

UNIVERSITY OF DUBLIN, TRINITY
COLLEGE

DOCTORAL THESIS

**Explaining and predicting the
adoption, timing and location of
terrorism in civil conflicts**

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Declaration of Authorship

I, Christian OSWALD, declare that this thesis titled, “Explaining and predicting the adoption, timing and location of terrorism in civil conflicts” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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UNIVERSITY OF DUBLIN, TRINITY COLLEGE

Abstract

School of Social Sciences and Philosophy
Department of Political Science

Doctor of Philosophy

**Explaining and predicting the adoption, timing and location of
terrorism in civil conflicts**

by Christian OSWALD

This thesis examines the adoption, timing and location of terrorism in civil conflicts. It analyzes the effect of territorial advances on the timing and location of state-based and one-sided violence, the effect of battlefield dynamics on the timing and location of terrorism, and the predictive power of commonly used independent variables explaining rebel use of terrorism. The thesis consists of three papers.

The first paper addresses the timing and location of state-based and one-sided violence in civil conflicts. Territorial control is central to civil conflict dynamics because it is a precondition for successful insurgency and determines how rebels interact with civilians and the government, their recruitment and funding structures, and ultimately how successful rebels are in challenging a government. While strategic locations such as natural resources or infrastructure nodes have been argued to increase conflict intensity, it is less their mere presence but more the active struggle over controlling these territories that increase conflict intensity. Using recent advances in estimating local territorial control in civil conflicts with spatial and temporal variation on the monthly level, I argue that momentum in the form of territorial advances determines the timing and location of both clashes between a government and rebels and violence against civilians. I use spatial regression models and fine-grained grid cell data for Nigeria from 2009 until 2017 and find evidence for the hypothesized relationship.

The second paper addresses the timing and location of terrorism in civil conflicts. Previous studies identified battlefield dynamics, and relative rebel losses in particular, to determine the timing of terrorism and which first-level administrative regions are more likely to experience terrorism. By changing the unit of analysis to the grid cell-month, I provide a localized approach to explain and predict both the timing and location of terrorism in civil conflicts using data on civil conflicts in Africa between 1989 and 2013. I argue that battlefield dynamics in the form of number of clashes and their intensity determine the timing and location of terrorism in civil conflicts. I further distinguish between three distinct types of terrorism by target choice which indicate the intended shock level. Using generalized linear mixed effects models, I find evidence for the hypothesized relationship with regards to the number of clashes while there is evidence only for a distinct terrorism target choice with regards to rebel and government casualties.

The third paper introduces the idea of data-driven theory building

by testing the predictive power of previously identified explanatory variables. Previous studies used null hypothesis significance testing and predicted probabilities to determine explanatory power but this approach can deliver misleading results. One of many advantages of prediction is to test how well theories perform on unseen data. After all, theories should be able to both explain and predict well. The aim of this paper is to provide the foundation for a unified theory of rebel use of terrorism in civil conflicts by determining the relative importance of individual variables, illustrating their substantive effects, and exploring interaction effects present in the data as a complement to more traditional theory building. I use random forests, out-of-sample cross-validation, and interpretable machine learning techniques to analyze available data for rebel group use of terrorism in civil conflicts in Africa, the Middle East and Asia. Results suggest that some variables seem to be of crucial importance while other variables seem to have limited predictive power.

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To my parents

Chapter 1

Introduction

Terrorism is a widespread feature in some civil wars but not in others (Young & Findley 2011). While violence against civilians has received some attention for a while, the phenomenon of terrorism in civil conflicts has only recently received increased scholarly attention (Polo & González 2020, Asal, Phillips, Rethemeyer, Simonelli & Young 2019, Ash 2018, Polo & Gleditsch 2016, Bakker, Hill Jr & Moore 2016, Coggins 2015, Stanton 2013). It is a valid question to ask why we should study terrorism in civil conflicts and what specifically the difference is to violence against civilians. One-sided violence against civilians as defined by the Uppsala Conflict Data Program has to result in casualties while there is no such requirement for terrorism (Eck & Hultman 2007). In addition, while violence against civilians is certainly also intended to send some message to a wider population, it is arguably one of the most important factors for terrorist attacks (Hoffman 2006). It can be regarded as a form of signaling and the aim is to instil fear in a population by sending a message to an audience beyond the immediate victims that there are more attacks to come, that nobody is safe, and that attacks can happen anywhere at any moment in time (Crenshaw 1981, McCormick 2003, Kydd & Walter 2006, Cronin 2009, Hoffman 2006, Stanton 2016). One-sided violence against civilians or civilian victimization are thus mostly much broader categories than terrorism (Fortna, Lotito & Rubin 2018, Fortna, Lotito & Rubin 2020) while terrorist attacks which do not result in casualties do not qualify for stricter definitions of violence against civilians. Terrorism is also oftentimes about the shock it causes in a wider population and to send a message about strength which oftentimes does not necessarily reflect reality (Conrad & Greene 2015). There is thus a distinct difference between terrorism and violence against civilians, and it is important to analyze terrorism in civil conflicts too since it has different underlying intentions and as a result a different underlying decision-making

