2006 on the Second Iraqi War, we present the empirical tests and discuss the results vis-à-vis our expectations. It is important to note that, depending on the field of study, IED attacks are ascribed to insurgents' activities or terrorist activities. Following the approach of similar works (Braithwaite and Johnson 2012, 2015) we focus on insurgents' attacks. The main difference between the two consists in their primary target. IED attacks as insurgents' actions mainly target military personnel. This definition is reflected in the selection of event data.

Ultimately, the study aims to enhance our causal understanding of counterinsurgency practices. On the policy making side, it will be a useful benchmark of strategies adopted by public stakeholder and of military tactics. The results largely confirm our expectations towards the main hypothesis. On the other hand, the simulation of synthetic controls shows several limitations and an over-estimation of significant effects.

4.2 Related Work and Introduction of the Theoretical Framework

4.2.1 Recent Literature on Insurgency and Counterinsurgency

Most works on insurgency and counterinsurgency focus on the most important resource in the type of warfare: the populace. Population is in fact key for insurgency and counterinsurgency (Raleigh and Hegre 2009). Fields manual on both sides of the barricades have highlighted how actions in these context should be aimed at capitalizing such a resource (Irish Republic Army 1985; US Army and US Marine Corps 2008).

What we know from the literature and from historical records is that rebels and counterinsurgents interact with the local populace in two main ways: by providing public goods and protection, or by violence and threats (Oswald et al. 2020; Schutte 2017a, 2017b). At times, the interaction is even '*unvoluntary*' as civilians may be collaterals of operations against other belligerents more than primary targets. For counterinsurgents, the prominent example of this would be the US campaign in Vietnam (Kocher, Pepinsky, and Kalyvas 2011). Indiscriminate aerial strikes where in fact described as a 'cleaner way' to wage war (Van Creveld 2011) and the 'doctrine of firepower' is still very common in contemporary operations (Lyall 2013; Ricks 2007). The literature has offered two alternative and competing explanations to describe the effect indiscriminate violence on civilians. This type of violence, in fact, may create *deterrence*, or may create *alienation.* The former suggest the existence of negative effect of indiscriminate on mobilization and persistence of violence (Kalyvas 2006; Schutte 2017b; Schutte, Ruhe, and Linke 2020). In the context of *Alienation* instead, indiscriminate violence is said to increase mobilization and therefore rebels' activities (Berman, Shapiro, and Felter 2011; Kocher, Pepinsky, and Kalyvas 2011; Schutte 2017b)[19].

[19] An extensive discussion of the two theories has been purposefully omitted from this chapter. See

Similarly, as argued in this paper, the *quality* of violence exerted by the warring parties on each other may affect the subsequent tactical choices and actions of the counterpart. It has been shown that the behavior of belligerents has a reactive component (Braithwaite and Johnson 2012, 2015; Linke, Witmer, and O'Loughlin 2012) grounded in '*tit-for-tat*' mechanism (Axelrod and Hamilton 1981). There is in fact evidence to maintain that a strong and widespread response from counterinsurgents – such as airstrikes, drone strikes, artillery, and more broadly indirect fire - may in first place thwart insurgents' action. Yet, on the long run, they seem to rebound even more fiercely (Maoz 2007). Accordingly, several works have shown how '*unproportioned responses'* towards the insurgency may be highly ineffective from a counterinsurgency perspective (Braithwaite and Johnson 2012; Rosendorff and Sandler 2004). In practice, the exertion of excessive coercion seems to further aggrieve not only the populace, but also rebels. Overall, that translate in further attacks.

The choice of IEDs as mediums to carry out these attacks reside in the relative availability of the components needed to craft these lethal explosives. Most of these components are in fact typically used in civilians' applications and easily looted by

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Chapter 3 for an extensive review.

rebels. In other cases, rebels rely on heritage ordnance (i.e., USSR material in Afghanistan) or on unexploded ordnance of the counterinsurgents (Schutte 2017b). All in all, these technical characteristics reduce the opportunity cost of resorting to these weapons. Furthermore, their use seldom requires physical presence on the battlefield – therefore circumventing direct engagement with the better equipped and better organized counterinsurgents (Salvi and Spagnoletti 2021b). Ambushes of this sort in fact, tend to cluster around location whereby counterinsurgents operate (Braithwaite and Johnson 2012; Townsley, Johnson, and Ratcliffe 2008). Furthermore, IEDs are used to reduce the tactical maneuvering of counterinsurgents, 'reducing their ability to engage with the local population' and therefore 'undermining the more holistic ambitions of counterinsurgency operations' (Braithwaite and Johnson 2012, 34).

Several studies have developed nuanced methodological approaches to addresses this puzzle and to estimate whether indiscriminate violence is productive for counterinsurgents (Kalyvas and Kocher 2009; Lyall 2010, 2017; Raleigh 2012; Schutte 2017b). Among others, Lyall (2009) resorted to statistical matching to compare Chechnyan hamlets who received a '*treatment*' – i.e. artillery fire – against non-shelled ones used as '*controls*'. Similarly, to evaluate the effect of indiscriminate violence on the local populace, Schutte (2017b) resorted to Matched Wake Analysis (Schutte and Donnay 2014) to test how '*treated*' areas show lower levels of civilians' collaboration with the perpetrator. Braithwaite and Johnson (2012, 2015) in two seminal contributions have thoroughly analyzed the geo-temporal unfolding of counterinsurgency and insurgency actions on the case of Iraq. They demonstrated how these *sorties* cluster in space and time. Furthermore, they have shown a strong interdependence between some 'COIN' operations and insurgents' attacks. Furthermore, they show how some spatial features increase the opportunities and the motivation of rebels to carry out their attacks.

analyzed the spatial and temporal distribution of said events in the case of the Iraqi insurgency.

In this study, building on this strand of the literature, we offered a systematic comparison of IED attacks prevalence after the exertion of indiscriminate and selective violence by counterinsurgents. We therefore further specify the proposed relationship of some studies (Braithwaite and Johnson 2012). Furthermore, we narrow down our empirical enquiry to the relative comparison post-treatment of IED attacks expanding the hypotheses of Braithwaite and Johnson (2015, 120) by focusing on the *quality* of violence exerted by counterinsurgents. Matched Wake Analysis constitutes and ideal methodological tool to isolate the proposed effect: its main features and characteristics are further described in the methodology section.

Moreover, as we discuss in the coming sections, most comprehensive studies – as well as our first modeling step - allow for a relative comparison between instances of selective violence and indiscriminate violence. Despite the recent advancements in micro-level studies, few works have focused on the absolute reactive behavior of insurgents to counterinsurgency practices and tactics on the field (Salvi, Williamson, and Draper 2020). That is, relative approaches do not fully clarify how rebels interact on the battlefield with counterinsurgents. This work will attempt to unveil the absolute effect of a treatment – indiscriminate violence – on IED attacks resorting to a preliminary approach to synthetic counterfactuals to employ in a Matched Wake Analysis.

4.2.2 Theoretical Outline

As discussed above, this project aims to extend the current understanding of prevalence of rebels' IED attacks looking at their geo-temporal distribution in the case of the Iraqi Insurgency. There have been several theoretical contributions that account for the variation to be explained. In that regard, the work of Kalyvas (2006) in his seminal contribution, emphasizes how control zones are crucial in shaping combatants behavior. Yet, control zones are at times relatively static in the case of particularly asymmetric and urban insurgency. Often times, belligerents fight fiercely for modest territorial advancements (Braithwaite and Johnson 2015). American troops - for example - had a solid and extensive presence in the city of Ramadi - Iraq - during the eight months of the homonymous battle in 2006. The US forces - among others - included SEAL's Task Unit Bruiser, 506th Parachute Infantry Regiment (the '*Band of Brothers*'), the 75th Ranger Regiment and 8th Marines. The latter – among the finest units in the US military - had several strongholds around and within the city (with Camp Ramadi being the main one) with large concentration of infantry forces, armored battalions, and spec-ops units. Yet, insurgents' violence during the whole campaign exhibited a considerable variation. Rebels' territorial control – particularly in urban areas – was rather capillary and often times escaped the logic of binary classification of control zones.

This posits the need to consider other contributing factors to the geo-temporal distribution of IED attacks. As maintained by several authors (Braithwaite and Johnson 2015; Kocher, Pepinsky, and Kalyvas 2011) these actions are strongly related to counterinsurgency operations. Lack of fine-grained data has constrained most of these analysis to an aggregate level[20], which does not allow to fully appreciate the micro-level dynamics of interaction between insurgents and counterinsurgents.

To systematize the relation between the two parties, authors have often referred to the concepts of '*denial*' and '*punishing*' strategies (Braithwaite and Johnson 2015; Galula 2002; Toft and Zhukov 2012). *Denial* strategies have the main objective of compartmentalizing conflict areas, therefore limiting maneuvering of rebels and shutting down networks that fuel their capabilities. *Punishment* strategies on the other hand aim to thwart the momentum of the insurgency hampering the 'resolve' (Braithwaite and Johnson 2015) of rebels to keep pushing their war effort. Similarly to the discourse on selective and indiscriminate violence, the literature suggests *denial* strategies are more effective on the long run as they aim to 'dry out' the well from which rebels draw their resources and reinforce their capabilities (Galula 2002). Similarly, other works have unveiled how counterinsurgency and counterterrorism operations, often times result in violent backslashes instead of reducing insurgents' activities through deterrence (LaFree, Dugan, and Korte 2009).

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[20] With the notable exception of (Braithwaite and Johnson 2012, 2015; Linke, Witmer, and O'Loughlin 2012; Schutte and Weidmann 2011; Toft and Zhukov 2012).

Building on this literature we explore these dynamics of '*reactive behaviors*' that belligerents develop while fighting each other. That is, in this project we claim that insurgents adopt a reactive behavior when they come in contact the counterinsurgency troops. We hypothesize that they conduct their asymmetric warfare in response to specific inputs from the opposing warring party. The core mechanism is that of a tit-for-tat (Axelrod and Hamilton 1981). However, not every action is equally likely to generate a response on the battlefield (if any) as suggested by the literature on *denial* and *punishment*. In fact, anecdotal evidence from Iraq, suggests that instances of indiscriminate violence from counterinsurgency forces tend to generate surges in insurgents' violence as well as large-scale search and seize operations – even more so when civilians are involved. Conversely, SpecOPS, surgical strikes and '*clear, hold and build operations*' - when completed - seem to generate fewer responses from the counterpart. Insurgents may capitalize on brute-force approaches – such as IED attacks - after exertion of indiscriminate violence to (1) retaliate (2) re-state their presence on the field (3) show resilience to the populace to maintain a reputational status. It is worth noting, that these theory and evidence-driven speculation on the motivations of rebels will not be tested explicitly in this work. Instead, we decided to focus on the isolation of the effect of indiscriminate violence on IED attacks. Furthering the approach proposed by Braithwaite and Johnson (2015) we derive a testable implication on the *tit-for-tat* behavior of insurgents.

Specifically:

[H1] Higher levels of IED attacks are expected in geo-temporal proximity of counterinsurgents' exertion of indiscriminate violence as compared to selective violence.

As mentioned above, this hypothesis aims to estimate the relative effect of indiscriminate violence on IED attacks by counterinsurgents. However, making use of simple synthetic counterfactuals, we also move a first step toward the estimation of the absolute of effect indiscriminate violence. Therefore:

[H2] Higher levels of IED attacks are expected in geo-temporal proximity of counterinsurgents' exertion of indiscriminate violence.

To test our hypotheses, we will be using data from Significant Activity reports (SIGACT). They include over 390,000 events deemed as 'significant' in Iraq from 2004 to 2009 and have been made available by the ESOC data project. Each event includes – among others - relevant information on event type, initiator, date, georeferenced, location, casualties. We make use of data from 2006, a crucial year for the Iraqi insurgency. This timeframe witnessed extremely relevant counterinsurgency operations such as the aforementioned Battle of Ramadi, which lasted from March to November in the Al Anbar Governorate. The capital of the governorate has always been the pulsating core of the insurgency and the number of actions from insurgents has been growing steadily throughout 2006. A similar trend is observed throughout the whole country as portrayed in the aggregate time-series in **Figure 15**. Rebels' actions kept growing dramatically in 2007, and so did counterinsurgency actions with the so-called '*troops surge*'. We purposefully decided to omit 2007 from our sample as the surge may have biased the results due to the larger amount of counterinsurgents' actions. A very large number of treatment and control events is far from ideal for Matched Wake Analysis. An overabundance of the former may in fact lead to overlapping in spatial and temporal windows. In turn, that may lead to an inflation of the effect estimates. Conversely, an overlapping of treatment and control in the same geo-temporal windows, may bias downwards the estimates provided by the model[21]. In short, 2006 provides an ideal candidate timespan to test our proposed relationship offering a tactically and strategically relevant narrative in terms of operations that unfolded in that period, and a safer methodological ground due to the distribution of events.

To address the self-evident endogeneity problem between the conflict variables, we make use of statistical matching on spatial areas with different levels of insurgents' activities and a difference-in-difference approach. Matching is made in continuous space/times 'units' and based on a variety of structural conditions - such as population, distance from the capital, ethnic composition and other geographical features. The Matched Wake Analysis employed in this paper is further detailed in the next sections.

[21] See https://github.com/kdonnay/mwa.

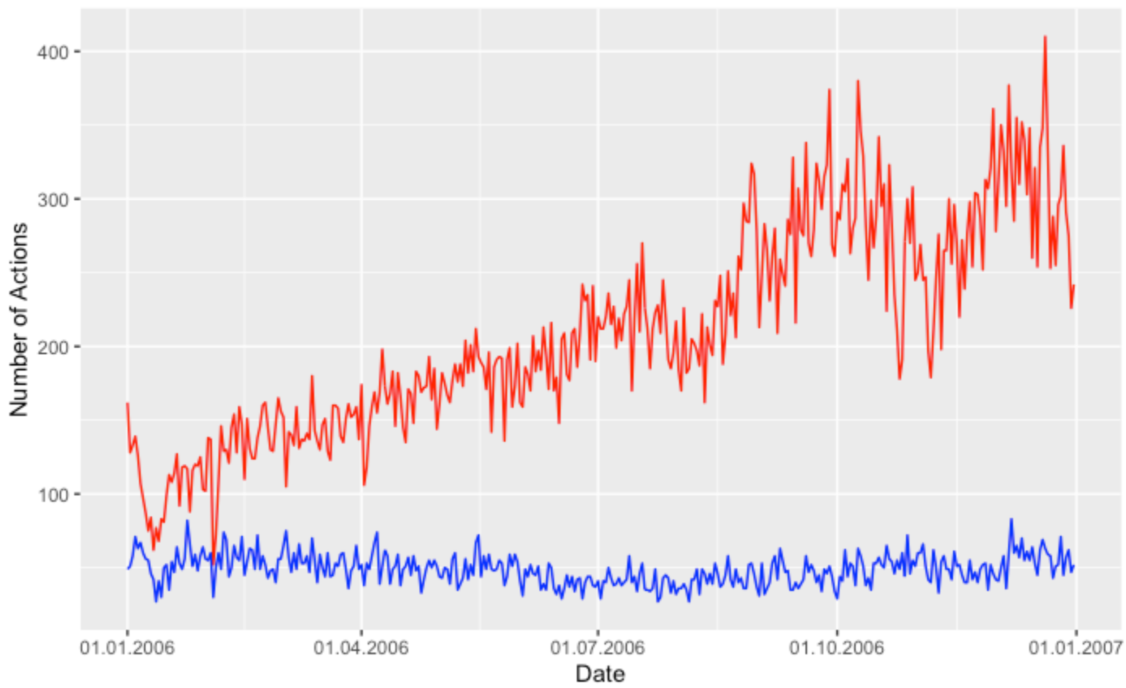

Figure 15: Insurgents (red) and Counterinsurgents (blue) actions in SIGACTs Data. Iraq, 2006.

4.3 A Simulated Baseline Approach

As highlighted above, extant studies have been extremely beneficial for the understanding of the variation of IED attacks and its interplay with indiscriminate and selective violence perpetrated by counterinsurgents. Yet, modeling the absolute effect of these conflict processes is a demanding task. The co-occurrence of insurgents' violence and counterinsurgency practices in spatial-temporal windows cannot provide definitive evidence of causal relationship through standard quantitative techniques such as regression analysis. As already proposed in a previous piece (Salvi, Williamson, and Draper 2020), we propose a specific route to estimate the absolute causal relationship between conflict events: crafting and comparing simulated counterfactual events against the observed treatment. This is quite an undertaking as the it implies defining heuristics that define of 'plausible areas' – and eventually 'plausible times' - for specific conflict events that we will refer to as '*risk sets'*. Crafting definitions of this kind is intrinsically problematic as it posits several selection risks. And yet, the benefit of creating synthetic controls belie the fact that they might provide us of expected levels of the Dependent Variable - in this case insurgents' carrying out IED attacks - in geo-temporal windows that have a high risk of experiencing indiscriminate violence, but ultimately did not. The comparison between the observed events and the properly crafted artificial control de facto allow us to isolate the causal effect of indiscriminate violence in absolute terms. For the sake of this contribution, the absolute comparison with synthetic control events will complement the relative comparison with observed events – i.e., instances of selective violence. It is worth specifying that this paper will only focus on the spatial heuristics for synthetic control events. That is, we will focus on locations with high likelihood of witnessing instanced of indiscriminate violence by counterinsurgents. The time component is purposefully overlooked in the current formulation and will be analyzed in future contributions.

As discussed above, relative comparisons are quite common in the literature and Matched Wake Analysis make them particularly convenient (Oswald et al. 2020; Schutte 2017b). Nonetheless, our approach focuses on expanding this method allowing comparison to a baseline while 'partitioning out the unobservable or unmeasurable variables that are inherently correlated with both the locations of indiscriminate violence' by counterinsurgency forces and the likelihood of the occurrence of IED attacks – 'such as a location's strategic military importance or its pre- and intra-war social networks'(Salvi, Williamson, and Draper 2020, 4). The main hurdle – onto which the whole approach rests upon - is that of understanding what heuristics should be used to create said events. To study the effect of counterinsurgent violence on IED attacks. The literature has provided several answers to this conundrum. The work of Lyall (2009) considers all Chechen villages as plausible control points before matching;

similarly, Kocher, Pepinksy, and Kalyvas (2011) examine all hamlets within the Republic of Vietnam during the Vietnam War. In these approaches, the likelihood of occurrence of events in each location is weighted by relevant spatial covariates.

In our contribution, we rely on findings on recent research that investigates the spatial diffusion of conflict and the logistics of war focusing on road networks and population settlements. In particular, scholars have identified the significance of road networks in determining where insurgents' activities unfold (Zhukov 2012). Roads are of primary importance for tactical maneuvering, and they represent an asset for both insurgents and even more so for counterinsurgents. The latter most often benefit from increased technological and operational capabilities that are strongly dependent on road networks. Accordingly, it is very common for insurgents to carry out hit-and-run attacks and IED attacks on major roads that connect strategic locations to disrupt counterinsurgents operations. In our specific case, looking at the Iraqi insurgency over 60% of all indiscriminate violence events occur within 5 kilometers of primary roads[22]. It should be noted that the area mentioned above accounts for only 17% of the Iraqi soil. As for IED attacks, 65% of the total number events (see the operationalization below) occur

[22] 5 kilometers at each side, thus 10 kilometers total.

within 5 kilometers of primary roads[23]. As mentioned in the literature review and in accordance with recent works on counterinsurgency (Kilcullen 2015; Schutte 2017b), populace is a key resource for both belligerent parties. The lack of human settlements de-facto deprives warring party of one of their primary aims, that of seeking influence on the population. For such reason, we included a heuristic based on settlements and hamlets. In fact, when adding this spatial constraint, we observe that 80% of all indiscriminate violence events occurred within a 5 kilometers buffer around settlements[24]. As for insurgents attack through IEDs, 88% of them occur in the same buffer. The settlement-covered area however constitutes almost 40% of the whole country.

Using the two '*risk-sets*' we simulate a set of points representing '*synthetic control events'*. That is, we generate coordinates within the specified heuristics that represent location whereby indiscriminate violence perpetrated by counterinsurgents has a high likelihood of occurrence, but ultimately did not take place. The prevalence of IED events taking place in the proximity of these synthetic controls is then compared with

[23] Ibid.

[24] Ibid.

prevalence of IED events occurring in proximity of observed instances of the treatment to determine their absolute effect. The process, in practice follows the approach of a previous work and is represented in (Salvi, Williamson, and Draper 2020). It consists in generating several spatial buffers of varying width around primary roads and population settlements[25] (see the left facets of **Figure 16** and **Figure 17**) . The selection of the buffers' width consisted in an iterative process to maximize events' coverage while minimizing the amount of land areas captured. As mentioned above, the optimal width appears to be equal to 5 kilometers at each side of the spatial object under consideration, thus 10 kilometers overall. Such specification allows us to capture the majority of events of interest while keeping a conservative approach towards the percentage of land covered[26]. The resulting buffer takes the form of a spatial polygon overlaid to the

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[25] Most of the GIS processing is carried out through the *sf* package (Pebesma 2018) making use of R programming language. Iterative preliminary tests have been carried out using QGis (https://qgis.org/).

[26] With regards to the road buffer, selecting 4 kilometers at each side, we capture 56% of the instances of indiscriminate violence and 60% of IED events. Such specification covers 14% of the whole country. A buffer of 6 kilometers at each side of the spatial object instead, captures 66% of the instances of indiscriminate violence and 70% of IED events. In this case, the land area covered equals the 20% of the whole country. A similar pattern is observable in the case of settlements. In this case the buffer of 4 kilometers of radius covers 80% of the indiscriminate violence events, 84% of the IED events and 36% of

original spatial objects – i.e., primary roads and settlements: the buffers are portrayed in the center facets of **Figure 16** and **Figure 17.** The right facets of the same figures show the distribution of the observed events in comparison with the buffers. In order to simulate synthetic control events, we followed two main approaches: firstly, we generated random points with uniform random sampling within the road and settlement buffer respectively. We specified the number of ideal points to simulate setting it equal to the number of events captured by the respective buffers (roughly 16000 for the roads buffer and roughly 21000 for the settlements buffer). As a second approach, we relied on a point process model specifying the parameter of intensity – or points per unit area – equal to that of the actual treatment events (Salvi, Williamson, and Draper 2020). As discussed in the robustness section (see below) the two techniques yielded similar results: for such reason the paper will present only the results originated from uniform random sampling. Self-evidently, both approaches come with the strong assumption: each combination of latitudes and longitudes coordinates within the buffers is deemed as a suitable candidate for instances of indiscriminate violence. As already pointed out in a previous contribution (Salvi, Williamson, and Draper 2020), this is a rather shallow

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the land area. As for the buffer of 6 kilometers of radius: it captures 85% of the indiscriminate violence events, 92% percent of the IED events and covers more than 43% of the total land area.

criterion. Other variables may play a crucial role in increasing the likelihood of indiscriminate violence by counterinsurgents in some areas of the buffers, but not in others. The implications of such simplification are further discussed in the conclusion; yet, for the sake of this work, we aim to offer a preliminary comparison between the relative and absolute effect of the treatment on the incidence of IED attacks. To this end, the assumption should not bear excessive consequences over the results: accordingly, we feel that the spatial heuristics centered on primary roads and settlements should offer a suitable delimitation of territory already. As mentioned above, modeling time-related heuristics is beyond the scope of this paper. For such reason, the ‘date of occurrence’ of synthetic controls has been randomly sampled from those of observed events for each month, creating a temporal distribution similar to that of the actual instances of indiscriminate violence (Salvi, Williamson, and Draper 2020).

Thus, we resorted to Matched Wake Analysis (details below) to test empirically our hypotheses. The simulated events are used as controls while the observed instances of indiscriminate violence serve as treatment for the geo-temporal windows. In the next sections, we detail the nature of the data used as well as the model employed and the tuning of the parameters.

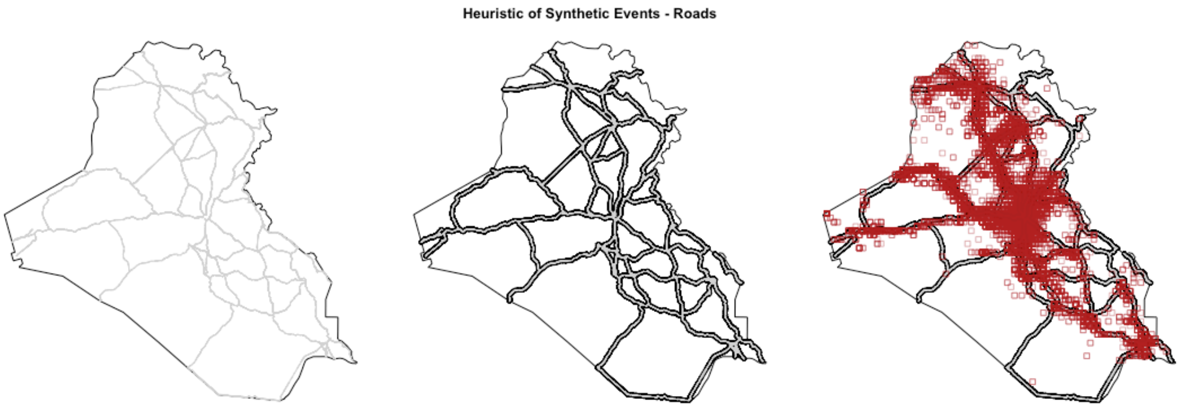

Figure 16: Heuristic of synthetic events based on primary roads. The left facet shows the network of primary roads. The center facet shows the overlaying of a 5 kilometers buffer (at each side). The right facet shows the spatial distribution of treatment events in comparison with the road buffer.

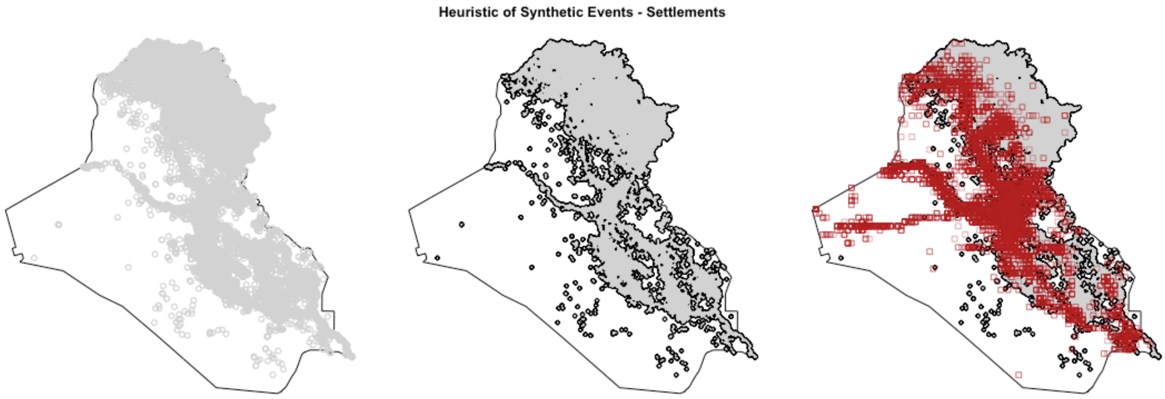

Figure 17: Heuristic of synthetic events based on human settlements. The left facet shows the full sample of settlements. The center facet shows the overlaying of a 5 kilometers radius buffer onto each settlement. The right facet shows the spatial distribution of treatment events in comparison with the settlement buffer.

4.4 Empirical Analysis

4.4.1 Data

As already mentioned, to test the substantive relation proposed in the hypotheses, as well as to test the methodological approach based on synthetic controls, we focus on the case of the Iraqi insurgency throughout 2006. For this, we use data from Significant Activity reports (SIGACT). This dataset is an ideal candidate for our analysis as it provides the most comprehensive coverage of interactions between insurgents and counterinsurgents in the context of the Iraqi insurgency. It consists of geo-referenced events with a detailed and fine-grained description of the actors involved, locations, timing, and casualties. The full SIGACT dataset for 2006 is composed of over 97285 observations each representing an event taking place on the Iraqi soil (or in close proximity in some cases). Originally, they were coded by the US military from reports originated at the platoon level (Schutte 2017b) thus providing a unique perspective on the unfolding of the insurgency[27]. Each unique event is described by a *type* and a

[27] Their merits notwithstanding, these data may suffer from under-reporting of certain categories of events (e.g., US Air Force operations, private contractors' actions). An extensive comment is provided by

category. While *types* identify the broader taxonomy of each event, *categories* describe events in detail and has been used to code the independent variables and the dependent variable. A full table of categories is recounted in **Appendix 2**. In particular, there are 104 unique combinations of types and categories, fully reported in **Appendix 2**.

Type	Events Count
Criminal Event	13314
Enemy Action	27426
Explosive Hazard	32559
Friendly Action	17614
Friendly Fire	232
Non-combat Event	2529
Other	619
Suspicious Incident	357
Threat Report	2635

Table 6: SIGACTs event types and count. Iraq, 2016.

Table 6 recounts event types for the subset used in this paper, together with count of events. To code our variable of interests, we mainly relied on 'Enemy Actions' (which

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(Schutte 2017b). To date, despite these issues, SIGACTs data offer one of the most comprehensive sources of information on the operations carried out in Iraq.

includes insurgents' actions), 'Friendly Actions' (including actions of the US-led coalition) and 'Explosive Hazard' (pertaining enemy forces). **Table 7** portrays the detailed coding rules followed to cluster events into the broader categories of Indiscriminate Violence, Selective Violence and IED attacks. The classification for the first two clusters is coherent with the coding provided by Schutte (2017b).

Starting from the independent variables: the main criterion used to code counterinsurgents' indiscriminate violence is to include categories that rely on '*indirect fire'*. Despite the high professionalization of the US-led troops, the latter has a high risk of collaterals. While 'standalone' Air Force activities - such as bombing operations - are not recorded in this dataset, '*close air support'* to platoons on the ground is a quite common category and has been coded as an indiscriminate exertion of violence[28]. Similarly, we include attacks carried out with artillery and unmanned aerial vehicles (UAV). As for ground operations, we included '*escalation of force*' has they mainly rely on indirect fire. As for coding selective violence we rely on a selection criterion centered 'direct fire actions' with targets specified as insurgents. The resulting event categories are: 'direct attack', 'patrol' (with engagement), 'small unit actions',

[28] It is interesting to note how, despite the strict rules of engagement of the coalition forces, instances of indiscriminate violence – particularly *indirect fire* – were quite common.

‘cordon/search’ and ‘Sniper OPS’. As for the dependent variable – IED attacks by insurgents – we relied on several categories encompassing presence of IEDs and other explosive devices. We therefore included the following categories: ‘*IED explosions*’, ‘*IED pre-detonation*’, ‘*Mine Strike*’[29]. We decided to include also two ‘near-misses’ categories: ‘*IED found/cleared*’, ‘*Mine found/cleared’*. While these events did not fully unfold – as the ordnance was identified preemptively – they were still planted and prepared with the same strategic goals of those which detonated[30]. That is, according to our reasoning, they still concur to the total variation of IED attacks by insurgents, despite their outcome.

[29] While IED are commonly activated through remote-controlled devices, mines – commonly activated by pressure plates- serve a similar strategic purpose to insurgents. Therefore, they were included in the cluster of the dependent variable.

[30] See the robustness tests section for further detail on their impact.

	Indiscriminate Violence	Selective Violence	IED Events
Event Categories	Close Air Support	Direct Attack	IED Explosion
	Artillery	Patrol	IED found/cleared
	UAV	Small unit actions	IED pre-detonation
	Escalation of Force	Cordon/Search	Mine found/cleared
		Sniper OPS	Mine Strike
Count	3446	4973	29382

Table 7: Event categories coded for the empirical testing. The count of each coded variable is reported in the last row.

Applying such taxonomy, we obtained three clusters – as shown in **Table 7** – consisting in 3446 treatment events (indiscriminate violence by counterinsurgents), 4973 observed control events (selective violence) and 29382 instances of the dependent variable (IED Events). Their spatial distribution throughout the full sample is depicted in **Figure 18**. It is worth noting that most events take place around primary roads and settlements (with the central cluster of events located around the area of the capital). Similarly, **Figure 19** depicts the temporal variation of the three variables.

Figure 18: Data Points representing instances of Selective Violence, Indiscriminate Violence and IED Attacks respectively. Iraq, 2006.

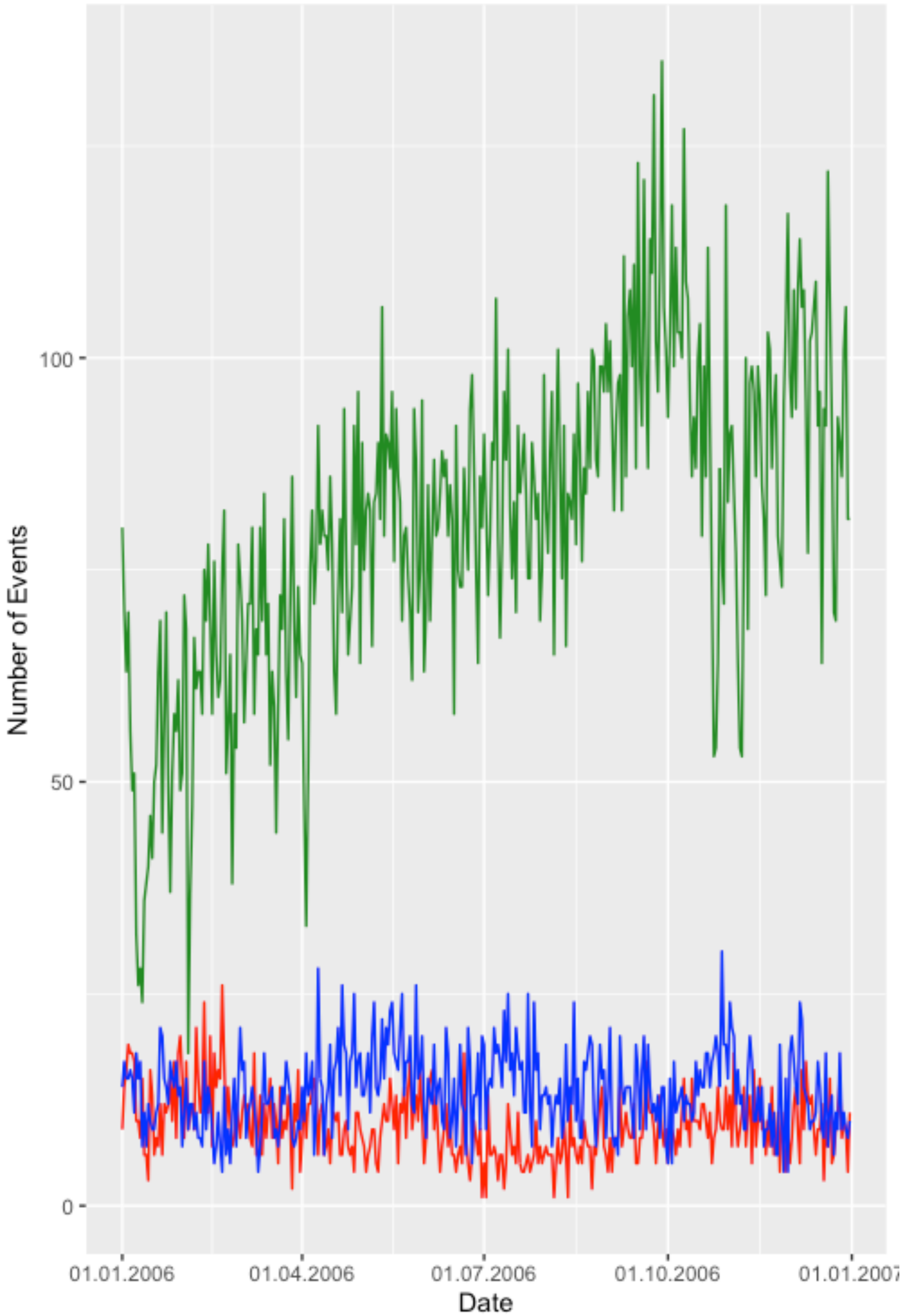

Figure 19: Time-series of instances of Selective Violence (blue), Indiscriminate Violence (red) and IED attacks (green). Iraq, 2006.

As for the variables used for matching geo-temporal windows in the Matched Wake Analysis, we selected a series of theory-driven indicators that may influence the incidence of IED attacks in specific locations and times. In particular, we use spatial data on nightlights emissions from DMSP OLS (Koren and Sarbahi 2018; Weidmann and Schutte 2016) and population density from SEDAC (Raleigh and Hegre 2009; SEDAC 2005). Furthermore, we computed distance to the capital city (Tollefsen and Buhaug 2015) and distance from major roads[31] (Zhukov 2012). The events data are linked to the spatial covariates by nearest neighbor mapping using relevant information from rasters and vectors.

4.4.2 Modelling Strategy: Matched Wake Analysis

As discussed above, Matched Wake Analysis is an ideal candidate to test our prepositions. It allows to overcome the modifiable areal unit problem (henceforth MAUP). In simple terms, common aggregation rules in geo-temporal windows (i.e.,

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[31] Such matching variable is omitted from the Matched Wake Analysis that relies on the road buffer to avoid systematic biases.

grid cells), have the intrinsic risk of having a strong dependency between the spatial unit of choice and the levels of the dependent variable (Cressie 1996; Schutte and Donnay 2014).

Events pertaining to the independent variables are classified as '*treatments*' or '*controls*'. In this substantive case, treatment events are instances of indiscriminate violence by counterinsurgents as detailed in the Data section. As for controls, we have two variants: the relative comparison uses instances of selective violence, whereas the absolute comparison employs events simulated within the road and settlement buffers respectively. The model generates a balanced sample with sliding geo-temporal windows – thus varying the temporal and spatial width of the '*wakes*' – and match them using *Coarsened Exact Matching* (henceforth CEM) on the spatial covariates that describes the characteristics of the location.

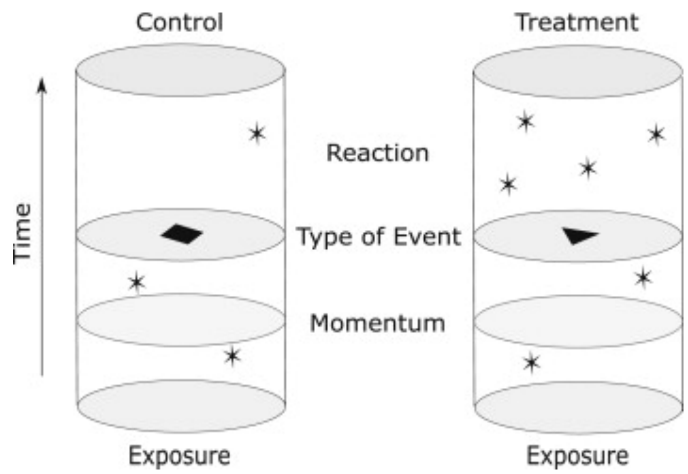

Figure 20: Conceptual illustration of Matched Wake Analysis. Reproduced from (Schutte and Donnay 2014). Events are codified as treatments (triangle shape – here instances of indiscriminate violence) and controls (square shape- here instances of selective violence at first, then synthetic controls).

The model not only matches wakes on spatial features, but also considers pre-intervention trends of the dependent variable (the '*momentum phase*'). Subsequently, a difference-in-differences approach to estimate the effect of the treatment over the dependent variable. That is, the model aims to create 'ceteris-paribus' condition, whereby the only difference between two wakes is the occurrence of a treatment [32].

Figure 20 shows a conceptual illustration of the methodology as illustrated in the original paper by Schutte and Donnay (2014). The two cylinders – or '*wakes'* - represent two geo-temporal units with the vertical and horizontal side representing a time and space window respectively. The square at the center of the left-side '*wake*' represents the treatment, while the triangle in the other '*wake'* depicts a control event. The stars depict the occurrence of the dependent variable events. We can see how both wakes are split in pre-treatment/pre-control areas to account for prior levels of the dependent variable.

[32] **Appendix 2** includes another visual representation of the procedure. It is worth noting that, as the author of the model puts it: "counts were aggregated for each of the pre- and post-intervention period which solves the problem of serial correlation that Difference-in-Differences designs are otherwise prone to"(Schutte and Donnay 2014, 12).

With this setup, we estimate a model specified as:

$$\eta_{post} = \beta_0 + \beta_1 \eta_{pre} + \beta_2 indiscriminate\ violence + u$$

whereby, η is the count of dependent events. Therefore, while η_{post} represents the count of post-treatment IED attacks. η_{pre}, on the right-hand side of the equation represents the count of pre-intervention IED attacks. Accordingly, β_1 represents the coefficient estimated for pre-intervention dependent events. β_2 is the coefficient that depicts the average effect of indiscriminate violence by counterinsurgents.

It is worth noting that the model requires to specify temporal and geographic windows of interest. In the paper, we present a specification that investigates the proposed relationship in a time window of 45 days and in a spatial window of 10 kilometers. This specification is in line with our theoretical design and aims to unveil the interrelations between insurgency and counterinsurgency actors at the local level, and in a disaggregated timescale.

4.4.3 Relative Effect of Indiscriminate Violence: Results

In this section we evaluate the treatment effect of counterinsurgents' indiscriminate violence on IED attacks as compared to that of selective violence by the same perpetrators. This empirical setup reveals a positive effect of indiscriminate violence by counterinsurgents on the subsequent number of IED attacks. Not all, the significant geo-temporal windows are contiguous as depicted in **Figure 21**. The effect in the immediate geo-temporal proximity is not statistically significant, therefore we cannot be sure about the nature of the effect in the immediate aftermath of indiscriminate violence. The first significant effect of indiscriminate violence appears roughly after 10 days, and near the treated area, roughly at 6 kilometers. This window has a relatively small estimated effect – roughly 0,332. That is, for 100 instances of indiscriminate violence, we would observe about 33 additional IED attacks by insurgent. As the spatial distance increases, however, we notice a stronger positive treatment effect – around 0.652 – at 10 kilometers from the exertion of indiscriminate violence. Such attacks have the appearance of being retaliatory behaviors. Despite the non-significance of the geo-temporal windows in close proximity of the treatment, we may cautiously speculate that that the disruptive potential of indiscriminate attacks has a sort of dazing effect. Yet, increasing the temporal distance we notice increasingly strong treatment effects in the full spatial window. At the 20 days mark, for instance we observe significant effects ranging from 0,539 – at 4 kilometers – to 1,248 – at 10 kilometers. As for the 25 days mark, we see very strong positive effects at 8 to 10 kilometers from the exertion of indiscriminate violence. In this geo-temporal aggregation, the estimates peak at 1,703 – the largest effect found by our model (25 days and 10 kilometers). As day passes, the effect persists in the full spatial window, with lower estimates at short spatial distance from the treated area. Finally, we found no significant windows at the 45 days mark.

Overall, the treatment effect of indiscriminate violence ranges from a 0.332 to a 1.703 increase in the dependent events in geo-temporal windows that are significant at the 95% level. Therefore, the average treatment effect is 0,908. That is, on average for 100 instances of indiscriminate violence by counterinsurgents, we observe roughly 91 additional IED attacks. The full list of significant geo-temporal windows, as well as their p-values and estimated effects, is reported in **Appendix 2**.

In short, insurgents seem to be particularly reactive near locations where counterinsurgents operated with peaks after roughly three to four weeks from the treatment. Also, after more than 20 days from the instance of indiscriminate violence, we observe significant large estimates close to the location of the accident. That suggests that after a certain number of days, IED attacks tend to get back closer to the original location where counterinsurgents operated. The positive effect largely confirms our hypothesis on the relative comparison between indiscriminate and selective violence. While it is not surprising that IED attacks tend to cluster around counterinsurgency operations (Braithwaite and Johnson 2012) it is important to note how the type of violence exerted by counterinsurgents makes a significant differences in shaping subsequent actions from rebels. It appears that indiscriminate violence is not an optimal tactic to thwart the insurgents' morale or their war effort. Unfortunately, due to the presence of other non-significant geo-temporal windows, we cannot fully appreciate the dynamics between these events in their entirety. Interestingly, we notice that increasing the temporal specification of the model to 60 days and the spatial one to 20 kilometers, the significant positive effect does persist and seem to diffuse in space up to 20 kilometers from the treated location. Similarly, the effect reverberates in time up to 55 days, around the 10-15 kilometers window. The contour plot of this last specification is included in **Appendix 2**.

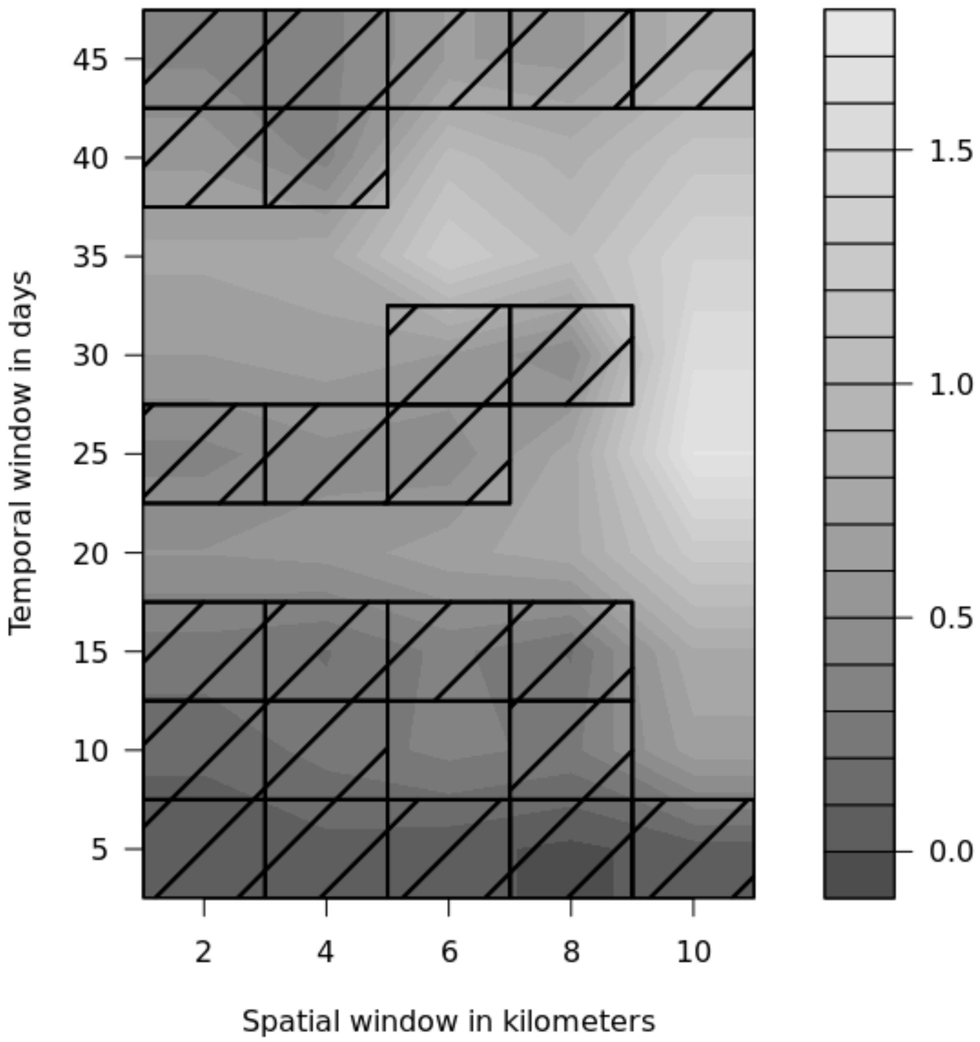

Figure 21: Results of the relative effect model. The dependent variable is the count of IED attacks. Instances of indiscriminate violence and instances of selective violence are used as treatments and controls respectively. The contour plot shows the average treatment effect estimated through the difference-in-differences approach. The clear squares depict geo-temporal windows whereby the estimate is significant at 95% level. Squares overlaid with lines show that the estimated effect is not significant. The bar on the right-hand side shows the legend of the direction of estimated effects.

4.4.4 Absolute Effect of Indiscriminate Violence: Results

In this section we evaluate the treatment effect of counterinsurgents' indiscriminate violence on IED attacks against two sets of simulated points. The simulated points are based on the heuristics presented in **Section 4.3**. One set of points is generated within a buffer built onto the Iraqi road network, while the other is generated around human settlements. In the first case, 'distance from major roads' – used as variable for matching in the other specification – was omitted. The empirical tests following the two heuristics yields inconclusive results. The main problem resides in the overabundance of significant estimates in the geo-temporal windows. Even from a qualitative analysis of **Figure 22** and **Figure 23** one can notice that the clear squares are predominant in the contour plot as compared to the ones in **Figure 21**. This is particularly true for the model based on the settlement buffer, which shows 43 significant estimates in geo-temporal windows[33]. This unfortunately reveals that the two heuristics are far from efficient in terms of replicating the distribution of significant estimates in space and time obtained from real control events.

[33] The areas overlaid with lines in the contour plot are just two.

Interestingly however, the actual estimated effect size shows some similarities with the analysis that features observed control events. These estimates, for the model based on the roads buffer ranges from 0.27 to 1,388. As in the model built with observed data, there are no significant negative estimates. The mean value is 0,675, with a standard deviation of 0,265. Furthermore, the mean, the minimum and the maximum are somewhat close to the one of observed events. As for the model based on the settlements buffer, all the estimates are – again - positive as in the model with observed data. The estimates range from 0,32 to 1,56 Furthermore, some of the estimates – at similar temporal and spatial parameters – show some similarities with the one from the original model. The mean in this case is roughly 0,801 with a standard deviation of 0,296. For these two specifications, the full list of significant geo-temporal windows, as well as their p-values and estimated effects, is reported in **Appendix 2**.