process.

1.1 Research gaps and contributions

In the following subsections, I briefly summarize previous findings and highlight the research gaps I identify and address in this thesis.

1.1.1 The timing and location of violence in civil conflicts

Previous research has identified economic conditions, foreign interventions, ethnicity, or natural resources amongst other factors which affect conflict intensity (Lacina 2006, Holmes, Gutiérrez De Piñeres & Curtin 2007, Eck 2009, Hegre, Østby & Raleigh 2009, Lujala 2009, Lu & Thies 2011, Balcells & Kalyvas 2014, Wischnath & Buhaug 2014, Butler, Cunningham & Gates 2017, Chaudoin, Peskowitz & Stanton 2017). However, I argue that it is not the mere presence of for example natural resources that increases conflict intensity. It is the active armed struggle between a government and rebels to control these resources to use them as a financial resource which is responsible for this intensification. Likewise, foreign interventions do not take place if a government is capable to police its territory and contain an insurgency. They take place if a government has lost effective control over some parts of the territory and outside actors step in seeking to establish full government control again. The common theme is that territorial advances explain increased conflict intensity rather than natural resources or foreign interventions themselves. Indeed, controlling territory is an almost necessary condition for rebels to start and sustain an insurgency and to establish funding and recruitment structures to prolong their armed struggle (Weidmann 2009).

Chapter 2 addresses this gap by estimating the effect of territorial advances on the timing, location, and intensity of state-based and one-sided violence. Territorial control oftentimes changes quite rapidly over the course of a conflict and can be patchy at times. Previously used data were restricted to binary variables indicating whether rebel groups control some territory but this gives no indication of how much territory is under their control and it oftentimes lacks subnational or temporal variation at desirable levels. I make use of recent advances in estimating monthly levels of territorial control in civil conflicts on a hexagonal grid cell level

(Anders 2020) to analyze the effect of territorial advances during the conflict between the government of Nigeria and Boko Haram and the Islamic State from 2009 to 2017. Using spatial regression models, I find evidence for the hypothesis that territorial advances increase the risk and intensity of state-based and one-sided violence.

1.1.2 The timing and location of terrorism in civil conflicts

Previous research identified rebel losses as crucial determinant for the timing of terrorism in civil conflicts. Terrorism is used as a mobilization tool in times of need to provoke a heavy-handed government response and activate out-group antagonism (Polo & González 2020). While it is valuable to know when to expect terrorist attacks, some knowledge of possible locations of these attacks is necessary to be able to use this information in a more meaningful way. Likewise, first-level administrative regions which contain capital cities, are relatively deprived, experience ongoing armed conflict or attacks by other rebel groups are more likely to experience terrorism (Ash 2018). While useful, the size of first-level administrative regions varies significantly, with some of them being larger than many European countries such as the United Kingdom or Austria. In addition, without some knowledge about the timing of these attacks, we are left guessing when to raise alert levels.

Chapter 4 addresses this gap by changing the unit of analysis to the grid cell-month using data on all civil conflicts in Africa from 1989 to 2013. Drawing on recent advances to match terrorist attacks to recognized rebel groups (Fortna, Lotito & Rubin 2020) and building on the literature on the timing and the location of terrorism and battle events in civil conflicts (Ash 2018, Polo & González 2020, Kibris 2021), I explain and predict the timing and location of terrorism in civil conflicts jointly using generalized linear mixed effects models with spatial and temporal lags. Distinguishing between different targets of terrorism, I explore the intended shock level of rebel groups by differentiating attacks on infrastructure, combatants and government, and civilians while also keeping a variable capturing a more general definition of terrorism. I find that the number of clashes between a government and rebels and distance to the province capital are consistently linked to the occurrence of any type of terrorism while rebel and government casualties are only linked to the occurrence of terrorism against combatants and government. I also find that countries such as

Nigeria or Somalia reach higher risk levels earlier than for example Chad or Djibouti.