Overall, we are skeptical towards these results and – in turn – towards the two heuristics. While there are some similarities with the original estimates, they are not enough to motivate their viability. It should be noted that theoretically we do in fact expect larger positive estimates of the absolute effects in comparison to the relative effects. The reason for that resides in the fact that a geo-temporal window where a '*real*' control event occurred, experienced some form violence even if not indiscriminate. Conversely, an area where indiscriminate violence was likely but did not take place is expected to be less prone to subsequent IED attacks. That is, since no violence was really exerted, logic suggests that we would observe larger post-intervention effects.

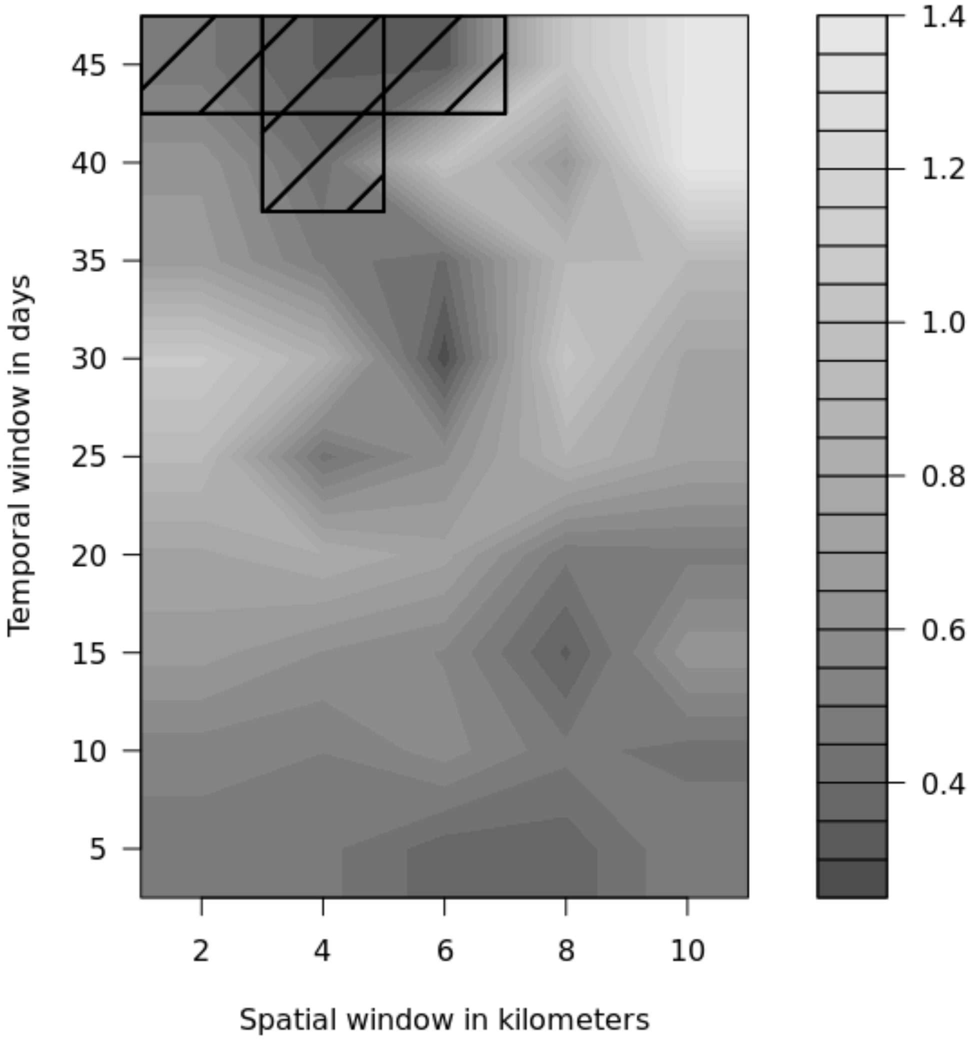

Figure 22: Results of the absolute effect model using the roads buffer. The dependent variable is the count of IED attacks. Instances of indiscriminate violence and simulated events (within the roads buffer) are used as treatments and controls respectively. The contour plot shows the average treatment effect estimated through the difference-in-differences approach. The clear squares depict geo-temporal windows whereby the estimate is significant at 95% level. Squares overlaid with lines show that the estimated effect is not significant. The bar on the right-hand side shows the legend of the direction of estimated effects.

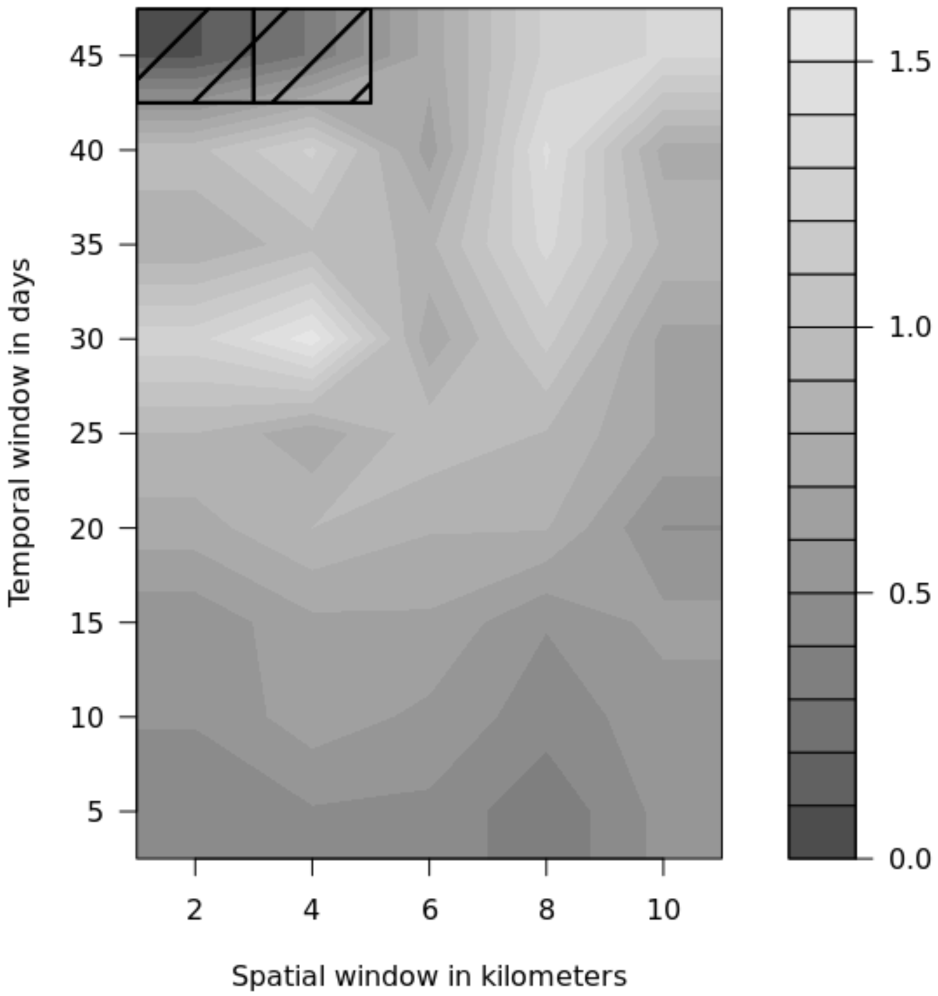

Figure 23: Results of the absolute effect model using the settlements buffer. The dependent variable is the count of IED attacks. Instances of indiscriminate violence and simulated events (within the settlements buffer) are used as treatments and controls respectively. The contour plot shows the average treatment effect estimated through the difference-in-differences approach. The clear squares depict geo-temporal windows whereby the estimate is significant at 95% level. Squares overlaid with lines show that the estimated effect is not significant. The bar on the right-hand side shows the legend of the direction of estimated effects.

4.4.5 Robustness

As mentioned throughout the section of this papers, we conducted several robustness checks. In all cases, we specified different parameters for the temporal and geographic windows required by Matched Wake Analysis. In particular, we extended and reduced the parameters by 20 units for the temporal one, and by 10 kilometers for the spatial one. No noticeable difference has been noticed aside from those reported at the end of **Section 4.4.3**.

As for the model including selective violence, we tested for different coding rules of the dependent variable – i.e., IED attacks. Specifically, we iteratively removed events falling within the following categories: '*Mine found/cleared*', '*IED found/cleared*'. Even in this case, the were no noticeable changes in the results, if not for slight variations in the estimated effect. It is important to note that the effect, in all cases, was still positive.

As for the simulated events models, as mentioned above we tested for different widths of the buffers. Unfortunately, that did not improve the overabundance of significant windows and the relative inaccuracy of the estimated effects.

4.5 Conclusion

In this paper, we seek to answer the following research question: why do some conflict zones exhibit more IED attacks than others? We investigate what drives the variation in the location and timing of these attacks. Having reviewed the main contributions in the field of civil war and counterinsurgency, we used principles from theoretical works to formulate two testable implications. We maintain that indiscriminate violence exerted by counterinsurgents results in more IED attacks, both in comparison with selective violence and in absolute terms.

We empirically tested our hypothesis on the Iraqi insurgency using SIGACT event data from 2016 coded by the US military using Matched Wake Analysis. Our results show how indiscriminate violence systematically increases subsequent IED attacks perpetrated by insurgents. On the contrary, selective use of force is more efficient in preventing – or at least in provoking less - subsequent IED attacks.

The results obtained from the model that uses observed events, provide us with thought-provoking insights. As discussed in the results' section, the estimates show a peculiar geo-temporal pattern of reaction that match with the scholarly theoretical framework. The positive effect of indiscriminate violence on IED attacks is moderate in close geo-temporal proximity of the treatment event, yet at the increase of the spatial distance, as days pass, the effect becomes stronger. These results seem to suggest that indiscriminate violence does not create deterrence of sort. On the contrary, it triggers a tit-for-tat behavior. It goes without saying that the presence of non-significant windows suggests us to be cautious about the statement as we cannot be confident about the direction of the effect for all level of aggregation. It is also possible that indiscriminate violence by counterinsurgents creates deterrence towards other actions (e.g., direct sorties) and pushes rebels to adopt more indirect tactics – i.e., IEDs and explosives. Yet, the reactive narrative is widely maintained in the literature discussed throughout the paper and thanks to our substantive and methodological contribution, we may have added further support to this theoretical strand. Further contribution will focus on further disaggregating the scope of the analysis. In this paper, we considered the full country in our sample. Yet, dynamics in urban areas may be profoundly different from those of remote areas (Kilcullen 2015).

As for the models using synthetic controls, we attempted to leverage the clustering behavior around settlement and roads to estimate the absolute effect of indiscriminate violence on IED attacks. The intuition was that of creating two plausible risk-sets were instances of indiscriminate violence by counterinsurgents were likely, but ultimately did not happen. Unfortunately, the overabundance of significant window across the whole geo-temporal specification suggests a low accuracy of our two heuristics. Interestingly, however, the sign and size of the estimate show some similarities with those obtained by the model that employs observed events. Further contributions may consider different simulation techniques to perfect the heuristics, accounting not only for the spatial component, but also for the temporal one. Among others possible improvements, we plan to 'simulate' events through a probabilistic model. An example may consist in a classifier (e.g., a random forest algorithm), trained on observed data. In this context, we may use false positives estimated by the model and interpret them as 'high risk' geo-temporal points. Other alternatives include Monte-Carlo simulations or other resampling methods.

All in all, this work makes three main contributions in the substantive and methodological domain. First and foremost, we evaluate the relative effect of indiscriminate incumbents' violence on IED attacks clarifying their causal relationship through Matched Wake Analysis. Secondly, we attempted to offer a tentative framework for utilizing synthetic control events. Thirdly, we attempted to test empirically the absolute effect of indiscriminate violence on IED attacks. While the simulated controls approach has not been as satisfactory as expected – and should be evaluated with caution – we feel that it constitutes a further step onto a relatively unresearched strand of the literature that bears the promise of clarifying causal relationships between interconnected and highly correlated conflict events.

5 FORECASTING THE INCIDENCE OF IED ATTACKS IN IRAQ: A LIKELIHOOD BASED APPROACH TO PREDICT COUNT TIME SERIES

ABSTRACT

Improvised explosive devices (IED) have been one of the most common forms of indiscriminate violence employed by insurgents in contemporary asymmetric wars. In Iraq they had a devastating effect, yielding more than half of the total coalition casualties between 2016 and 2017. Can we successfully predict waves of these attacks? This contribution presents a series of models that seek to predict the incidence of IED attacks in Iraq during the Iraqi Insurgency. Building on the literature on the micro-foundations of civil conflict and on counterinsurgency, we predict IED attacks relying on fine-grained daily events drawn from SIGACTs data. We focus, in particular, on types of actions carried out by the US-led coalition to capture the tit-for-tat nature of rebels' violence. Based on previous contributions, we seek to evaluate the predictive performance of belligerents' behaviors on the battlefield. Furthermore, having acknowledged the autocorrelation that characterize rebels' actions, we seek to model the latter to obtain accurate predictions of IED attacks. We test our models on a sample of daily observations based on the Iraqi Insurgency from 2004 to 2009, using likelihood-based methods for count time series. This work contributes to the literature on conflict forecasting and presents and out-of-sample validation to inferential models based on reactive behaviors.

5.1 Introduction

Insurgents' attack can take many shapes and may declinate in different forms. Yet, Improvised Explosive Devices (henceforth IED) have been a dominant strategy in contemporary insurgencies. As discussed in **Chapter 3**, the relative availability of materials needed to craft them, make them an extremely viable strategy for insurgents. This is confirmed by the widespread usage of those means both in Iraq and Afghanistan in the form of vehicle-born IEDs, rigged bunkers and 'pseudo-mines'. While the coalition forces have been progressively implementing countermeasures to mitigate the risk of these attacks, or to disrupt their logistics[34], their threat remained a constant presence on the battlefield. In fact, insurgents quickly adapted to make their devices more sophisticated (Wilson 2007). IEDs yielded severe casualties among the ranks of the coalition forces, being the leading cause of battle related deaths (Braithwaite and Johnson 2012; Moulton 2009). It has been estimated that these attacks caused three out of five killings in action, with an average death per incident around 1.5 (Bird and Fairweather 2007). Such relatively low average per attack should give the reader a

[34] While the main countermeasures consisted in targeted spec-ops raids resting upon intelligence reports, jammers has been used to interfere with the radio spectrum used to remotely activate IEDs (Wilson 2007).

measure of the incidence of IED detonations. As observed by military experts, counterinsurgents cannot out-armor or out-engineer the problem of IEDs (Moulton 2009). This is extremely problematic given that one of the key advantages of regular troops in insurgencies is the technological superiority: IED attacks almost nullify this strategic vantage point and forces counterinsurgents to adopt more complex and holistic mitigation strategies[35]. Having clarified the importance of better understanding the patterns of these attack, due to their salience in insurgency scenarios, this paper seeks the answer the following research question:

RQ: Can we successfully predict the incidence of IED attacks?

This contribution presents a series of models that seek to predict the incidence of IED attacks in Iraq during the Iraqi Insurgency. In line with the broader dissertation, we focus on the dependency between insurgents and counterinsurgents actions. As per evidence shown in **Chapter 3** and in **Chapter 4**, rebels' actions – and IED attack in particular – seem to cluster temporally and spatially around counterinsurgency

[35] In this context see the simulation-based work of (Parunak, Sauter, and Crossman 2009).

operations [36]. More specifically, the types of actions conducted by counterinsurgents seem to matter in shaping the location and timing of insurgents' response. In line with other scholarly works (Lyall 2009; Schutte, Ruhe, and Linke 2020) exertion of indiscriminate violence appears to have an escalating effect and seem to trigger spatial expansion of insurgents activities. In this piece, we aim to test the predictive power of our previous findings developing forecasting models that include count of disaggregated conflict events classified by type of action and type of actor. If, as suggested by the literature (Schutte 2016), event data do in fact incapsulate micro-dynamics of conflict that regulate how the latter contracts and expands in space and time, then we should be able to find tangible benefits by including them in early warnings models[37]. Similarly, we know from previous works (Braithwaite and Johnson 2012; Brandt, Freeman, and Schrodt 2011; Townsley, Johnson, and Ratcliffe 2008) that insurgents attacks tend to cluster in time and space. In this paper we want to account for their temporal autocorrelation and make use of the latter to obtain better predictions. In simple terms, we posit that past incidence of IED attacks, as well as their past trends over long periods

[36] See also (Braithwaite and Johnson 2012, 2015).

[37] A broader theoretical discussion on the effect of indiscriminate violence is purposefully omitted to avoid repetitions. For an extensive presentation of the theoretical framework see **Chapter 3** and **Chapter 4.**

of time, can be strong predictors of future incidents. For such reason, the choice of a suitable model that considers the temporal interdependence of these events is of paramount importance (see below).

As mentioned in **Chapter 2**, an increasing number of works on micro-foundations of civil war have turned their attention to out-of-sample evaluation (Hegre et al. 2017; Schrodt 2006; Schutte 2016). It has been shown that forecasting applications can effectively work as benchmarks for causal theories being byproducts of the latter (Beck, King, and Zeng 2000, 21). In turn theory-driven model, seem to improve accuracy enable scholars to make predictions in a shorter time horizon (Blair and Sambanis 2020). That is, forecasting and significance oriented modeling can complement each other (Chadefaux 2017) while mutually exclusive approaches possess intrinsic perils (Ward, Greenhill, and Bakke 2010). At the societal and organizational level, making accurate predictions and tuning models in ways able to provide actionable insights (D'Orazio 2020) is key for conflict alleviation and conflict resolution strategies[38]. As

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[38] It is not a case that international organizations, among other actors, have been developing their in-house models to make accurate predictions on global quandaries. For conflict see for instance (Halkia et al. 2020).

for our specific case, there have been several attempts to model the incidence of IED attacks. Examples include works that studied their temporal and spatial autocorrelation (Townsley, Johnson, and Ratcliffe 2008), others that seek to identify spatial patterns through swarming analysis (Brueckner, Brophy, and Downs 2010) and reactive models (Braithwaite and Johnson 2012, 2015). To date, however, few authors have adopted a predictive approach towards the incidence of IED attacks and mostly in the broader literature on terrorism[39].

In this paper, we test a novel technique to forecast the incidence of IED attacks at the daily and weekly level in Iraq on a sample that cover the Iraqi insurgency from 2004 to 2010. Once again, we make use of SIGACTs data to obtain daily and weekly countrywide counts of these incident that will serve as our dependent variable. Similarly, we aggregate events data to obtain counts of other relevant conflict processes depicting counterinsurgents' actions. As for the modeling, we employ a likelihood-based estimation for count time series that follows generalized linear models. These methods are provided in the *tscount* R-package (Liboschik, Fokianos, and Fried 2017) and have found a widespread application in ecology, epidemiology and geosciences

[39] See for instance (Bakker, Hill, and Moore 2014).

(Ferreira et al. 2020; Held et al. 2019; Held and Meyer 2019; White et al. 2019; Wilder et al. 2020). Their main benefits, in lay terms, is that they efficiently allow to model serial correlation of the response variable taking into account the conditional mean of the process which in turn is related to its past values, past observations and to covariates (Liboschik, Fokianos, and Fried 2017, 1). As discussed above, this is ideal for the sake of our study: the results largely confirmed our initial expectation as these models provides us with better predictions as compared to the typically used negative binomial.

This work contributes makes two main scholarly contribution to the literature on micro-foundations of civil war and to the literature on counterinsurgency. Firstly, in terms of substantive knowledge we assess the predictive power of reactive explanations to rebels' attacks. In the methodological domain, we test a novel approach to model count time series and apply it to conflict data. All in all, our paper succeeds in providing relatively accurate forecasts of IEDs incidence in a counterinsurgency scenario. We therefore hope to contribute to the practitioners' discourse on early warnings and counterinsurgency strategies as well.

The paper proceeds as follows: firstly, we will provide the readers with a brief introduction to the specific case. We discuss the nature of IEDs in the Iraqi insurgency and illustrate their main strategic end. Secondly, we present the data from SIGACT and discuss the coding rules used to derive aggregate counts of the processes of interest. We then present our modeling strategy as well as our results compared to a baseline negative binomial model. The results section largely focus on the daily level of aggregation as an illustrative case.

5.2 IEDs in the Iraqi insurgency

"The IED has become a widely used weapon for insurgents in Iraq for one reason: it works."(Moulton 2009, 1)

IEDs as briefly sketched above, are used as effective weapons by a large majority of insurgents' groups and terrorist organizations. Several works have demonstrated how their use is by-product of specific strategic considerations (Braithwaite and Johnson 2012; Townsley, Johnson, and Ratcliffe 2008). That is, their incidence in space and time is far from random and follow specific logics of clustering around previous attacks and counterinsurgents operations. On the practical side, given the relative availability of the materials needed to craft them, the massive projected damage, and their versatility of use, they have been a dominant strategy in most contemporary insurgencies. To a certain degree, they are used to compensate the relative imbalances in technology and capabilities between insurgents and counterinsurgents typical of asymmetric warfare. Vis-à-vis the data on casualties presented in the introduction, it is not a case that these attacks has been having an extensive media coverage in global outlets (Wilkinson, Bevan, and Biddle 2008). According to the definition of NATO, an IED is a:

'*device placed or fabricated in an improvised manner incorporating destructive, lethal, noxious, pyrotechnic or incendiary chemicals and designed to destroy, incapacitate, harass or distract. It may incorporate military stores, but is normally devised from non-military components.*' (NATO 2009)

The shallow boundaries of definition are well suited to describe the great variance in IEDs. In terms of embeddedness, they can be vehicle-born, person-borne, passive (e.g. land mines) or placed in natural or man-made structure of some sort (Wilkinson, Bevan, and Biddle 2008). Furthermore, their activation mechanism varies as well. The latter can be temporized, remotely initiated, or victims' activations through booby traps, pressure pads and pull switches (Wilkinson, Bevan, and Biddle 2008). The possibility of detonating IEDs when a target approaches is key to explain its effectiveness (Moulton 2009). In Iraq the most common activation modes consisted in suicide initiators, victims' activations. A typical example of the latter consists in electric switches activated by pressure plates or infra-red systems to detect motion (Moulton 2009). To avoid 'near-misses', insurgents would also guarantee a certain redundancy in activations' systems by, among others, an activation wire or a remote control to be operated by the perpetrator (Moulton 2009).

It is worth noting, as sketched in **Chapter 4**, that most of these devices can be easily crafted using materials such as fertilizers (Schutte 2017b). However, in areas with a long history of conflict – as in the case of Iraq – IED components were often times derived from remnants of previous war, that according to the Small Arms Survey tend to circulate more among non-state actors (Wilkinson, Bevan, and Biddle 2008). Therefore, as argued by Schutte (2017b) given that explosive materials from shells and unexploded ordnance can be easily extracted and fitted into IEDs, having these components recovered – or turned in – is of paramount importance to disrupt further attacks.

5.3 Data

To build our forecasting model we make use data from Significant Activity reports (SIGACT). Given the singular level of details offered by this collection of events, we decided to employ them in our study to build daily and weekly count variables that show the country-wide incidence of IED attacks. When compared to other datasets with the same geographical and temporal boundaries[40], it denotes an unprecedented coverage of the Iraqi insurgency with abundant details on each single action carried out by the forces on the battlefield. Each geo-referenced event is mainly classified based on two variables onto which we carry out our aggregation: categories, and types. The illustration of these variables is purposefully omitted from this paper to avoid repetitions: for an extensive discussion see **Chapter 4**.

Our full sample includes over 39000 events that we then aggregate at the daily and weekly level in a timeframe ranging from 2004 to 2010. That results in 2130 observations in the daily dataset, and 306 observations in the weekly dataset. To create our variable, we aggregate events belonging to specific categories that encapsulate the

[40] For instance ACLED or GED (Raleigh et al. 2010; Sundberg and Melander 2013).

concept of interest. **Table 8** illustrates our coding rules and presents the main conflict related variables obtained from the broader dataset. As for our dependent variable – IED attacks – we generated a count variable at the desired level of temporal aggregation. It includes all events occurring in a day – or in a week – that fall into the following categories: '*IED explosions*', '*IED pre-detonation*', '*Mine Strike*', '*IED found/cleared*', '*Mine found/cleared'*. This is coherent with the definitions provided in **Chapter 4.** It is worth noting that some categories that belong to the "*explosive hazard*" type were not included in our count. Specifically, we omitted events depicting '*false IED reports*' and '*hoaxes*'. **Figure 24** and **Figure 25** show the time-series and the time-series decomposition of our dependent variable. In **Figure 25** we can see a seasonality effect that follows a yearly pattern. Yet, the remainder – that can be interpreted as the variation unexplained by the seasonal component – remains noticeable. For such reason, we expect a significant effect stemming from other components, such as our conflict counts. The plots depicting the weekly time-series are included in **Appendix 3**.