1.1.3 The predictive power of explanatory variables and theory building

The literature outlined above has identified several variables explaining the occurrence of terrorism and the number of terrorist attacks and victims for countries, conflicts, and rebel groups. These studies used null hypothesis significance testing and predicted probabilities to determine and illustrate the importance of variables. However, such an approach is at risk of producing misleading results due to an overreliance on statistical significance and a neglect of predictive performance (Ward, Greenhill & Bakke 2010, Schrodtt 2014). Moreover, it has long been argued that machine learning algorithms, and tree-based algorithms in particular, are better in quantifying uncertainty and detecting more complex relationships in data than more commonly used linear or generalized linear regression models (Schrodtt 2014, Hindman 2015). Lastly, theories should be able to both explain and predict well, but theoretical expectations in the study of terrorism in civil conflicts have been limited to explanation. Prediction is thus a measure for theory testing and improvement.

Chapter 5 will address this gap by analyzing available data (Polo & González 2020) and determining the predictive performance of commonly used independent variables to establish the foundation for a unified theory of rebel use of terrorism in civil conflicts. The data are chosen not to criticize a paper, empirical approach, or findings but rather because it is to the best of my knowledge the most complete available dataset on the rebel group-conflict-month level which also includes a number of variables of interest. It contains information about 205 rebel groups in the Middle East, Asia and Africa between 1989 and 2009. I use random forests and cross-validation to determine the predictive performance and relative importance of individual variables. However, the focus of this chapter is less on performance metrics, which are decent, and more on the importance of different variables, their substantive effects, and interaction strengths in the data with other variables. I find that while some variables are of quite high predictive power, others have seemingly little influence in driving the success of the model.

1.2 Relevance and implications

To summarize, this thesis explores the occurrence, timing and location of violence in civil conflicts from a series of new perspectives. Drawing upon recent advances in measurement and using appropriate modeling approaches, it provides new empirical evidence to questions of scholarly and substantive effect. What explains the timing and location of state-based and one-sided violence in civil conflicts? When and where do rebels use terrorism in civil conflicts? Which factors predict terrorism in civil conflicts? This thesis provides answers to these questions and avenues for future research to further enhance our understanding of the geography of conflict, the effects of territorial advances, the determinants of terrorism in civil conflicts, and the disaggregated study of civil conflict more generally.

Previous research has pointed to a number of factors such as natural resources, foreign interventions, and other geographical features such as the location of capital cities, excluded ethnic groups or economically deprived regions to explain increased conflict severity. However, this thesis shows that increases in conflict intensity are less about geographical locations *per se* and more about the armed struggle to take control of these locations, and indeed foreign interventions for example are oftentimes caused by rebels gaining territorial control in parts of a country. It further stresses the importance of spatial aspects and using appropriate empirical approaches when modeling spatially and temporally dependent outcomes (Franzese & Hays 2007, Franzese & Hays 2008). Chapter 2 thus enhances our understanding of local conflict dynamics and intensity.

Likewise, the literature on terrorism in civil conflicts has identified factors contributing to the timing and the location of future terrorist attacks separately, and while it is valuable to know under what conditions terrorism becomes more likely in the following month and which administrative regions are more at risk of terrorism, an empirical approach which seeks to explain and predict the timing *and* location of terrorism jointly at a spatial unit lower than first-level administrative regions yields overall more actionable and relevant results. It also illustrates that multilevel modeling is an appropriate choice for cross-national studies of political violence and beyond as advocated by some (Gelman & Hill 2007). Different baseline probabilities for terrorism in civil conflicts for countries such as Nigeria, Mali or Ethiopia illustrate this usefulness. Chapter 3 therefore enhances

our understanding of the occurrence of terrorism in civil conflicts and reactive violence more generally.