Variables	Events categories:
IED Attacks	IED Explosion, IED found/cleared, IED pre-detonation, Mine Strike, Mine found/clared
Crime	Arson, Carjacking, Extortion, Hijacking, Kidnapping, Looting, Mugging, Murder, Sabotage, Shooting, Smuggling, Theft
Threats	Threats of Ambush, Assassination, Attack, Carjacking, Direct fire, IED, Indirect Fire, Intimidation, Kidnapping, Looting, Murder, Raid, Recon, Sabotage, Safire, Small Arms, Smuggling, Sniper OPS, Theft
Propaganda	Propaganda, Sermons, Demonstrations
Counterisurgents' Indiscriminate Violence	Close Air Support, Unmanned Aerial Vehicle, Escalation, Artillery
Counterisurgents' Selective Violence	Direct fire, Attack, Patrol, Small unit actions, Cordon/Search, Sniper OPS
Counterisurgents' Policing	Police Actions, Vehicle Interdiction, Arrest, Confiscation
Rebels' Indiscriminate Violence	Indirect Fire
Rebels' Selective Violence	Direct Fire, Sniper OPS
Turn-in of unexploded ordnance	Remnants of war – turn in

Table 8: Event categories coded for the empirical testing.

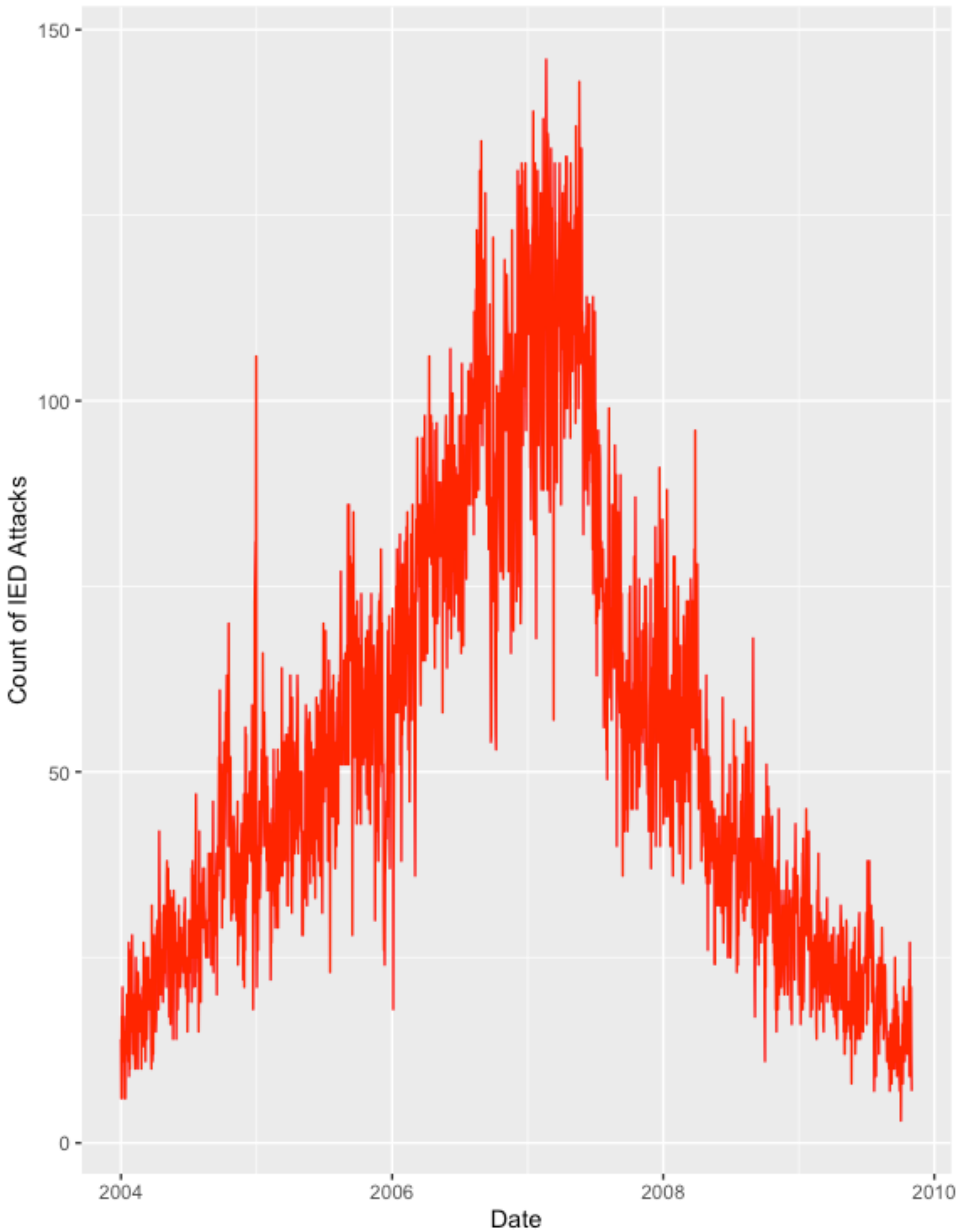

Figure 24: Daily distribution of IED attacks over time. Iraq, 2004-2010

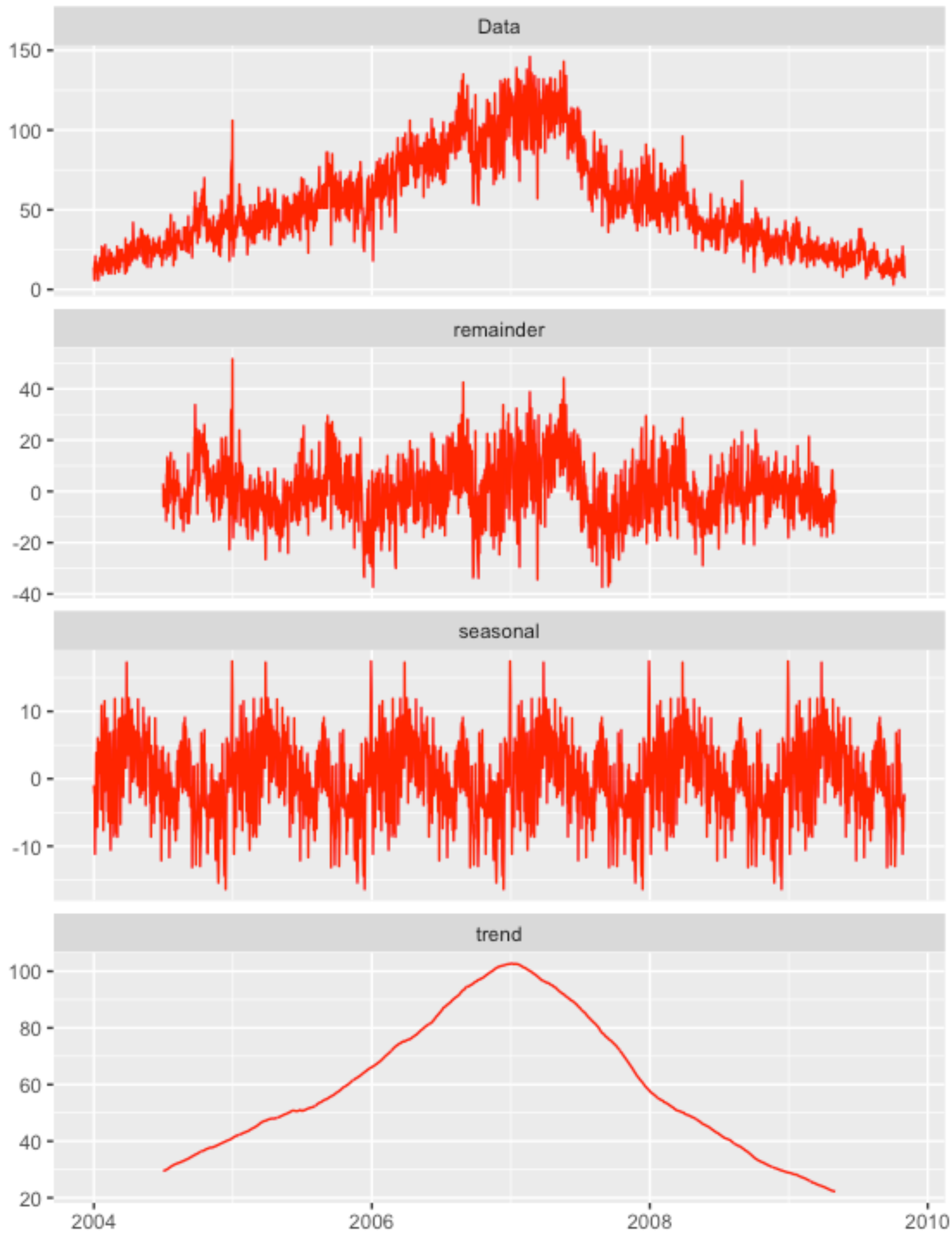

Figure 25: Daily time-series decomposition of IED Attacks. Iraq, 2004-2010. The first quadrant shows the distribution of data over time while the following ones show the remainder, the seasonality, and the trend respectively.

As for indiscriminate and selective violence, we adopted the same criteria presented in our previous contribution. That is, we coded as indiscriminate violence all those events that rely mainly on indirect fire. Conversely, selective violence implies a targeted and direct engagement between combatants. As for counterinsurgents, we coded as indiscriminate violence the following event categories: '*Close Air Support*', '*Unmanned Aerial Vehicle*', '*Escalation of force*', '*Artillery*'. Selective violence instead, is constituted counts of the following events: '*Direct fire'*, '*Attack'*, '*Patrol'*, '*Small unit actions'*, '*Cordon/Search'*, '*Sniper OPS'*.

To maximize our predictive power, here we decided to include further count variables derived from SIGACT data that may be strong predictors of IED attacks. We included two variables depicting instances of indiscriminate and selective violence perpetrated by rebels as well. As we discussed above, rebels' actions tend to cluster in time and incorporating information about their other attacks may contribute to forecast IED strikes. Furthermore, to account for the role of counterinsurgents' '*denial'* strategies, we included a count variable of policing events. Similarly, we decided to account for the relevance of remnants of war in counterinsurgency settings by including a variable that represent the turn-ins of unexploded ordnance to the coalition forces. According to the literature the latter should provide indications of the current climate and attitudes of the populace towards counterinsurgents (Schutte 2017b). To capture a similar concept, as well as the effort of insurgents to obtain the favor of the local population – or at least to create an anti-coalition sentiment – we included a count of propaganda events. Finally, we included a count variable depicting criminal events as a proxy for instability as well as a count of insurgents' '*threats*' to counterinsurgents, to government forces and to civilians.

Table 9 and **Table 10** provide descriptive statistics of our variables at the daily and weekly level of aggregation respectively. As the reader may notice from these tables, we decided to include three structural variables commonly used in the literature as proxies for opportunities and seasonality of conflict events: temperature, night lights and rainfalls (Harari and La Ferrara 2018). Data on nightlights emissions are drawn from DMSP OLS (Koren and Sarbahi 2018; Weidmann and Schutte 2016), while data on rainfalls and temperature are drawn from xSub (Zhukov, Davenport, and Kostyuk 2019). Unfortunately, the country-level scope of our analysis prevented us from including more predictors depicting spatial features or demographics, given that they would have been relatively time-invariant across the whole sample.

Descriptive statistics - Daily Aggregation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
IED Attacks	2,130	53.64	30.34	3	29	74	146
Crime	2,130	14.66	19.01	0	2	20	111
Threats	2,130	2.57	4.44	0	0	3	53
Propaganda	2,130	1.10	1.75	0	0	2	27
Counterinsurgents’ indiscriminate	2,130	6.33	5.69	0	1	10	31
Counterinsurgents’ selective	2,130	8.43	7.09	0	2	13	44
Counterinsurgents’ policing	2,130	4.57	4.05	0	1	7	23
Rebels’ selective	2,130	27.90	22.86	0	10	37	146
Rebels’ indiscriminate	2,130	15.81	13.18	0	5	23	113
Temperature	2,130	22.60	9.74	5.31	13.18	32.04	36.15
Rainfall	2,130	1.48	1.56	0.00	0.04	2.53	6.18
Night Lights	2,130	0.08	0.004	0.07	0.07	0.08	0.09
Turn-in of unexploded ordnance	2,130	1.20	2.78	0	0	0	15

Table 9: Descriptive Statistics of the daily sample.

Descriptive statistics - Weekly Aggregation

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Crime	306	102.08	125.36	2	14	155.5	526
IED Attacks	306	373.36	204.06	52	198	493.5	859
Propaganda	306	7.63	7.29	0	4	10	85
Threats	306	17.91	27.54	0	1	27	152
Turn-in of unexploded ordnance	306	8.35	17.74	0	0	4.8	72
Counterinsurgents’ indiscriminate	306	44.09	35.56	0	8	72	136
Counterinsurgents’ selective	306	58.68	44.55	0	13	93	206
Counterinsurgents’ policing	306	31.83	22.86	0	12	49	104
Rebels’ selective	306	194.20	152.39	9	79.2	242.8	593
Rebels’ indiscriminate	306	110.04	84.38	7	31	155	498
Temperature	306	22.47	9.75	5.31	13.18	32.00	36.15
Night Lights	306	0.08	0.005	0.04	0.07	0.08	0.09
Rainfall	306	1.47	1.53	0.00	0.04	2.53	6.18

Table 10: Descriptive Statistics of the weekly sample.

5.4 Modelling Strategy

As briefly sketched in the introduction, we employ a likelihood-based estimation for count time series that follows generalized linear models. The latter is implemented in the *tscount* R-package (Liboschik, Fokianos, and Fried 2017) and have found a widespread application in several scientific fields (Ferreira et al. 2020; Held et al. 2019; Held and Meyer 2019; White et al. 2019; Wilder et al. 2020). Their main advantage resides in their ability to model serial correlation of the response variable taking into account the conditional mean of the process (Liboschik, Fokianos, and Fried 2017, 1). In practice they allow to estimate models by quasi conditional maximum likelihood. It is important to note that the conditional distributions can follow a Poisson distribution or a Negative Binomial distribution. For illustrative purpose we define our *tscount* model with a conditional Poisson distribution for the number of IED attacks carried out at time-aggregation IED_t as (Liboschik, Fokianos, and Fried 2017):

$$IED_t|\mathcal{F}_{t-1} \sim Poisson(\lambda_t)$$

In a basic specification of the model, assuming a logarithmic link and specifying just one lagged covariate X we would have:

$$log(\lambda_t) = \beta_0 + \beta_1 IED_{t-1} + \alpha_1 \lambda_{t-1} + \beta_3 X_{t-1}$$

Here, β_1 is the coefficient estimated onto previous values of the dependent variable (here at 1 previous observation). α_1, similarly shows the estimated coefficient onto previous values (here defined as 1) of the conditional mean. In lay terms, the choice of this model should allow us to better model the temporal interdependence of IED attacks as compared to simpler models. For such reason we test several specifications including different values of previous observations and different values of conditional means to capture time recurring patterns in the incidence of the response variable. Similarly, we estimated a *tscount* model both its Poisson form and in its Negative Binomial Form, as well as testing for identity and logarithmic link. To compare are results against a baseline, we also estimate a relatively simpler negative binomial model.

As for the out-of-sample validation strategy, we seek to predict one-step-ahead (thus one day or one week) values of our response variable[41] resorting to a moving windows approach. In practice, our training set for the daily model includes the first 1123 days[42]. We estimate coefficients on that slice of the data and subsequently use them to predict one temporal step ahead i.e., the 1124th day. From there we iteratively expand the training portion of the data by one step – day 1124 - and predict the 1125th data. The process continues until the end of the timeframe of the sample. This process results, for the daily model in 1000 predicted values while for the weekly model in 100 predicted values. To clarify the number of predicted values obtained, it is worth specifying, that

[41] Based on the epidemiological contribution of (Held et al. 2019; Held and Meyer 2019).

[42] The weekly training set instead includes the first 205 observations.

the predictors described in the data section have been included in the model with a lag of 7 days. This of course caused a reduction of our data consisting in 7 observations for the daily model and in 1 observation for the weekly model.

This sliding window approach has been chosen due to the panel structure of our data. That is, other techniques such as random assignment or sampling based on the outcome to create a training and a test set bear the risk of mixing the past and the present, thus providing unrealistic predictions.

Therefore, for each of our model we obtained the predicted number of IED attacks at the country level for each day/week.

5.5 Results

5.5.1 Baseline Negative Binomial Estimation

In this section we present briefly illustrate the results of our baseline that consists in a negative binomial model for the daily sample. As mentioned in the previous section all covariates were included with a temporal lag of 7 days, both in the weekly model and in the daily one. **Table 11** show the results obtained in the in-sample estimation. While *Model 1* solely includes *Temperature*, *Rain* and *Night Lights*, *Model 2* has a broader specification also including *Crime*, *Threats* and *Propaganda*. Finally, *Model 3* present the full specification. It is worth noting that most of the coefficient signs are compatible with our expectations, even though this is not the purpose of this paper. However, we are sceptic towards the effective significance of this estimates as the model – given its baseline purpose – is extremely simple and does not include any nuance such as fixed effect or bootstrapped/clustered standard errors. It is also interesting to see how the estimated effect is small for most of our variables, except for *Night Lights*.

	Dependent variable:		
	Count of IED Attacks		
	(1)	(2)	(3)
Lag Temperature	-0.003	-0.005***	-0.005***
	(0.002)	(0.001)	(0.001)
Lag. Rain	-0.031***	-0.045***	-0.032***
	(0.011)	(0.008)	(0.007)
Lag Night Lights	-99.094***	-66.118***	-41.169***
	(2.795)	(2.284)	(2.244)
Lag Crime		0.015***	0.008***
		(0.001)	(0.001)
Lag Threats		0.009***	0.002
		(0.002)	(0.002)
Lag Propaganda		-0.007	-0.007*
		(0.004)	(0.004)
Lag Counterinsurgents' Indiscriminate Violence			0.027***
			(0.001)
Lag Counterinsurgents' Selective Violence			0.002*
			(0.001)
Lag Counterinsurgents' Policing			-0.009***
			(0.002)
Lag Rebels' Selective Violence			0.006***
			(0.001)
Lag Rebels' Indiscriminate Violence			0.002***
			(0.001)
Lag Turn-in of unexploded ordnance		-0.028***	0.004
		(0.003)	(0.003)
Constant	11.586***	8.899***	6.661***
	(0.224)	(0.185)	(0.183)
Observations	2,123	2,123	2,123
Log Likelihood	-9,602.027	-8,971.330	-8,631.453
theta	4.925***	9.717***	14.574***
	(0.162)	(0.362)	(0.594)
Akaike Inf. Crit.	19,212.060	17,958.660	17,288.910

*p**p***p<0.01

Table 11: Models' estimation with different specification of the Negative Binomial Regression. DV: IED Attacks.

Having estimated our naïve model, we then proceed to test its predictive power through the technique detailed in the Modeling Strategy section. For each time unit we compare the predicted number of IED attacks to the observed values. In **Figure 26** we show the results of this comparison computing and plotting the Mean Absolute Errors (henceforth MAE) due to their intuitive interpretation. We see that the full specification achieved a MAE of roughly 11.8, which is the smallest among the three models, thus the best. That is, Model 3 predictions on are on average 11.8 offs from the observed number of attacks.

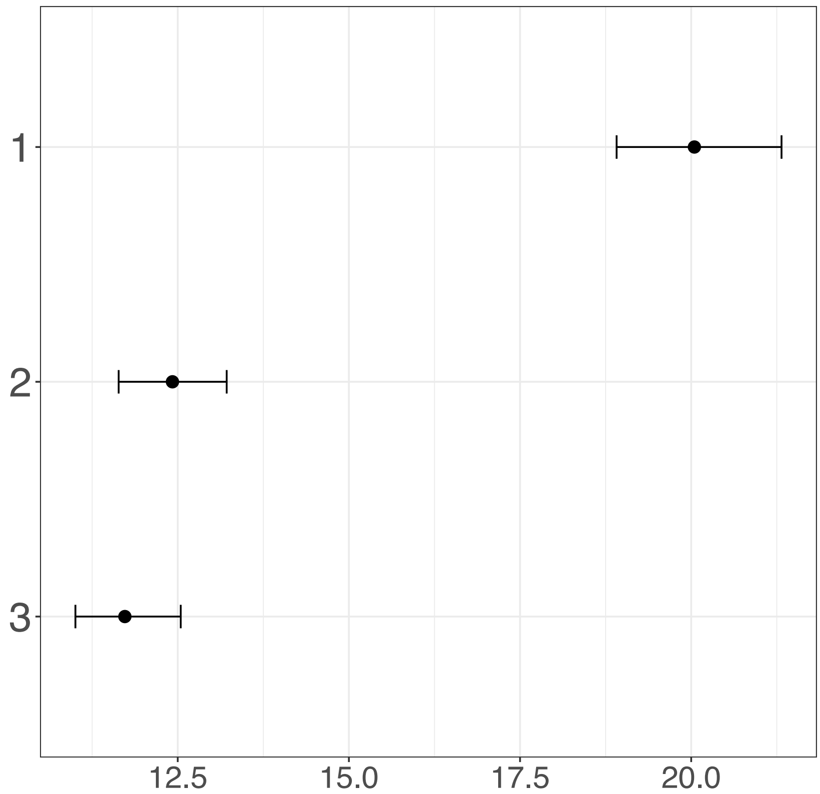

Figure 26: Out-of-sample Mean Absolute Errors and bootstrapped 95% confidence intervals for the baseline model at the daily level of temporal aggregation. The numbers correspond to those in Table 11.

We applied the same modeling workflow to the weekly model which, for the full specification has a MAE of 51.142.

5.5.2 In-sample estimation and model selection

In this section we present the models estimated through *tscount* the daily sample. As mentioned above, the conditional distributions can follow a Poisson or a Negative Binomial. Furthermore, the link can be either identity or logarithmic. We tested all these combinations specifying a model similar to *Model 3* presented in **Table 11**. That is, we included all our predictors. As for the parameters of previous observations and previous values of the conditional mean, our first test included the values of the past 7 days and the conditional mean from a year back (365 days) to account for the seasonal pattern observed. To assess the probabilistic calibration of the predictive distribution, we use the probability integral transform (henceforth PIT) (Liboschik, Fokianos, and Fried 2017, 11). **Figure 27** portrays the PIT for the different types of models. In theoretical terms, a perfect predictive distribution would result in a PIT that resembles to a uniform distribution (Liboschik, Fokianos, and Fried 2017). The identity link, at first glance, performs worse than the logarithmic one. Similarly, the negative binomial seems to be a better predictive distribution as compared to the Poisson. As a further check, we ran a marginal calibration of the four models (**Appendix 3)** that analyze the difference in average predictive cumulative distribution function and the empirical cumulative distribution function of the observations (Liboschik, Fokianos, and Fried 2017). Even in that case, the negative binomial with a logarithmic link performs better than the other models. As a final check we compute several metrics reported in **Table 12** (Liboschik, Fokianos, and Fried 2017). For most of the scoring rules, a lower value is preferable. Accordingly,

	Logarithmic score	Quadratic score	Spherical score	Ranked Probability score	Dawid-Sebastiani	Normalized Squared Error score	Squared Error Score
Nb Log	3.733	-0.03120	- 0.1739	5.898	5.594	0.9901	1.353
Nb Ide	3.679	-0.03207	-0.1763	5.646	5.513	0.9901	1.117
Poi Ide	3.828	-0.02993	-0.1731	5.753	5.805	19.676	1.117
Poi Log	3.961.531	-0.02879	-0.1704	6.028	6.016	21.766	1.353

Table 12: Scoring rules for conditional distribution and link selection. Daily model.

These metrics confirms our previous choice and therefore we proceed with a negative binomial and a logarithmic link. As a next step, we further refine our model by testing for several specifications of the past observations parameter and of the past means parameter. Once more we resort to a PIT (**Figure 28)** and compute scoring rules **(Table 13)**: we report in graphical forms just the test conducted for the selection of past means parameter. The optimal choice appears to be that of setting the value of the past mean to 180 days, while the value of past observations ranging from 1 to 7 days (thus including seven terms in the model). **Table 14** shows the estimation of the model reporting the coefficients, the bootstrapped standard errors, and the 95$^{\%}$ percent confidence intervals for the chosen specification. As we can see, while most of the coefficient estimated on the past observations and on the past mean are statistically significant, most of our predictors are not. Interestingly, the only significant variables are *Rebels' Selective Violence, Crime, Counterinsurgents' indiscriminate*. The latter is a particularly welcomed finding given our theoretical interest for its escalating effect. Yet, we can see most of the coefficient to be extremely small.

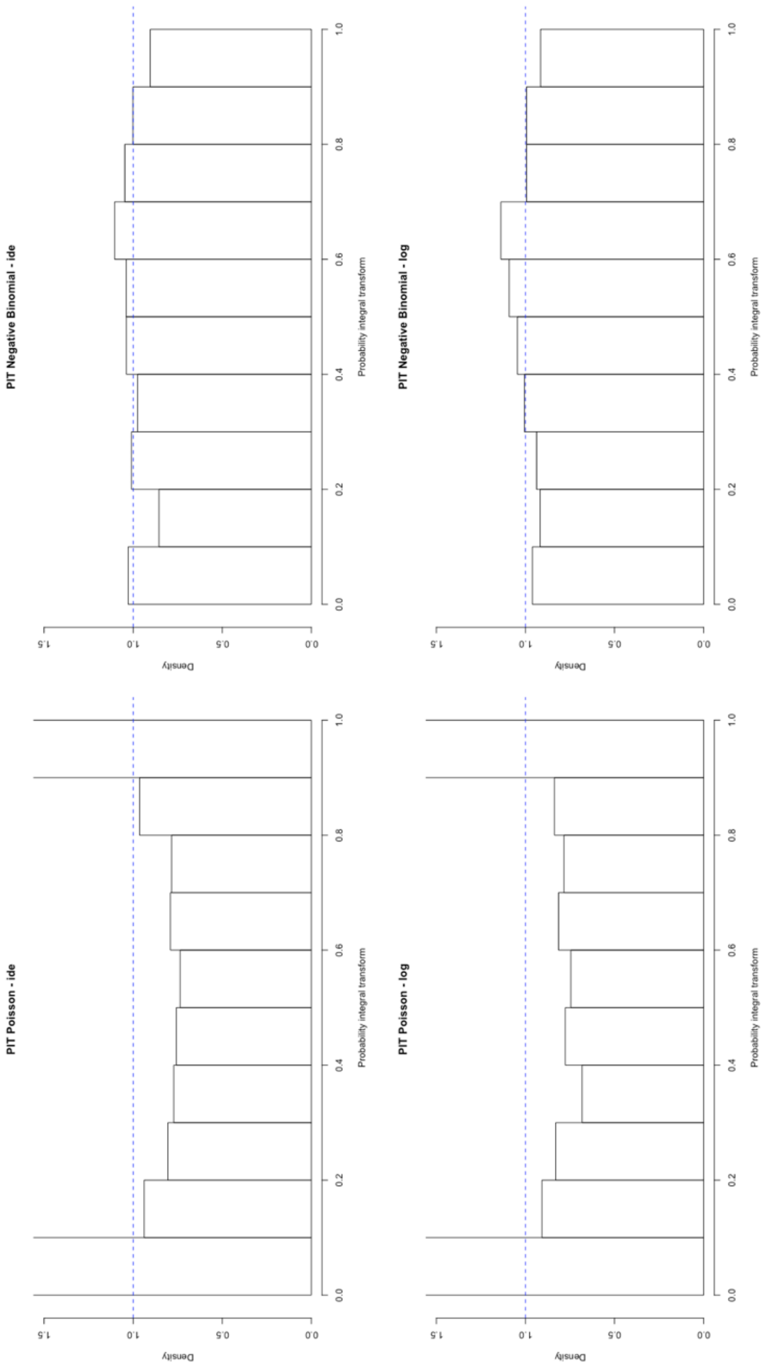

Figure 27: Probability Integral Transform for the selection of the conditional distributions and for the selection of the link. Daily sample.

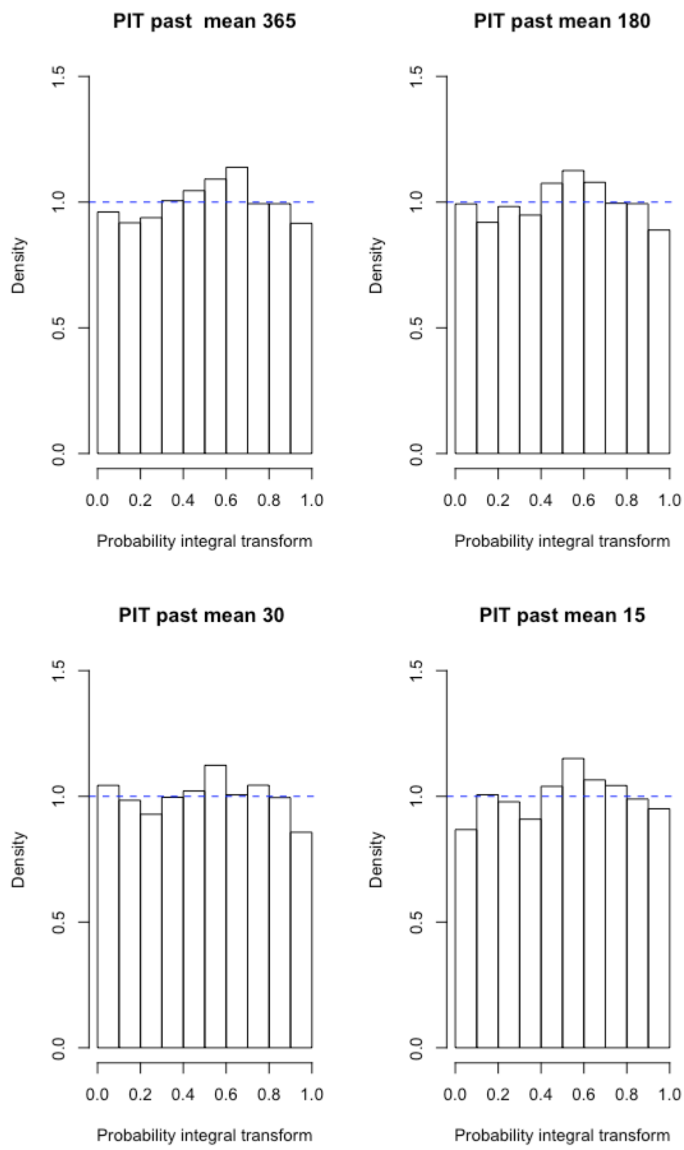

Figure 28: Probability Integral Transform. Used for selecting past mean parameters. Daily sample.

	Logarithmic score	Quadratic score	Spherical score	Ranked Probability score	Dawid-Sebastiani	Normalized Squared Error score	Squared Error Score
Nb 365	3.733	-0.031	-0.173	5.898	5.594	0.990	1.353
Nb 180	3.727	-0.031	-0.174	5.865	5.582	0.990	1.272
Nb 30	3.790	-0.029	-0.168	6.295	5.713	0.990	1.539
Nb 15	3.787	-0.029	-0.169	6.295	5.708	0.990	1.758

Table 13: Scoring rules for selecting past means parameters. Daily model.

	Estimate	Std.Error	CI(lower)	CI(upper)
(Intercept)	1.40e+00	0.204119	9.97e-01	179.731
Beta 1	3.45e-01	0.021449	3.03e-01	0.38691
Beta 2	1.21e-01	0.022883	7.66e-02	0.16631
Beta 3	7.45e-02	0.023081	2.92e-02	0.11969
Beta 4	8.10e-02	0.023226	3.55e-02	0.12655
Beta 5	4.50e-02	0.023105	-2.36e-04	0.09033
Beta 6	3.07e-02	0.022988	-1.44e-02	0.07575
Beta 7	7.29e-02	0.021933	2.99e-02	0.11590
Alpha 180	-2.69e-02	0.010177	-4.69e-02	-0.00697
Lag Crime	1.58e-03	0.000414	7.66e-04	0.00239
Lag Threats	1.05e-03	0.001270	-1.44e-03	0.00354
Lag Propaganda	-1.24e-03	0.002655	-6.45e-03	0.00396
Lag Counterinsurgents' Indiscriminate	6.76e-03	0.001094	4.61e-03	0.00890
Lag Counterinsurgents' Selective	7.98e-05	0.000913	-1.71e-03	0.00187
Lag Counterinsurgents' Policing	-1.23e-03	0.001514	-4.20e-03	0.00173
Lag Rebels' Selective	1.63e-03	0.000460	7.27e-04	0.00253
Lag Rebels' Indiscriminate	8.50e-04	0.000619	-3.63e-04	0.00206
Lag Temperature	3.04e-04	0.000818	-1.30e-03	0.00191
Lag Rainfall	5.59e-03	0.005196	-4.59e-03	0.01578
Lag Night Lights	-7.07e+00	1.961.403	-1.09e+01	-322.289
Lag Turn-in	-1.32e-04	0.002219	-4.48e-03	0.00422

Table 14: In-sample estimation of a tscount model with Negative Binomial Conditional Distribution at logarithmic link. Betas represent the coefficient estimated on the past observations (1 to 7 days in the past). Alpha represents the coefficient estimated onto the past mean (180 days in the past).

Having evaluated our model in sample, before proceeding to present the out-of-sample validation, we want to draw the reader's attention to the plot of predicted values presented in **Figure 29**. That serves the purpose of being a preliminary assessment of the predictive power of our model.

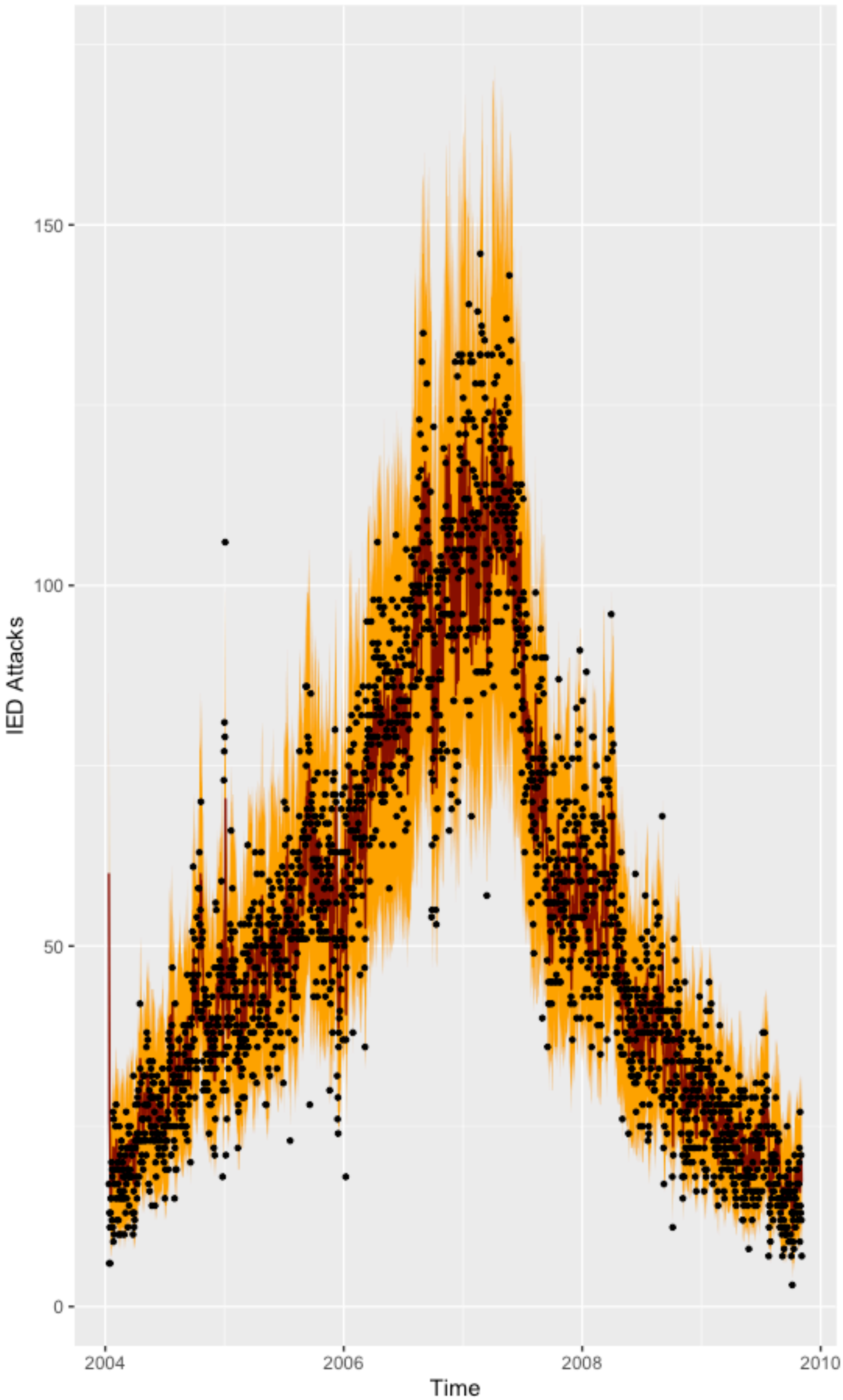

Figure 29: In-sample one-day-ahead predictions. The black points represent the observed events while the red line represent the predicted values. The buffer around the line illustrates the 95% confidence interval. Daily sample.

5.5.3 Out-of-sample validation

Applying the moving windows approach presented in the empirical strategy section, we generate 1000 predicted values for our daily model. A first assessment of the quality of our prediction can be conducted by generating a PIT once again. A qualitative assessment of **Figure 30** shows how the resulting distribution have some evident deviations from a uniform distribution both below the density value of 1 and above it. Yet, when compared to the out-of-sample PITs of previously discarded models, this model confirms to be relatively more accurate.

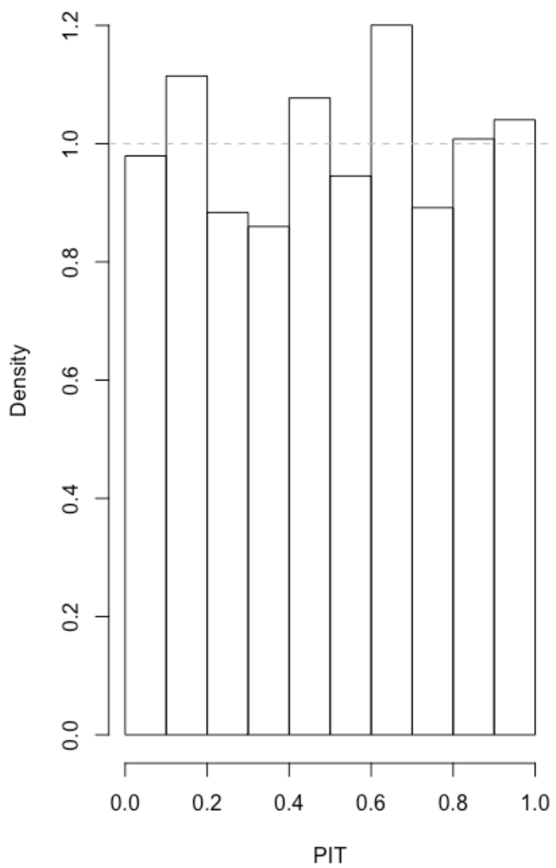

Figure 30: Probability Integral Transform – Out-of-sample validation with moving windows - Daily sample.

To provide more readable metrics of our forecasting performance, we generate a plot (**Figure 31**) of the one-day-ahead predictions of IED counts[43]. While the black dots represent the observed counts of IED attacks, the fan charts show the predictive distributions. On the lower panel, we see the Dawid-Sebastiani scores and the logarithmic scores respectively for each point in time. The model seems to perform well but, to instantiate a relative comparison against our baseline, we prefer to compute the more readable MAE. The latter for this model is roughly 7,83. That is, on average our models' predictions are off by 7,83 attacks. Considering the high levels of IED attacks in our sample, as well as the variance of the latter, we welcome this result as it confirms that our model has a considerable predicting power towards counts of IED attacks. Trying to further improve our accuracy, we estimated another model with the same parameters but with a slightly different specification. That is, we included just the conflict covariates that resulted significant in **Table 14**. As shown in **Figure 32**, visually this new iteration seems to perform better. Yet, when computing the MAE, we reduce our error to 7,68 which is a minor improvement.

[43] Based on (Held and Meyer 2019).

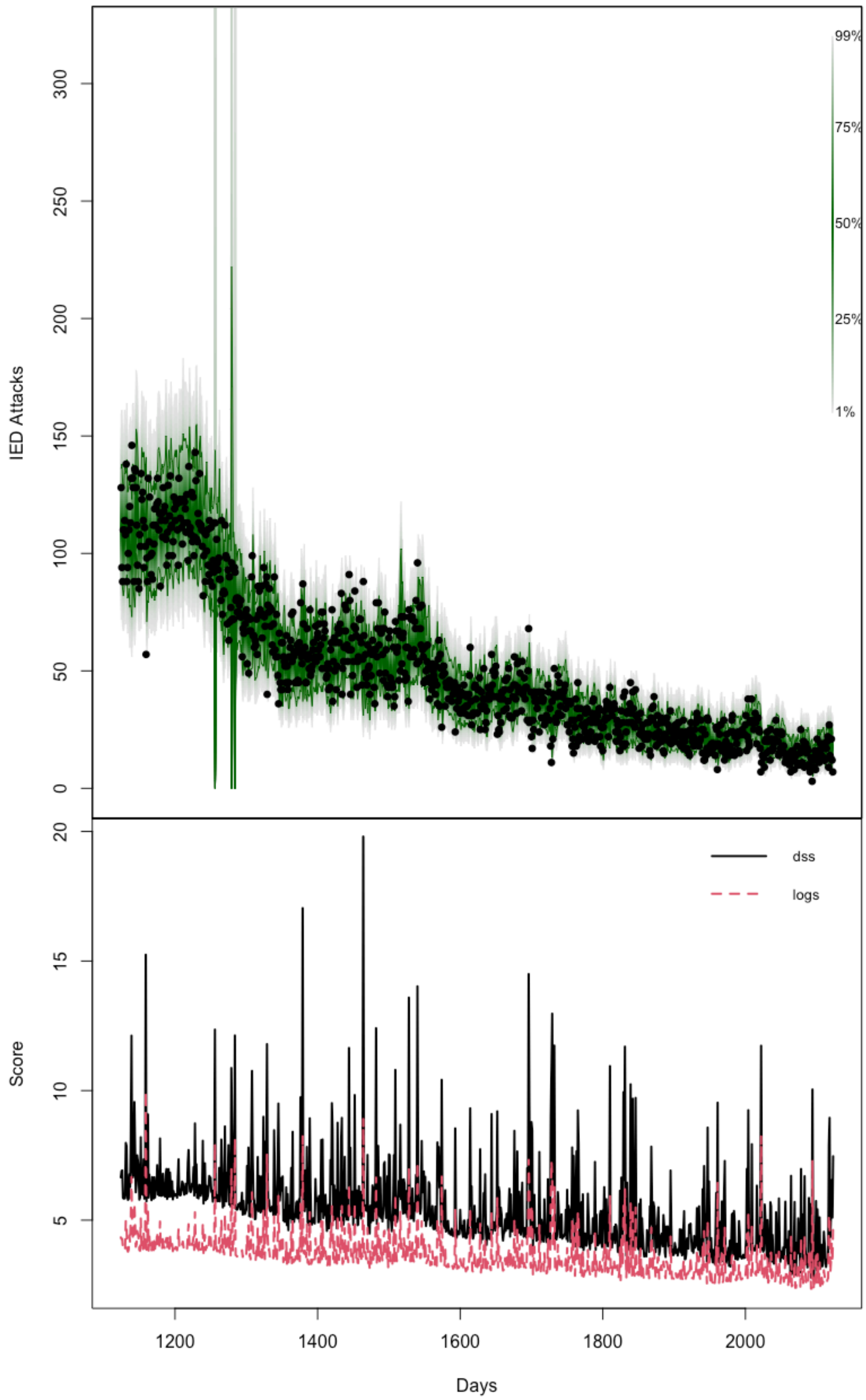

Figure 31: Out-of-sample one-day-ahead predictions. The black points represent the observed events, while the fan charts depict the predictive distributions. The quadrant below depicts the Dawid-Sebastiani scores and the logarithmic scores respectively for each point in time. Daily sample.

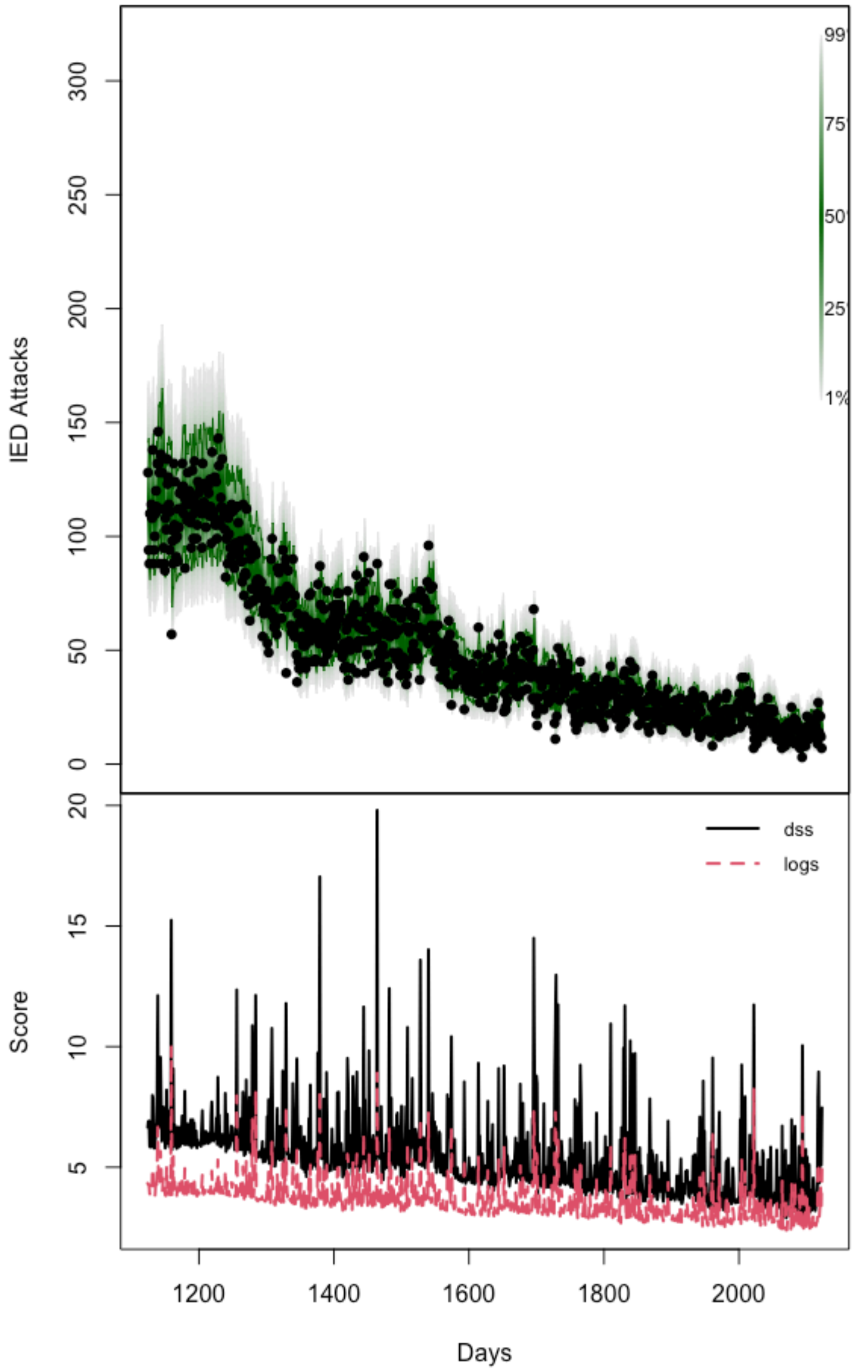

Figure 32: Out-of-sample one-day-ahead predictions for the refined model with only significant covariates. The black points represent the observed events, while the fan charts depict the predictive distributions. The quadrant below depicts the Dawid-Sebastiani scores and the logarithmic scores respectively for each point in time. Daily sample.

5.5.4 Notes on the Weekly Model

In this case the model the best fits our data appears to be – once more – the one with a negative binomial conditional distribution and a logarithmic link. As for the parameters on past observations and past means, we selected two lags for the former (respectively 1 and 2 weeks in the past) and one lag for the latter (of 1 week in the past). Tables and plots that replicate the model selection procedure are included in **Appendix 3** together with the in-sample estimation of the selected model. Once more, we apply the moving window approach a obtain 100 predictions on the expected levels of IED attacks. The MAE is 27.25 for the full specification as compared to the one from the baseline negative binomial that amounts to 51.14. Therefore, there is notable improved with respect to our naïve model. Of course, the MAE of the weekly model is much larger than the daily one given the level of temporal aggregation. As shown in **Figure 33** however, the model performs well in providing accurate forecast of the expected count of IED attacks.