Lastly, theories should be able to both explain and predict. Most studies focus solely on explanation and use a variety of linear regression models and predicted probabilities to illustrate substantive findings. Such an approach is at risk of producing misleading results and prediction serves to test theoretical expectations on unseen data through cross-validation. In addition, machine learning algorithms such as random forests are better in quantifying uncertainty and detecting complex patterns in data than linear regression models while keeping a certain level of interpretability and transparency. Chapter 4 illustrates how calculating variable importances, substantive effects such as accumulated local effects and partial dependencies, and exploring interaction strengths present in the data can help establish a framework for a unified theory of rebel use of terrorism in civil conflicts by determining which variables, or combinations of variables, drive the success of a model. A data-driven approach to theory testing and improvement is thus a valuable complement to more traditional theory building, and combining explanation and prediction should become more widespread as advocated by some (Schrodt 2014, Hofman, Watts, Athey, Garip, Griffiths, Kleinberg, Margetts, Mullainathan, Salganik, Vazire et al. 2021).

Chapter 2

Caught up in the moment: The effect of changes in territorial control on the timing, location and intensity of state-based and one-sided violence in civil conflicts

Abstract

Territorial control provides the foundation for rebels to initiate and sustain an insurgency. It also affects rebel tactics used against the government and local civilians and is therefore central to civil conflict dynamics. Studies explaining variation in conflict severity, mostly operationalized as the number battle-related deaths but also human rights violations, identify factors such as economic conditions, natural resources, and rebel and government characteristics which increase conflict intensity. However, these measures do not sufficiently take geography and conflict dynamics into account. For example, the mere presence of diamond mines or oil fields does not explain increased conflict intensity. It is the active struggle for territorial control over these resources that increases severity. I argue that momentum in the form of rebel or government territorial advances affects the timing, location and intensity of state-based and one-sided violence. Drawing on recent advances in measuring territorial control in civil conflicts and using spatiotemporal autoregressive models, I estimate the effect of changes of territorial control on the occurrence and intensity of state-based and one-sided violence. Evidence from Nigeria provides support

for the hypothesized relationship. This paper enhances our understanding of local civil conflict dynamics and contributes to the literatures on civil conflict severity and intensity, the geography of violence, and spatial analyses of civil conflicts by exploiting variation across time and space at the grid cell-month-level.

2.1 Introduction

Efforts by the Taliban to prepare retaking the country and center of power began in May 2021 with clashes in six provinces in South and Central Afghanistan, and the capture of Nerkh district near Kabul. In June, the Taliban were engaged in battles in 26 of Afghanistan's 34 provinces and captured a number of districts in Northern provinces. The following month saw more captures of districts and a new focus on urban areas such as Kandahar and Herat. By July 21, half the country's districts were under Taliban control. In August events accelerated even more: On 6 August the Taliban captured their first provincial capital, Zaranj in Nimroz in Southwest Afghanistan. Five days later the Taliban already controlled nine provincial capitals after the fall of Faizabad. Only nine days after capturing their first provincial capital, and after having captured many other strategically important cities such as Kunduz, Herat and Mazar-i-Sharif, the Taliban captured Jalalabad to the East of Kabul and later that day the capital Kabul and the presidential palace. All major Afghan cities were now under Taliban control. Many of the cities taken towards the end showed little or no local resistance because of the fear of being completely overrun and as a result surrendered. US military intelligence warned just four days prior to the capture of Kabul that the capital could fall to the Taliban within 90 days.¹ These events illustrate the importance of territorial advances and momentum in civil conflicts and the research question of this paper: *What is the effect of territorial advances on the timing and location of state-based and one-sided violence in civil conflicts and their intensity?* Making use of recent advances in measuring local levels of territorial control during civil conflicts over time (Anders 2020), this paper investigates the regional effect of changes to territorial control on the amount and intensity of state-based and one-sided violence in civil conflicts.

Scholars have looked at severity and escalation of civil conflicts in a variety of ways. These studies (Lacina 2006, Holmes, Gutiérrez De Piñeres & Curtin 2007, Eck 2009, Hegre, Østby & Raleigh 2009, Lujala 2009, Lu & Thies 2011, Balcells & Kalyvas 2014, Wischnath & Buhaug 2014, Butler, Cunningham & Gates 2017, Chaudoin, Peskowitz & Stanton 2017) have explained variation in the number of battle-related deaths in a country,

¹<https://www.theguardian.com/world/2021/aug/16/timeline-the-talibans-sweeping-offensive-in-afghanistan> & <https://www.newsweek.com/timeline-talibans-lightning-fast-takeover-afghanistan-1619740>, access 16 August 2021.

first-level administrative regions or PRIO-Grid cell for different temporal units. They identify economic conditions, foreign interventions, government and rebel group strength, ethnic mobilization and homogeneity, lower levels of food production and gemstone mining and oil and gas production leading to higher levels of conflict intensity while democracy and drug cultivation leads to lower levels. However, foreign interventions for example do not occur because a government successfully engages with insurgents. They take place if a government struggles to contain an insurgency, i.e. after insurgents challenged state authority and gained full or partial control of some parts of the country. Likewise, gemstone, oil and gas locations are not the cause of increased conflict intensity. It is the active armed struggle over controlling these resources which increases conflict severity locally. Thus territorial advances are a crucial component to any civil conflict and affect the likelihood, timing and more specific locations of violence, and indeed the ability to start and sustain an insurgency in the first place.

I depart from the above studies by taking a more localized approach. Looking at 0.25 decimal degree minimum diameter hexagonal grid cells on the monthly level for Nigeria, I utilize recent advances in measuring levels of territorial control to test the effect of territorial changes on the timing, location and intensity of violence in civil conflicts. I argue that territorial advances in civil conflicts are the key to explain the timing and location of state-based and one-sided violence and their intensity. Rebels advance by seizing or consolidating territorial control to which governments have to respond in the form of an increase in the number or severity of battles. After all, a state should hold the monopoly of legitimate use of physical force and is concerned with its territorial integrity and stability. As outlined above, the simple presence of for example gemstone mining or diamond mines in a country does not explain higher levels of conflict intensity but the attempt to control and extract these resources does. While previous studies have incorporated spatial information and geographic locations, measures of local territorial control and advances across time and space which capture to what extent which conflict party can utilize these locations were absent. Using estimates of territorial control through a Hidden Markov Model (Anders 2020), I use spatiotemporal autoregressive models to show that variation in state-based and one-sided violence in civil conflicts is systematically influenced by local territorial advances. Empirical evidence from Nigeria and the conflict between the government

and Boko Haram and IS provides support for these theoretical expectations.

This paper makes several contributions to the literature. To the best of my knowledge, this is the first study which investigates the effect of local territorial advances in civil conflicts on conflict intensity and the timing and location of violence. Previous studies have looked either at countries, first-level administrative regions, and PRIO-Grid cells on the annual or monthly level to explain conflict intensity. By further disaggregating the unit of analysis to smaller grid cells, this study contributes to our understanding of local effects on overall conflict intensity and illuminates which areas tend to be more affected by increased numbers of battles and casualties. These smaller grid cells better reflect the reality of patchy territorial control dynamics during active conflicts. Second, it introduces the concept of momentum in civil conflicts. I argue that recent changes in territorial control are more important than current levels of territorial control to explain the number of battles and casualties. The aforementioned example of Afghanistan but also the Islamic State advancing in Iraq and Syria, Boko Haram in Nigeria, or the Revolutionary United Front in Sierra Leone, illustrate the importance of momentum. As a result, a government is expected to pool resources locally to halt this momentum and prevent future territorial gains and consolidations. This oftentimes includes foreign assistance or interventions such as the United Kingdom and the United Nations in Sierra Leone or the Multinational Joint Task Force in Nigeria consisting of Nigeria, Cameroon, Chad and Niger. Likewise with regards to one-sided violence against civilians, evidence from Sierra Leone suggests that civilian victimization initially increases after rebels overtake territory (Oswald, Sauter, Weber & Williams 2020). The paper proceeds as follows: First the concept and importance of territorial control is introduced. This is followed by a review of the literature on civil conflict intensity and severity and the locations of violence. Next I derive theoretical expectations about the timing and location of state-based and one-sided violence based on changes of territorial control. After explaining why Nigeria is a good case to test these expectations, I describe data and methods and present empirical results. I conclude by discussing the implications and limitations of this study and avenues for future research.

2.2 Territorial control in civil war

Territorial control is a central concept in civil wars. It can be regarded as a precondition for the onset and continuation of insurgency because it provides the foundation for an organized effort to challenge a state (Weidmann 2009). Territorial control is defined as the "extent to which actors are able to establish exclusive rule on a territory" (Kalyvas 2006, 111). One central issue linked with territorial control is control over natural resources and their extraction. Rebels gaining control over territory with natural resources to extract can utilize this to fund their armed struggle and ensure their longevity (Conrad, Greene, Walsh & Whitaker 2019). Indeed, rebels controlling lootable gemstones, oil and gas resources, or drug production areas such as opium or cocaine can survive substantially longer (Fearon 2004, Lujala, Gleditsch & Gilmore 2005, Lujala 2009, Buhaug, Gates & Lujala 2009, Lujala 2010). Moreover, control over resources also affects conflict severity. Gemstone mining and oil and gas production in conflict zones increase severity while drug cultivation has a decreasing effect (Lujala 2009). Thus one aim of rebels seizing territory is to establish a funding source in the form of natural resources to challenge the state.