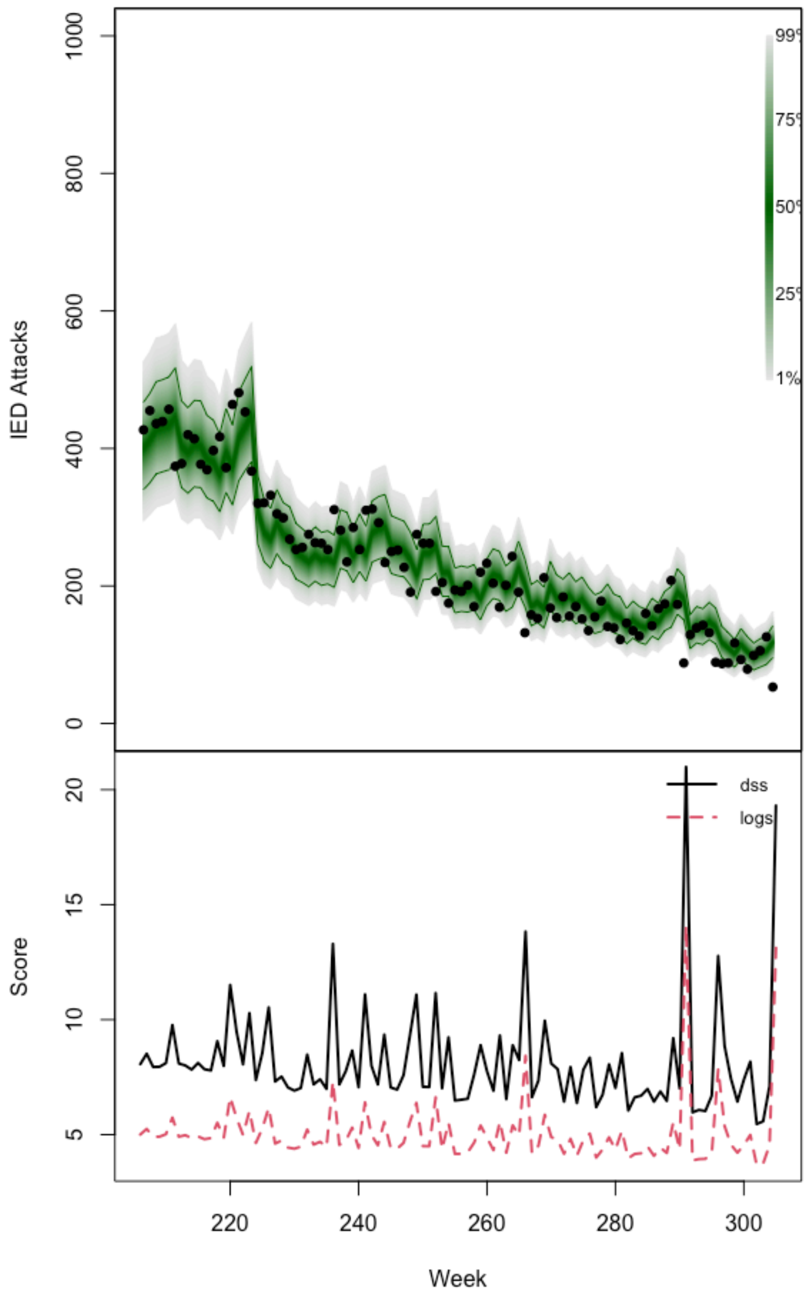

Figure 33: Out-of-sample one-day-ahead predictions. The black points represent the observed events, while the fan charts depict the predictive distributions. The quadrant below depicts the Dawid-Sebastiani scores and the logarithmic scores respectively for each point in time. Weekly Sample.

5.6 Conclusion

In this paper, we investigate the following research question: can we successfully predict the incidence of IED attacks? We offer a systematic attempt to produce accurate country-wide predictions pertaining the number of IED attacks at the daily and weekly level of aggregation. This serves as benchmark for theories on reactive behaviors in civil conflict and insurgencies, that constitute the pillar of this dissertation. To this end, making use of 6 years of SIGACTs data on the Iraqi Insurgency, we aggregated events to daily and weekly count time series. We maintain that counterinsurgents actions are core predictors of IED attacks. Furthermore, we seek to capture the serial correlation of these events that substantiate in their clustering over time. We expect both factors to play a crucial role in refining our predictions.

Our analysis rests upon a novel modeling technique that employs a likelihood-based estimation based on generalized linear models to predict count time series. Comparing our predictions to those estimated from a baseline negative binomial model, we can see important improvements. While on the one hand the inclusion of our main predictor – i.e., counterinsurgents' indiscriminate violence improves the accuracy of our models, the larger reduction in errors stem from the implementation of the proposed likelihood model that accounts for the serial correlation of IED events and for the conditional mean of the process. All in all, the average error in the predicted number of attacks is significantly reduced by the overall approach.

This paper wants to highlight the importance of out-of-sample validation in conflict research, proposing the latter as a further – extremely valuable - step to verify causal theories through the prediction of their observable implications. If, on the one hand, we welcome the reduction in forecasting errors achieved by our approach, we recognize the marginal contribution stemming from the inclusion of counterinsurgents actions is limited. Further works may seek to improve our results in several ways. Firstly, we suspect the predictors contribution washes out due to the chosen levels of aggregation. While we attempted to account for this eventuality by choosing on the temporal level, our spatial aggregation at the country level may be responsible for this relative shortcoming. A spatially disaggregated analysis may therefore be better suited. Alternatives may include a cell/week or cell/day aggregations, or even more advanced approaches in continuous space and time. A precious tool to implement the latter, has been identified in the "Caret Applications for Spatial-Temporal Models" R-package (henceforth CAST) (Kuhn 2008; Meyer et al. 2018). The latter provides a comprehensive toolkit to account for the spatial and temporal component of complex data when estimating advanced machine learning models and have been successfully used in leading works in other fields (Reitz et al. 2021; Sekulić et al. 2021). Furthermore, a spatial approach would allow researchers to include further local predictors. The lack of them is in fact a limitation of our contribution: rainfalls, nightlights and temperatures as mentioned above are aggregated at the national level. This choice of course makes us forego the rich level of detail that stems from local spatial data, and that may be extremely useful in a prediction-oriented application. Such an approach would also allow for the inclusion of further spatial predictors such as land-cover, ethnic groups, and settlements.   Another improvement, if keeping the national level of aggregation, may be obtained by changing the out-of-sample validation strategy. In particular, further works may consider 'time slicing' in order to iteratively re-sample from training data (Colaresi and Mahmood 2017).

6 CONCLUSION

This dissertation is constituted by a collection of essays – designed as standalone papers - that examine the variation in rebels' and insurgents' violence in civil conflict. We build on the literature on the micro-foundations of civil war and contribute to it by examining the impact of conflict processes onto said variation. Specifically, our overarching puzzle rests upon reactive patterns of rebels' violence as well as upon their unfolding in time and space, in response to specific counterinsurgents' and incumbents' tactics on the battlefield. In the three papers we focus on the cases of Iraq, Syria, and Lebanon to illustrate the how different '*stimuli*' may affect the geo-temporal variation in insurgents' attacks. While specific conclusions covering the more technical aspects are included in each article, here we recount the main features, contributions, and limitation of each piece.

The first contribution (**Chapter 3**) seeks to unveil why some instances of rebels' violence spread into adjacent sub-national spatial units and others do not. It elaborates on the theory-driven intuition that the nature of exerted violence and the targets of violence perpetrated by incumbents have a considerable effect on the incidence of rebels' attacks. Specifically, we examined the role of indiscriminate violence exerted in neighboring areas on subsequent rebels' attacks. The purpose of such investigation is that of linking the escalating effect of indiscriminate violence to the concept of conflict diffusion at the subnational level. We elaborated on the theories of alienation and deterrence in civil conflict and derived testable implications that include a spatial component of escalation. In detail, we proposed that escalation and spatial diffusion of rebels' actions is favored by instances of indiscriminate violence perpetrated by incumbents in the neighborhood. On the other hand, we claimed that exertion of selective violence reduces subsequent attacks and should contain their spatial unfolding. Furthermore, we proposed that violence against civilians in contiguous areas perpetrated by incumbents result in increased instances of rebels' attacks. Nonetheless, very high levels of violence against civilians will result in deterrence, thus reducing further attacks. Our empirical tests, carried out through spatial regression analysis, seem to confirm our prior expectations and benefits from a certain degree of robustness vis-à-vis several tests. Despite the promising result, we detailed several limitations of the paper in its conclusions. Nonetheless, we believe that this contribution may pave the way for further subnational-level studies that analyze the role of conflict processes and events to explain broader phenomena in conflict research.

The second contribution (**Chapter 4**) seeks to explain why some conflict zones exhibit more IED attacks than others. It therefore focuses on a narrower spectrum of civil conflict: insurgencies. We adopted an approach that aims at unveiling a causal path between counterinsurgents' indiscriminate violence and subsequent IED attacks. Specifically, we propose that indiscriminate violence exerted by counterinsurgents results in more IED attacks, both in comparison with selective violence and in absolute terms. To test the relative effect of our treatment – i.e., indiscriminate violence – we resorted to Matched Wake Analysis using SIGACT event data from 2016 coded by the

US military. The results are consistent with our hypothesis and show how indiscriminate violence systematically increases subsequent IED attacks providing us with specific indications on the distance and the number of days that separate the treatment from the retaliatory behavior. It follows, that a selective use of force is more efficient in provoking less subsequent IED attacks. In this contribution, we also adopted a simulated base-line approach to craft synthetic control events with the aim of assessing the absolute effect of indiscriminate violence. To this end, we elaborated two spatial heuristics representing locations where instances of indiscriminate violence were likely but did not occur. We then simulated events within the resulting buffer, and we used them as controls in a Matched Wake Analysis setting against observed treatments. Unfortunately, this approach manifested several limitations. First and foremost, the resulting model suffers from an overabundance of significant geo-temporal windows, which in turn suggests a low accuracy of our two heuristics

In final paper (**Chapter 5**), we seek to predict the country-wide number of IED attacks at the daily and weekly level of aggregation in Iraq during the Insurgency (2004-2010). We offer a systematic attempt to produce accurate predictions that – aside from their practical value - predominantly serve as test for theories on reactive behaviors in civil conflict and insurgencies. As discussed in the literature review (**Chapter 2)**, forecasting has been receiving a growing attention by conflict researchers and has an intrinsic value in enriching causal theories and in measuring their observable implications. In this specific contribution we resorted once more to SIGACTs data and to the case of the Iraqi Insurgency. We employed a modeling technique consisting in a likelihood-based estimation that retain many advantages of generalized linear models and seem better suited to predict count time series. As per prior expectations, our models consistently reduce the errors in the predicted number of IED attacks to a mean average error of roughly 7 incidents in the daily model. Taking the limitations of this approach into account, we can still acknowledge that this piece serves the purpose of increasing our predictive power towards these costly forms of insurgents' violence. Furthermore, by accounting for the serial temporal correlation of IED attacks, the model confirms through an out-of-sample validations the estimations and findings of several works in the field.

All in all, the broader dissertation contributes to the literature on the micro-foundations of civil conflict as well as to the scholarly work on counterinsurgency. While the methodological contributions are recounted with more detail in each specific paper, here we want to insist on the substantive value of this thesis. Specifically, we collocate this work in the strand of the literature that explores the interconnections between belligerents' actions in civil conflict. We based our investigation onto an overarching puzzle pertaining the role of indiscriminate violence and its alleged escalating effect. Albeit cautiously, we maintain that our results contribute to confirm that indiscriminate violence, may trigger temporal and spatial escalations of rebels' actions as responses. This broader finding has important implications for the literature as it shed further light on the unsolved tension between deterrence and alienation in civil war. Furthermore, the added value resides in the spatially and temporally disaggregated scope that characterize this dissertation. Our aim was that of providing granular indications on which subnational areas, or on which detailed windows of time suffers from a more severe risk of experiencing violence. Lastly, beyond the pure scholarly contribution, this work shows the effect of different counterinsurgency practices. It seems clear from the output of three essays, that selective interventions tend to hamper escalations of conflict – both spatially and temporally – as compared to indiscriminate exertions violence. While this may seem obvious from the theoretical works and empirical evidence presented through the manuscript, it is sufficient to look at our recent data from Syria, Lebanon and Iraq to realize how – in practice - indiscriminate actions are still considered a viable technique in most cases. Conversely, we hereby demonstrated how these strategies can punish incumbents and counterinsurgents. In turn, they may severely hinder conflict alleviation efforts as well as the work of international organizations engaged in conflict resolution. We conclude this dissertation by hoping that these findings will also be able to inform practitioners and policymakers in preventing the reactive spirals of violence illustrated by our contribution.

7 APPENDICES

APPENDIX 1 – CHAPTER 3

ACTORS' DICTIONARY - IRAQ

Government	Challenger	Civilian
Anbar Awakening	Asaib Ahl al-Haq	Civilians (Iran)
Global Coalition Against Daesh	Hezbollah Movement in Iraq	Civilians (Iraq)
Government of Iraq (2014-)	Islamic State (Iraq)	
Iraqi and/or Coalition Forces	Islamic State (Syria)	
Military Forces of Iraq (1979-2003)	Protesters (Iraq)	
Military Forces of Iraq (2014-) Counter-Terrorism Service	Rioters (Iraq)	
Military Forces of Iraq (2014-)	Sunni Liberation Army	
Military Forces of Iraq (2014-) Peshmerga		
Military Forces of Iraq (2014-) Popular Mobilization Forces		
Military Forces of United States		
Police Forces of Iraq (2014-) Asayish		
Police Forces of Iraq (2014-)		
Police Forces of Iraq (2014-) Rapid Reaction Force		

ACTORS' DICTIONARY – LEBANON

Government	Challenger	Civilian
Government of Lebanon (2016-)	Asbat al Ansar	Civilians (Lebanon)
Military Forces of Lebanon (2016-)	Fateh al Sham Front	Civilians (Palestine)
Police Forces of Lebanon (2016-)	HTS: HayatTahrir al Sham	Civilians (Saudi Arabia)
Prison Guards (Lebanon)	Islamic State (Lebanon)	Civilians (Syria)
	Islamist Militia (Lebanon)	
	Jund al Sham	
	Protesters (International)	
	Protesters (Iraq)	
	Protesters (Lebanon)	
	Protesters (Palestine)	
	Rioters (Lebanon)	
	Rioters (Palestine)	
	Rioters (Syria)	
	Saraya Ahl al Sham	

Actors' Dictionary – SYRIA

See the following page.

Government	Challenger	Civilian
Allied Syrian and/or Russian Forces	18 March Division	Civilians (International)
BSF: Syrian Border Security Force	1st Brigade of Damascus	Civilians (Iraq)
Fatemiyoun Brigade	1st Coastal Division	Civilians (Syria)
Fawj Maghawir al-Badiya	1st Regiment	
Golan Regiment	AAR:Ahfad al-Rasul Brigades	
Government of Russia	AAS: Ahrar al-Sham	
Government of Syria (2000-)	Abnaa Al-Qadasya	
Harakat Hezbollah al-Nujaba	Abu al-Walid Battalion	
Hezbollah	Ahmad al-Abdo Forces	
Hezbollah	Ahrar al-Sharqiyah	
KaB: Ba'ath Brigades	Ajnad al-Sham Islamic Union	
Military Forces of Iran (1989-)	Al-Ahrar Assembly	
Military Forces of Iran (1989-) Islamic Revolution Guard Corps	Al Baghir Brigade	
Military Forces of Iraq (2014-)	Al-Bakkara Youth Gathering (Syria)	
Military Forces of Iraq (2014-) Popular Mobilization Forces	Al-Baqir Brigade	
Military Forces of Russia	Al Haramain Brigades	
Military Forces of Syria (2000-) 12th Armored Brigade	Al-Malahim Division	
Military Forces of Syria (2000-) 4th Armored Division	Al-Omari Brigades	
MIlitary Forces of Syria (2000-)	Al Qaeda	
Military Forces of Syria (2000-)	Al-Safirah Brigade	
Military Forces of Syria (2000-)	Al Sham Corps	
Military Forces of Syria (2000-)	Al-Sham Corps	
Military Forces of Syria (2000-) Revolutionary Guard	Al-Thani Army	

Military Forces of Syria (2000-) Syrian Arab Air Force	Al-Wosta Division	
Military Forces of Syria (2000-) Syrian Republican Guard	Army of Mujahideen	

SPATIAL AND TEMPORAL VARIATION OF CONFLICT RELATED COUNT VARIABLES

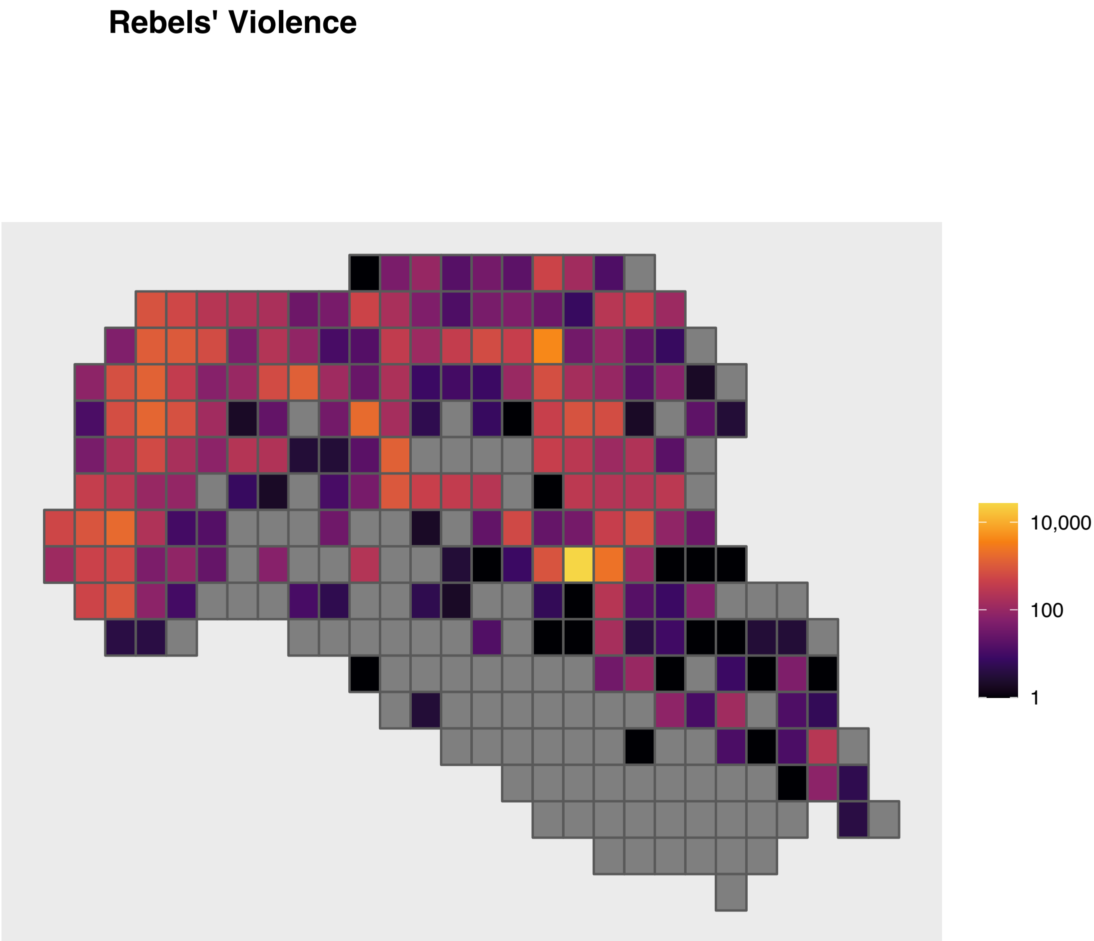

Figure 34: Spatial variation of rebels' violence ($log10$ count of events) in Syria, Iraq, and Lebanon (2011-2019) depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any event of this type.

Figure 35: Spatial variation of incumbents' selective and indiscriminate violence respectively ($log10$ count of events) in Syria, Iraq and Lebanon (2011-2019) depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any event of this type.

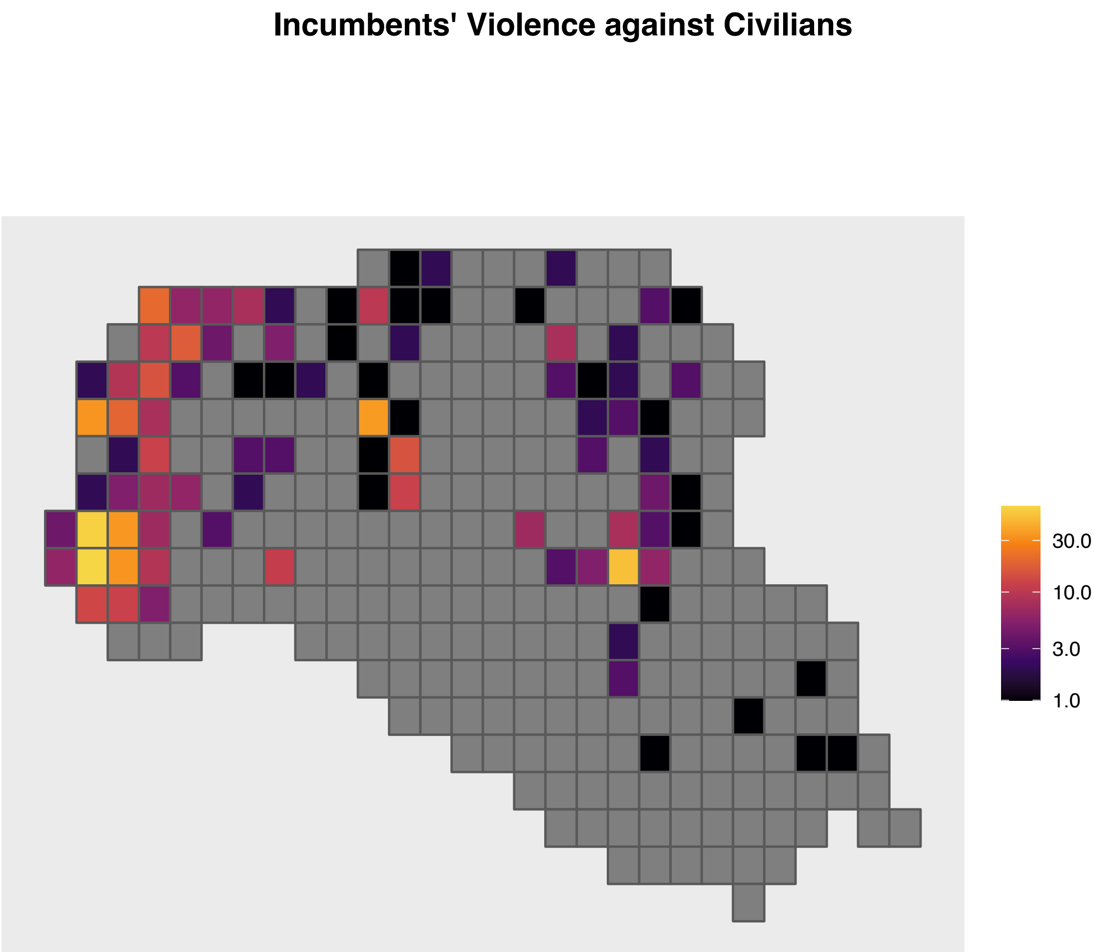

Figure 36: Spatial variation of incumbents' violence against civilians ($log10$ count of events) in Syria, Iraq, and Lebanon (2011-2019) depicted using PRIO-GRID cells as spatial units. Gray cells did not experience any event of this type.

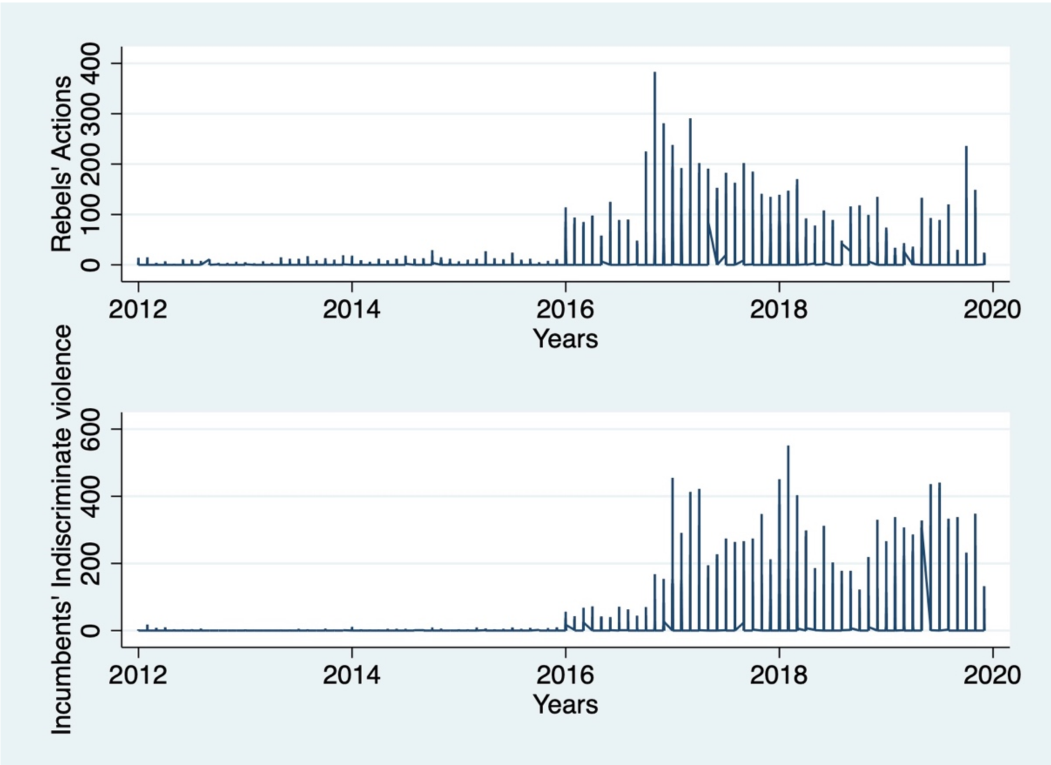

Figure 37: Time Series of Rebels' Actions and Incumbents' Indiscriminate Violence in Iraq, Lebanon and Syria from 2011 to 2019.

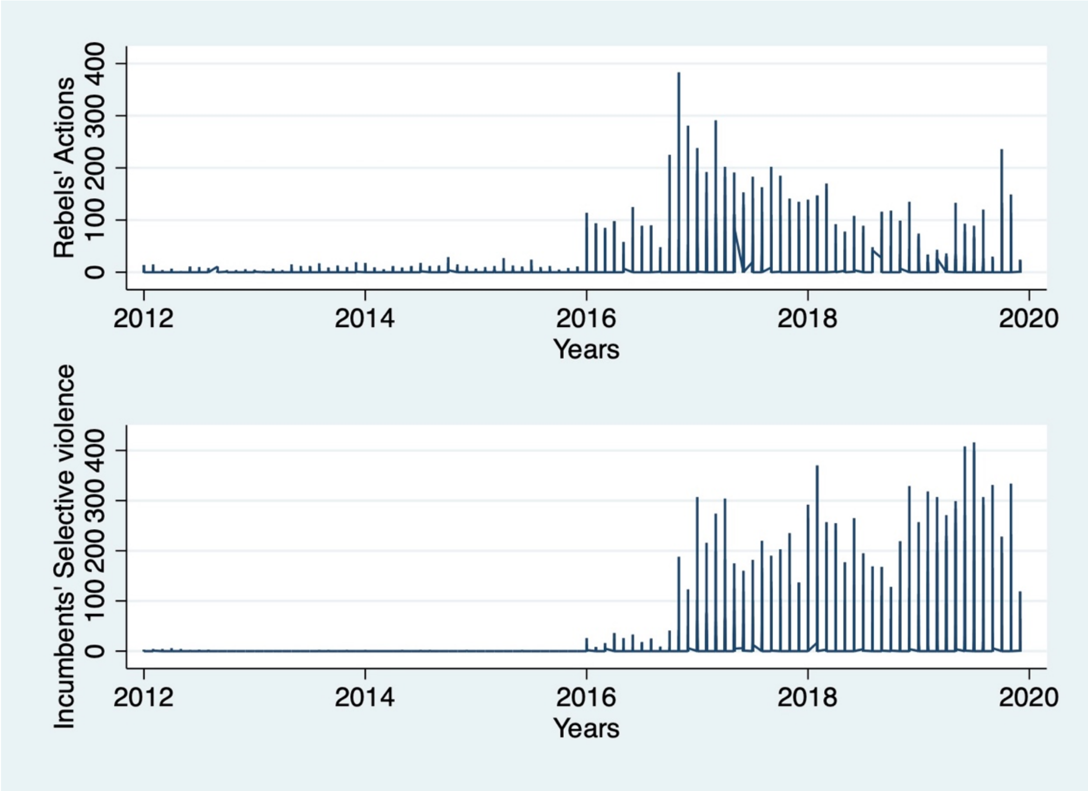

Figure 38: Time Series of Rebels' Actions and Incumbents' Selective Violence in Iraq, Lebanon and Syria from 2011 to 2019.

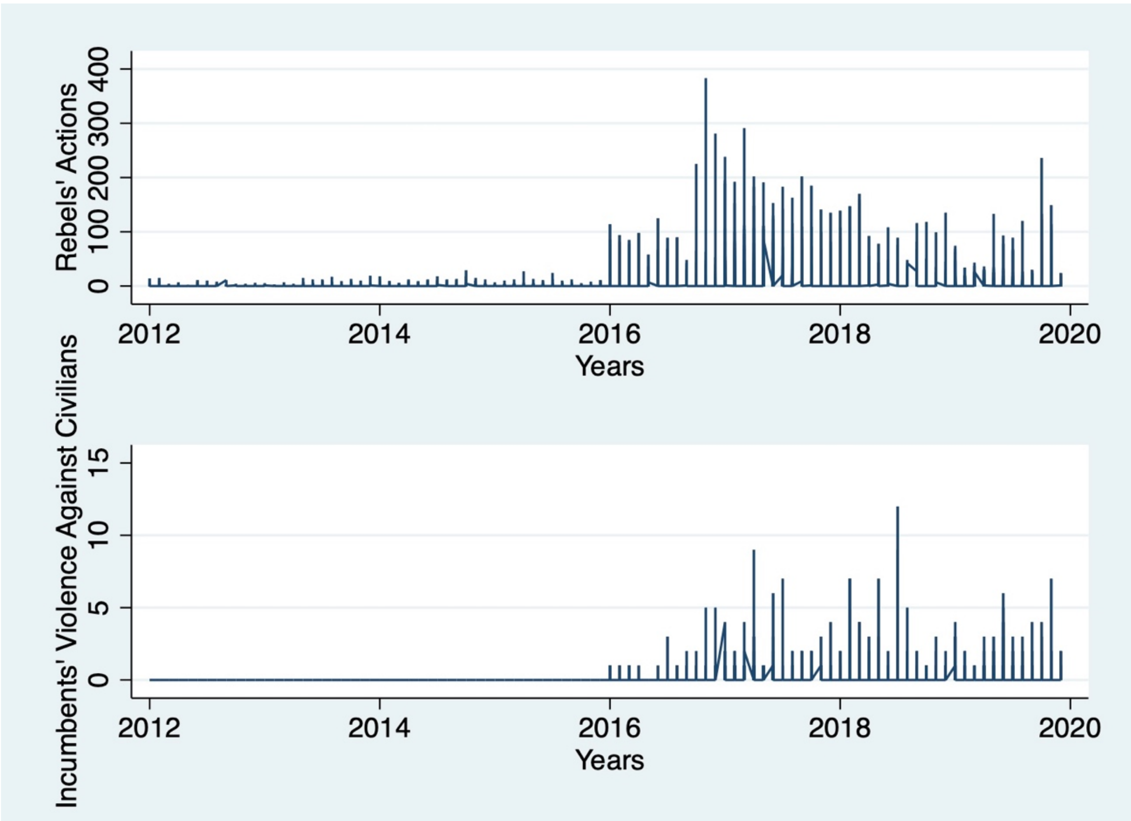

Figure 39: Time Series of Rebels' Actions and Incumbents' Violence against Civilians in Iraq, Lebanon and Syria from 2011 to 2019.

APPENDIX 2 – CHAPTER 4

VISUALIZATION AND TAXONOMY OF SIGACTS DATA

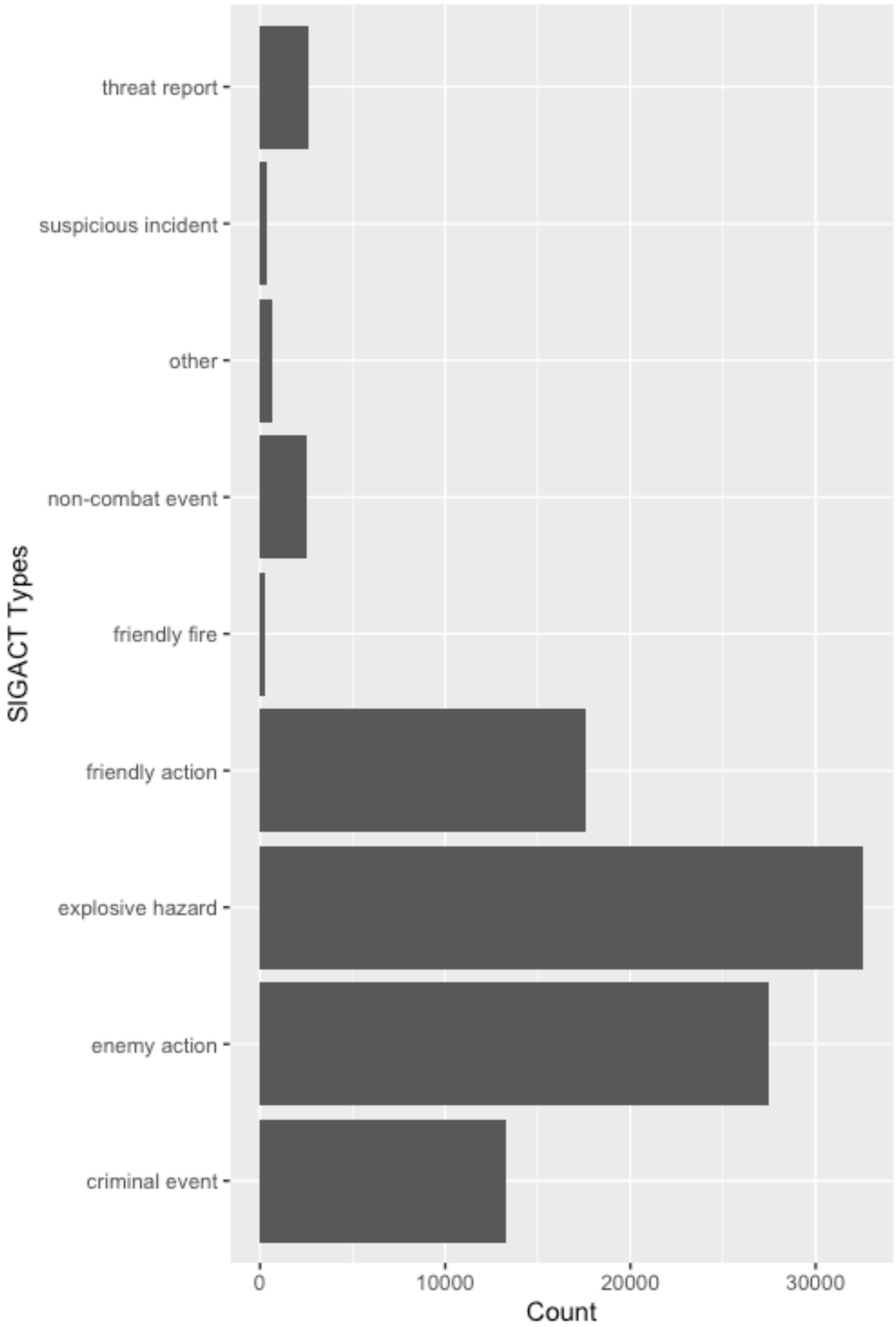

Figure 40: Bar-plot of SIGACTs events' type. Iraq, 2006.

"mugging"	"extortion"	"other"
"sabotage"	"looting"	"smuggling"
"arson"	"carjacking"	"theft"
"kidnapping"	"murder"	"ambush"
"assassination"	"safire"	"sniper ops"
"attack"	"indirect fire"	"direct fire"
"ied false"	"mine strike"	"mine found/cleared"
"ied suspected"	"ied hoax"	"unexploded ordnance"
"unknown explosion"	"ied found/cleared"	"ied explosion"
"search and attack"	"counter mortar patrol"	"convoy"
"movement to contact"	"close air support"	"counter mortar fire"
"arty"	"deliberate attack"	"recon"
"border ops"	"other offensive"	"medevac"
"confiscation"	"police actions"	"uav"
"surveillance"	"vehicle interdiction"	"arrest"
"tcp"	"other defensive"	"patrol"
"small unit actions"	"raid"	"cordon/search"
"detain"	"cache found/cleared"	"escalation of force"
"white-blue"	"green-white"	"blue-white"
"blue-green"	"green-green"	"green-blue"
"blue-blue"	"sermon"	"natural disaster"
"supporting cf"	"supporting aif"	"propaganda"
"meeting"	"tribal feud"	"equipment failure"
"demonstration"	"accident"	"rock throwing"
"elicitation"	"repetitive activities"	"tests of security"
"carjacking threat"	"looting threat"	"raid threat"
"small arms threat"	"theft threat"	"sabotage threat"
"intimidation"	"safire threat"	"sniper ops threat"
"smuggling threat"	"direct fire threat"	"ambush threat"
"assassination threat"	"murder threat"	"kidnapping threat"
"indirect fire threat"	"intimidation threat"	"ied threat"
"attack threat"		

Table 15: Categories of SIGACTs events. Iraq, 2006.

Types	Category	Events Count
criminal event	mugging	5
	extortion	6
	other	15
	sabotage	16
	looting	20
	smuggling	38
	arson	55
	carjacking	106
	theft	198
	kidnapping	1263
	murder	11592
enemy action	ambush	48
	assassination	50
	safire	283
	sniper ops	637
	attack	2596
	indirect fire	8656
	direct fire	15156
explosive hazard	other	13
	ied false	27
	mine strike	144
	mine found/cleared	271
	ied suspected	346
	ied hoax	574
	unexploded ordnance	1078
	unknown explosion	1139
	ied found/cleared	10925
	ied explosion	18042
friendly action	search and attack	2
	counter mortar patrol	5
	convoy	6
	movement to contact	10
	close air support	13
	ambush	18
	counter mortar fire	21
	arty	22
	deliberate attack	25
	recon	28
	border ops	44
	other offensive	49
	medevac	61
	confiscation	63

	police actions	69
	uav	73
	surveillance	76
	vehicle interdiction	96
	other	168
	sniper ops	211
	arrest	453
	tcp	539
	other defensive	588
	attack	626
	patrol	1249
	small unit actions	1266
	raid	1487
	cordon/search	1621
	detain	2656
	cache found/cleared	2731
	escalation of force	3338
friendly fire	white-blue	1
	green-white	9
	blue-white	18
	blue-green	31
	green-green	37
	green-blue	64
	blue-blue	72
non-combat event	sermon	1
	natural disaster	5
	supporting cf	5
	supporting aif	32
	propaganda	41
	meeting	53
	tribal feud	84
	equipment failure	235
	other	361
	demonstration	491
	accident	1221
other	rock throwing	71
	other	548
suspicious incident	elicitation	5
	repetitive activities	20
	tests of security	22
	surveillance	54

	other	256
threat report	carjacking threat	1
	looting threat	1
	raid threat	1
	small arms threat	1
	theft threat	4
	sabotage threat	7
	intimidation	12
	safire threat	17
	sniper ops threat	17
	smuggling threat	19
	direct fire threat	25
	ambush threat	36
	assassination threat	62
	murder threat	64
	kidnapping threat	112
	other	163
	indirect fire threat	189
	intimidation threat	300
	IED threat	727
	attack threat	877

Table 16: Unique combinations of SIGACTs types and categories with the observed count of their occurrence. Iraq, 2006.

MATCHED WAKE ANALYSIS – GRAPHICAL OVERVIEW

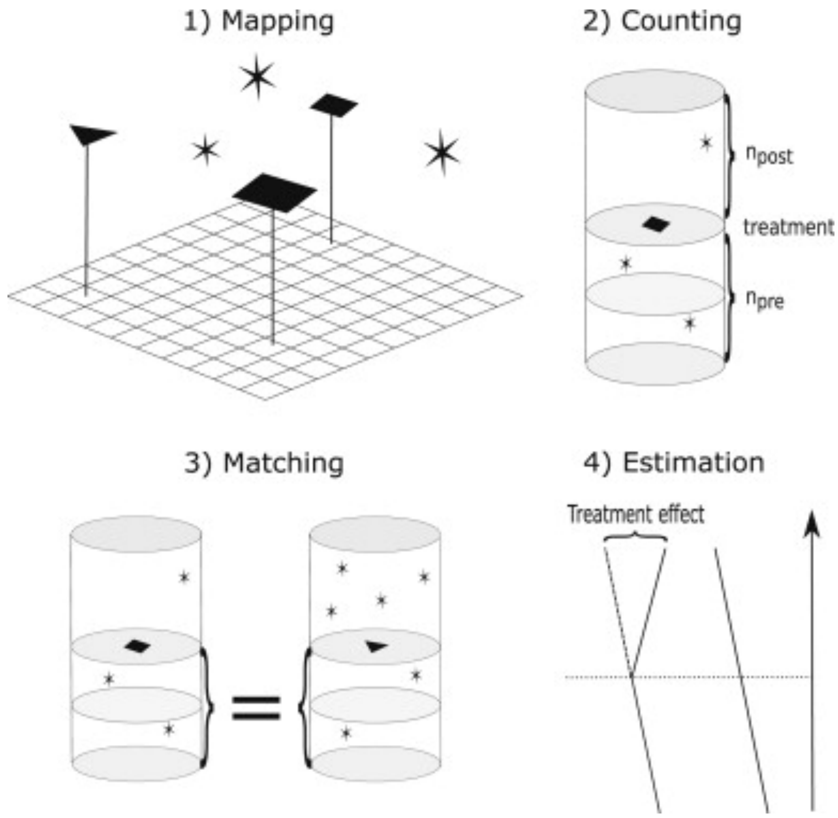

Figure 41: Graphical overview of Matched Wake Analysis. From (Schutte and Donnay 2014).

The first step shows how event data are mapped to extract spatial covariates and geographic information using nearest neighbor mapping. In step two, pre-treatment/pre-control dependent events are counted. The third step depict Coarsened Exact Matching: this is done based on trend and spatial covariates. In step four, the effect of the treatment is estimated using Difference-in-Differences regression on the matched sample (Schutte and Donnay 2014, 14).

MATCHED WAKE ANALYSIS – SIGNIFICATIVE GEO-TEMPORAL WINDOWS

	Time[days]	Space[km]	Effect Size	p.value	adj.Rsquared
1	10	6	0.332	0.014	0.7817
2	10	10	0.652	0.001	0.8588
3	15	10	0.789	0.001	0.8781
4	20	2	0.505	0.002	0.8610
5	20	4	0.539	0.005	0.8568
6	20	6	0.664	0.001	0.8651
7	20	8	0.764	0.001	0.8609
8	20	10	1.248	0.000	0.9024
9	25	8	0.748	0.007	0.8631
10	25	10	1.703	0.000	0.9069
11	30	2	0.599	0.019	0.8670
12	30	4	0.648	0.026	0.8659
13	30	10	1.583	0.000	0.9069
14	35	2	0.724	0.014	0.8720
15	35	4	0.776	0.021	0.8639
16	35	6	1.299	0.001	0.8614
17	35	8	1.035	0.005	0.8858
18	35	10	1.394	0.006	0.9113
19	40	6	1.044	0.012	0.8823
20	40	8	0.859	0.035	0.8932
21	40	10	1.160	0.048	0.9124

Table 17: Relative comparison - Combinations of temporal and spatial windows defined by days and coordinates. For each row, representing a window, we report the size of the effect, p-values and adjusted R-squared.

	Time[days]	Space[km]	Effect Size	p.value	adj.Rsquared
1	5	2	0.473	0.000	0.4515
2	5	4	0.464	0.000	0.4941
3	5	6	0.373	0.000	0.5453
4	5	8	0.368	0.000	0.6405
5	5	10	0.493	0.000	0.6337
6	10	2	0.523	0.000	0.5971
7	10	4	0.501	0.000	0.6523
8	10	6	0.574	0.000	0.6550
9	10	8	0.467	0.000	0.7710
10	10	10	0.430	0.000	0.8425
11	15	2	0.671	0.000	0.7071
12	15	4	0.597	0.000	0.7343
13	15	6	0.545	0.000	0.7865
14	15	8	0.340	0.001	0.8043
15	15	10	0.632	0.000	0.8618
16	20	2	0.740	0.000	0.7742
17	20	4	0.800	0.000	0.7464
18	20	6	0.721	0.000	0.7793
19	20	8	0.463	0.000	0.8257
20	20	10	0.485	0.000	0.8952
21	25	2	0.912	0.000	0.7215
22	25	4	0.432	0.000	0.7541
23	25	6	0.590	0.000	0.7635
24	25	8	0.850	0.000	0.8154
25	25	10	0.713	0.000	0.9099
26	30	2	1.062	0.000	0.7374
27	30	4	0.841	0.000	0.7511
28	30	6	0.270	0.018	0.8682
29	30	8	1.023	0.000	0.7666
30	30	10	0.734	0.000	0.8918
31	35	2	0.679	0.000	0.8246
32	35	4	0.487	0.000	0.8700
33	35	6	0.395	0.002	0.8693
34	35	8	0.899	0.000	0.8367
35	35	10	0.901	0.000	0.8897
36	40	2	0.635	0.004	0.8691
37	40	6	1.004	0.000	0.8594
38	40	8	0.635	0.003	0.8845
39	40	10	1.388	0.000	0.8715
40	45	8	1.032	0.000	0.8587

41	45	10	1.359	0.000	0.8946

Table 18: Absolute effect – Road Buffer - Combinations of temporal and spatial windows defined by days and coordinates. For each row, representing a window, we report the size of the effect, p-values and adjusted R-squared.

	Time[days]	Space[km]	Effect Size	p.value	adj.Rsquared
1	5	2	0.430	0.000	0.4758
2	5	4	0.490	0.000	0.4704
3	5	6	0.477	0.000	0.5353
4	5	8	0.320	0.000	0.6103
5	5	10	0.533	0.000	0.6270
6	10	2	0.510	0.000	0.6313
7	10	4	0.656	0.000	0.6258
8	10	6	0.575	0.000	0.6717
9	10	8	0.445	0.000	0.7486
10	10	10	0.551	0.000	0.7950
11	15	2	0.527	0.000	0.7663
12	15	4	0.676	0.000	0.7567
13	15	6	0.682	0.000	0.7889
14	15	8	0.507	0.000	0.8040
15	15	10	0.632	0.000	0.8383
16	20	2	0.754	0.000	0.8069
17	20	4	0.900	0.000	0.7746
18	20	6	0.809	0.000	0.7873
19	20	8	0.807	0.000	0.7887
20	20	10	0.496	0.001	0.8824
21	25	2	0.898	0.000	0.7731
22	25	4	0.726	0.000	0.7130
23	25	6	0.972	0.000	0.7821
24	25	8	0.894	0.000	0.8180
25	25	10	0.686	0.000	0.8924
26	30	2	1.266	0.000	0.7939
27	30	4	1.560	0.000	0.7810
28	30	6	0.726	0.000	0.8036
29	30	8	1.135	0.000	0.8236
30	30	10	0.666	0.000	0.8710
31	35	2	0.805	0.000	0.8445
32	35	4	0.959	0.000	0.8381
33	35	6	0.876	0.000	0.8175
34	35	8	1.336	0.000	0.8065
35	35	10	0.882	0.001	0.8630
36	40	2	0.970	0.000	0.8294
37	40	4	1.225	0.000	0.8162
38	40	6	0.648	0.000	0.8558
39	40	8	1.420	0.000	0.8750
40	40	10	0.764	0.003	0.9022

41	45	6	0.740	0.001	0.8461
42	45	8	1.227	0.000	0.8590
43	45	10	1.313	0.000	0.9087

Table 19: Absolute effect – Settlement Buffer - Combinations of temporal and spatial windows defined by days and coordinates. For each row, representing a window, we report the size of the effect, p-values and adjusted R-squared.

MATCHED WAKE ANALYSIS – RELATIVE EFFECT MODEL – INCREASE OF THE TIME PARAMETER

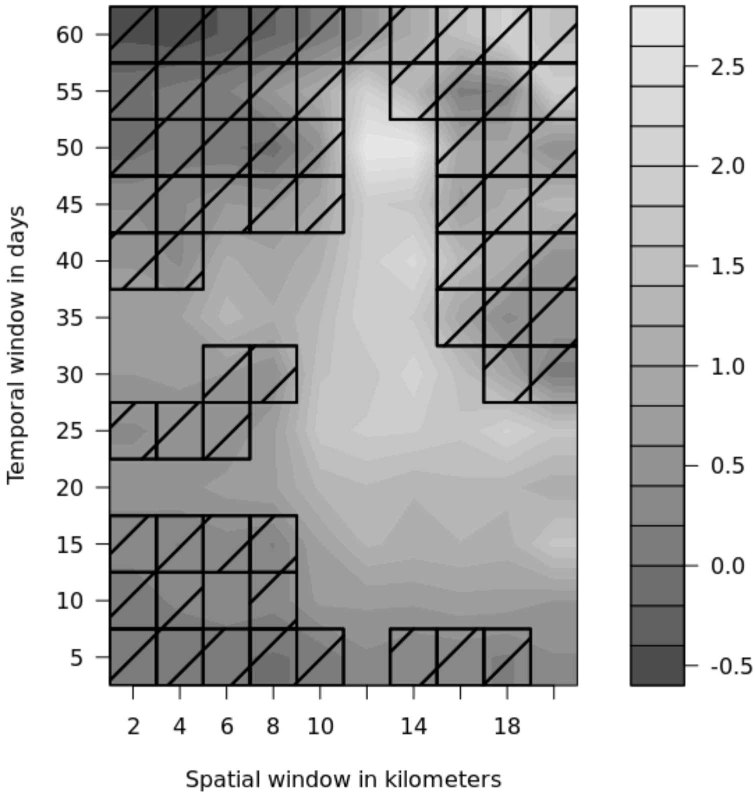

Figure 42: Results of the relative effect model with a 60-days horizon and a 20 kilometers spatial horizon. The dependent variable is the count of IED attacks. Instances of indiscriminate violence and instances of selective violence are used as treatments and controls respectively. The contour plot shows the average treatment effect estimated through the difference-in-differences approach. The clear squares depict geo-temporal windows whereby the estimate is significant at 95% level. Squares overlaid with lines show that the estimated effect is not significant. The bar on the right-hand side shows the legend of the direction of estimated effects.

APPENDIX 3 – CHAPTER 5

WEEKLY AGGREGATION – TIME SERIES

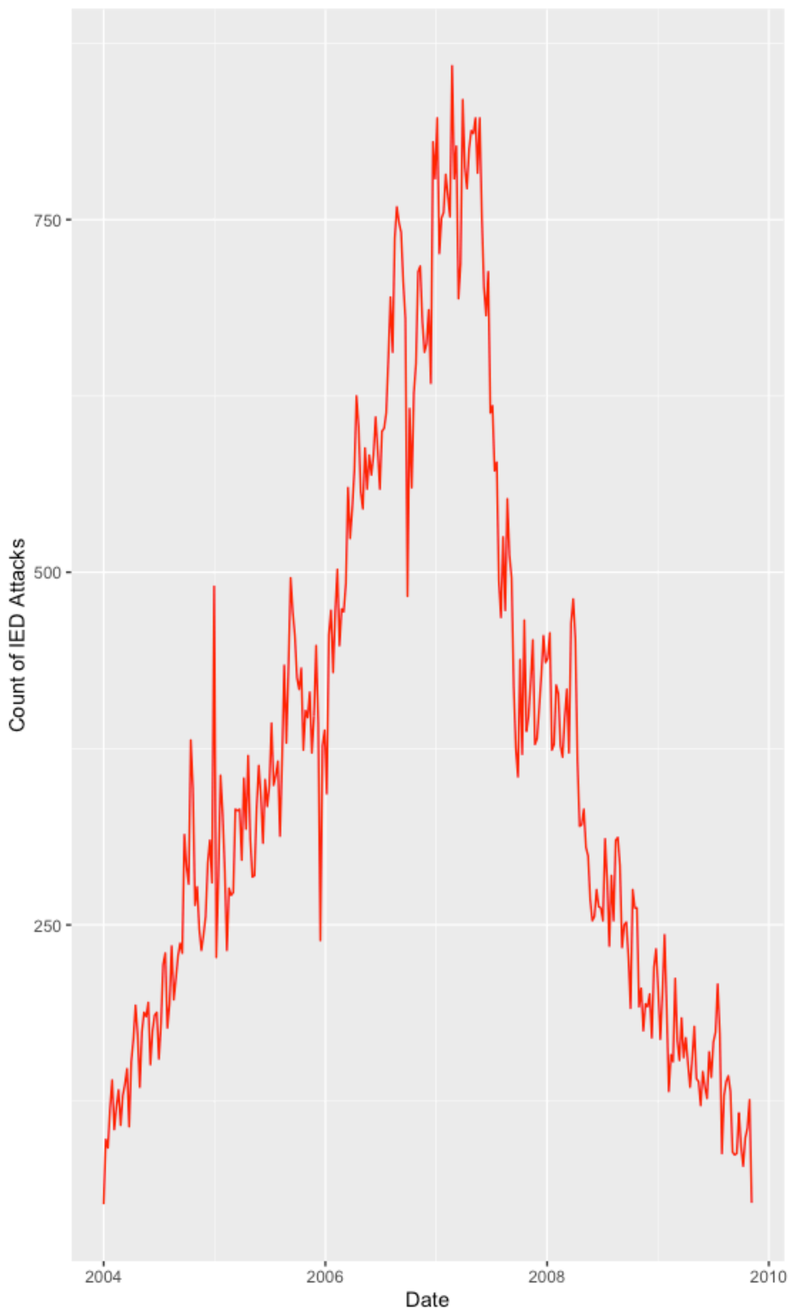

Figure 43: Weekly distribution of IED attacks over time. Iraq, 2004-2010

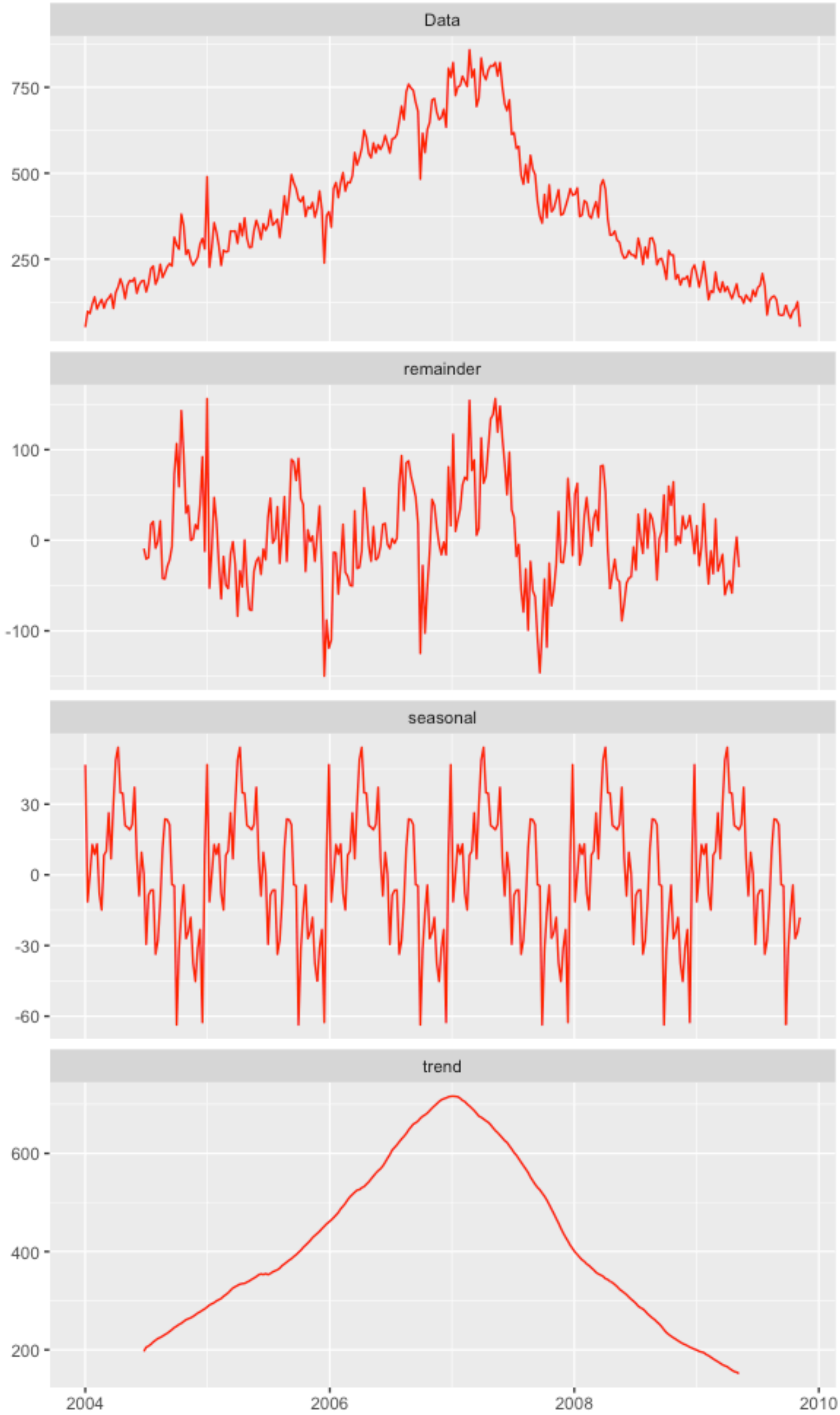

Figure 44: Weekly time-series decomposition of IED Attacks. Iraq, 2004-2010. The first quadrant shows the distribution of data over time while the following ones show the remainder, the seasonality, and the trend respectively.

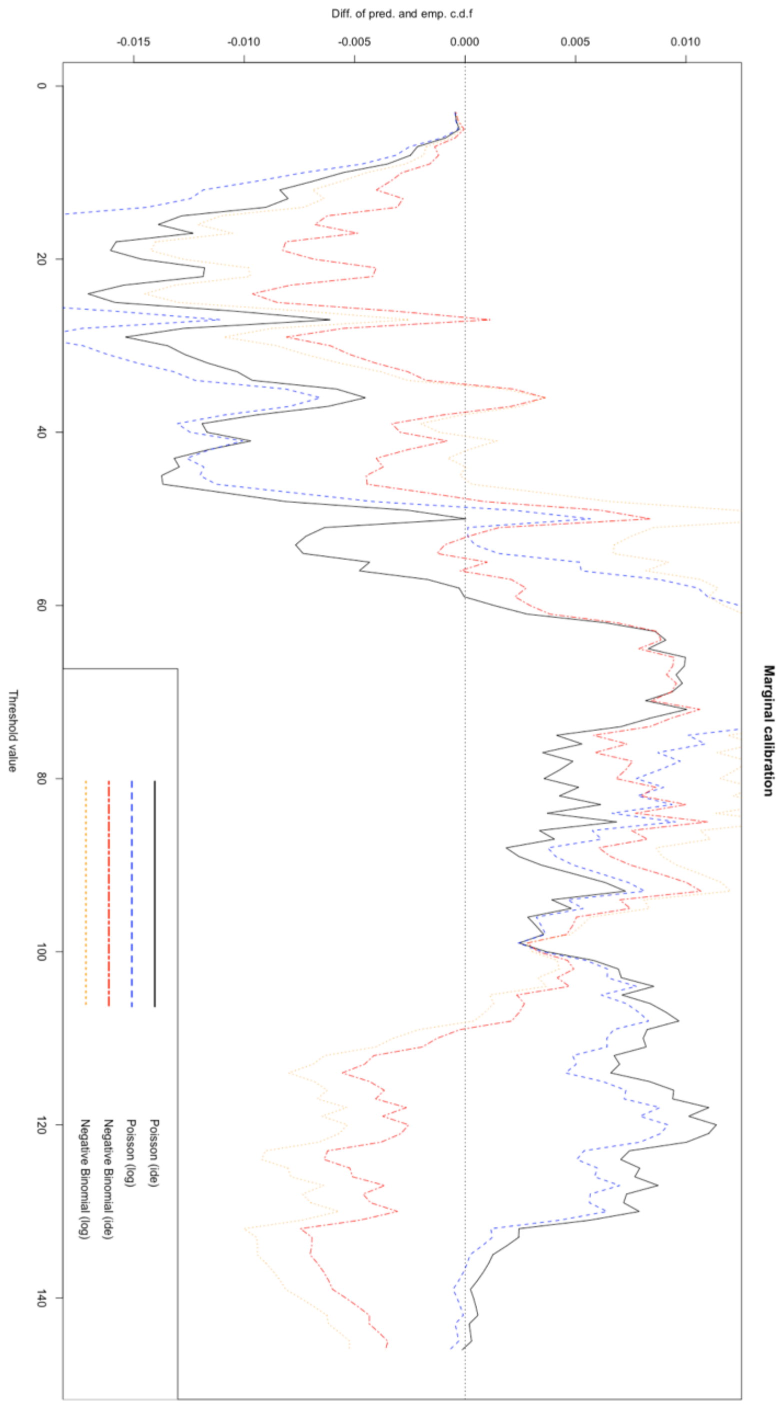

Figure 45: Marginal calibration for the first model selection.

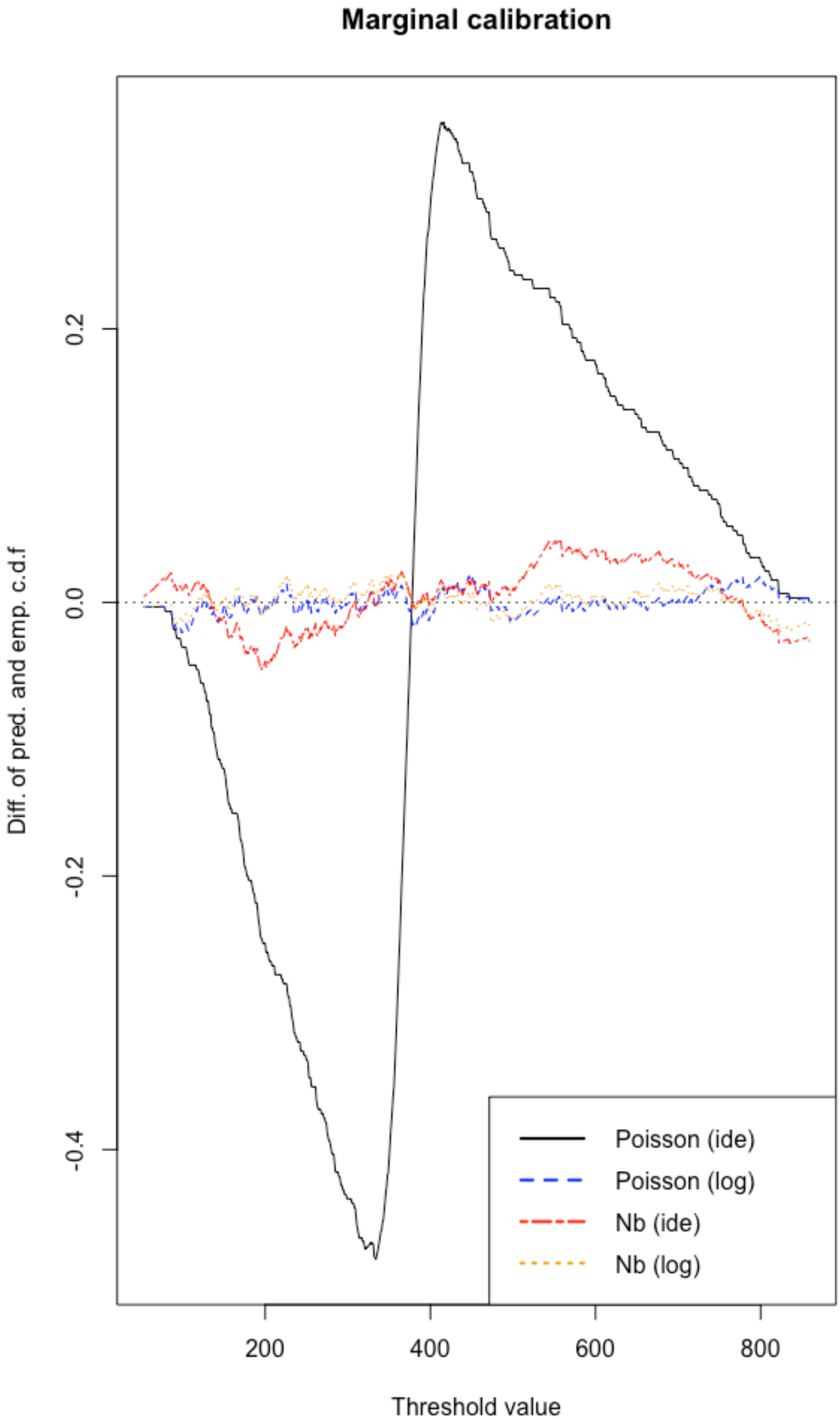

Figure 46: Marginal Calibration of the weekly models.

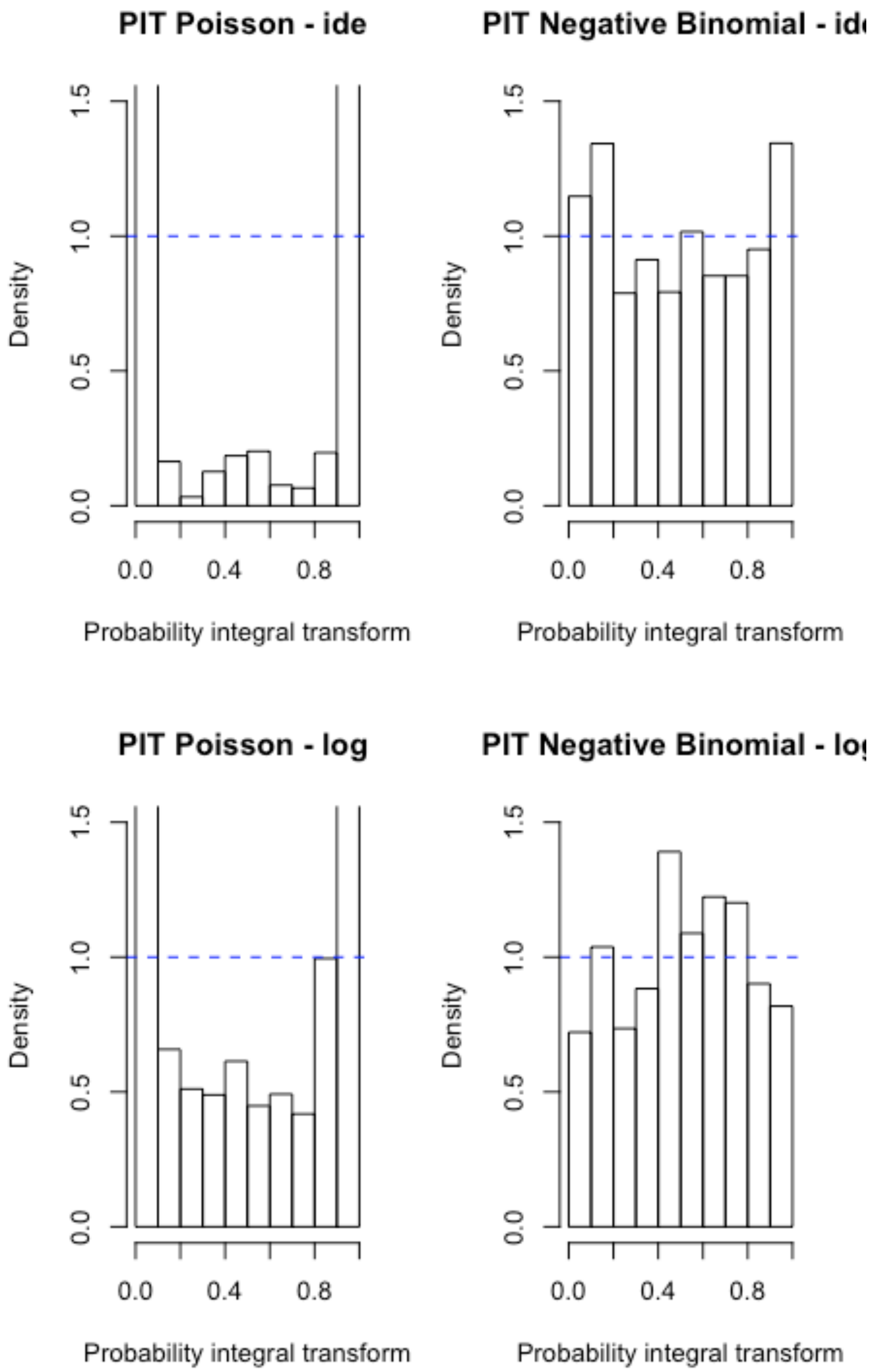

Figure 47: Probability Integral Transform for the selection of the conditional distributions and for the selection of the link. Weekly sample.

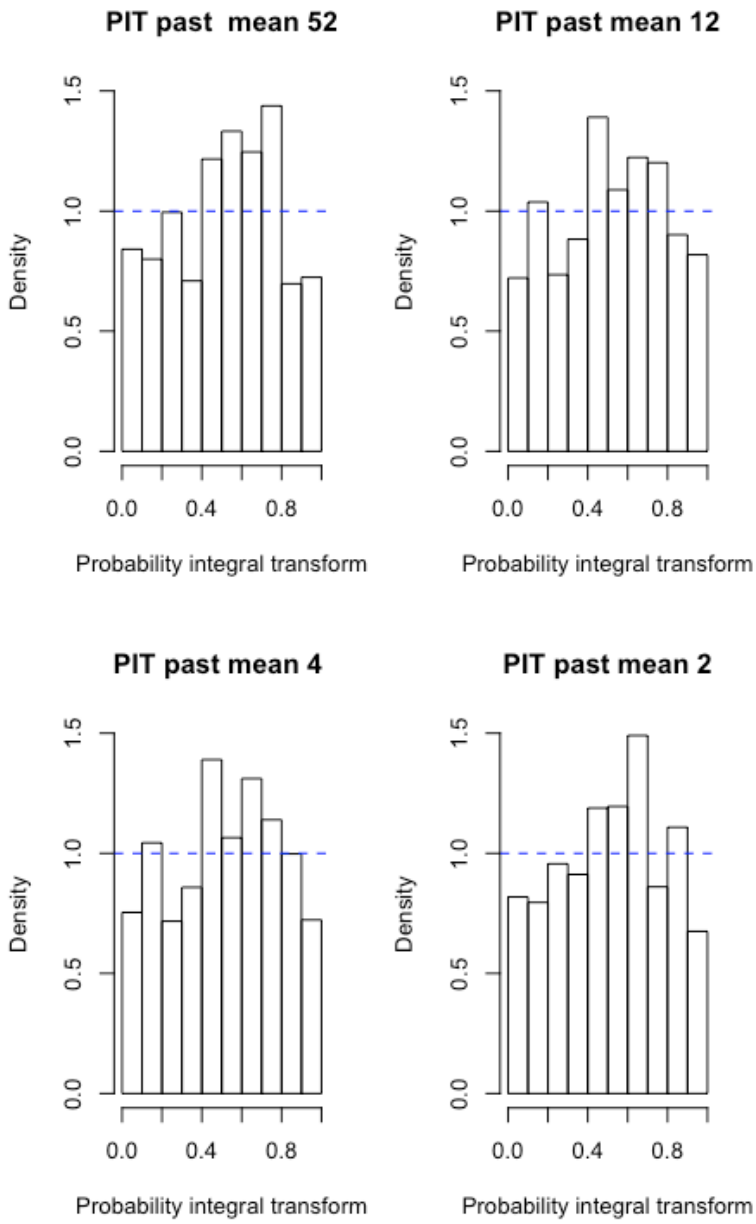

Figure 48: Probability Integral Transform. Used for selecting past means parameters. Weekly sample.

	logarithmic	quadratic	spherical	rankprob	dawseb	normsq	sqerror
Nb52	5.240.784	-0.007095679	-0.08363817	2.468.281	8.596.036	0.947541	2.045.876
Nb12	5.214.624	-0.007220073	-0.08432860	2.426.630	8.542.805	0.947541	1.986.425
Nb4	5.210.387	-0.007226590	-0.08443365	2.415.325	8.549.679	0.947541	1.964.475
Nb2	5.186.370	-0.007521996	-0.08595690	2.366.394	8.502.857	0.947541	1.920.058

Table 20: Scoring rules for selecting past means parameters. Weekly model.

	Estimate	Std.Error	CI(lower)	CI(upper)
(Intercept)	1.78e-01	0.131399	-0.079133	0.435940
Beta 1	4.82e-01	0.065425	0.353407	0.609869
Beta 2	1.37e-01	0.068989	0.001546	0.271976
Alpha 2	3.43e-01	0.075303	0.195131	0.490312
Lag Crime	8.77e-05	0.000115	-0.000137	0.000312
Lag Threats	1.36e-04	0.000383	-0.000615	0.000886
Lag Propaganda	5.60e-05	0.001100	-0.002100	0.002212
Lag Counterinsurgents' indiscriminate	6.67e-05	0.000297	-0.000516	0.000649
Lag Counterinsurgents selective	9.70e-05	0.000279	-0.000451	0.000644
Lag Counterinsurgents policing	-4.97e-04	0.000511	-0.001498	0.000504
Lag Rebels' selective	-5.36e-05	0.000158	-0.000362	0.000255
Lag Rebels' Indiscriminate	3.83e-05	0.000222	-0.000396	0.000473
Lag Temperature	2.44e-06	0.001148	-0.002249	0.002253
Lag Rainfall	5.84e-03	0.007507	-0.008875	0.020552
Lag Night Lights	5.87e-01	0.588577	-0.566792	1.740.389
Lag Turn-in	-3.41e-04	0.000461	-0.001244	0.000562

Table 21: Weekly in-sample estimation of a tscount model with Negative Binomial Conditional Distribution at logarithmic link. Betas represent the coefficient estimated on the past observations (1 to 2 weeks in the past). Alpha represents the coefficient estimated onto the past mean (2 weeks in the past).

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