Another factor highlighting the importance of territorial control is the ability to cooperate and collaborate with the civilian cooperation (Arjona 2016, Rubin 2020). Rebels without territory have more limited contact with the local population due to their clandestine nature whereas rebels holding territory are more exposed which creates more open opportunities for recruitment (De la Calle & Sánchez-Cuenca 2012). The recruitment process may well be coercive and violent though, and cooperation may be driven by fear of repression and displacement on the civilian side (Kalyvas & Kocher 2007). Thus recruitment may be forced, coerced or voluntary (Richards 2014). However, while domestically controlled territory makes rebels more likely to limit violence against civilians, territory controlled in the border regions of neighbouring countries removes this incentive to engage with the domestic population more peacefully (Stewart & Liou 2017). Still, evidence from Sierra Leone suggests that civilians initially suffer more immediately after rebels take over domestic territory. This initial increase in violence may also be a strategy to forcibly recruit labor to extract natural resources. Evidence from Sierra Leone suggests that civilian victimization was more prevalent near diamond mines (Oswald et al. 2020) and there is general evidence that rebels earning funding from

natural resources and higher levels of violence against civilians are linked to each other (Walsh, Conrad, Whitaker & Hudak 2018). Either way, territorial control provides the basis for recruitment on a larger scale compared to clandestinely operating rebel groups without territory.

In addition to control over resources for funding and enhanced recruitment opportunities, territory under consolidated control also serves as safe haven and command center from which to operate, derive strategies and organize future military plans. This is often coupled with rebel governance to ensure higher levels of civilian cooperation and lower levels of defection and information-sharing with the government (Arjona 2016). One way to achieve this is through provision of public goods to the entire local civilian population, going beyond known and likely supporters of a group's cause. This may also serve the purpose of gaining both domestic and international legitimacy (Stewart 2018). Another option is the establishment of formal or informal institutional arrangements, or capture of existing state institutions, to enforce rules and provide the opportunity for civilians to engage with rebel rulers (Mampilly 2012, Arjona 2016, Mampilly & Stewart 2021). Failure to establish such institutional arrangements complicates rebel efforts to hold territory, to fight the state, and its long-term survival (Mampilly 2012). This links back to creating and maintaining local networks and support structures required to launch and sustain an insurgency (Weidmann 2009). As a result, territorial control affects rebel aims and tactics as well as group lethality, recruitment strategy and bargaining power and position (De la Calle & Sánchez-Cuenca 2012). It is argued that rebel groups which control territory engage more in guerrilla attacks and direct encounters with enemy forces whereas rebels without territory rely more on bombings and generally indirect encounters (De la Calle & Sánchez-Cuenca 2015). Territorial control thus provides strategic benefits and affects how rebels engage with the local population and the state (Kalyvas 2006, Mampilly 2012).

Territorial control is therefore of central importance for civil war dynamics and intensity. It affects rebel extraction of natural resources, recruitment patterns, rebel interactions with the local population and the state, and ultimately the war efforts. As a result, rebels have an incentive to gain and maintain territorial control while governments have an incentive to prevent it. However, we lack estimates of territorial control which show variation across time and space with substantial geographical coverage. Existing data which cover a substantial number of countries

such as the Non-State Actors in Armed Conflict Dataset (Cunningham, Gleditsch & Salehyan 2013) and the Big Allied and Dangerous Data (Asal, Rethemeyer & Schoon 2019) provide binary indicators on the group level capturing whether a group controls some territory and thus do not capture subnational or substantive temporal variation. However, territorial control is dynamic and fluid across time and space. More recent advances introduce new measurement strategies using military intelligence reports (Rubin 2020) and rebel tactics (Anders 2020) which provide temporal and subnational variation. Rubin (2020) looks at the communist insurgency in the Philippines and uses intelligence assessments of influence over 12,450 villages within 567 municipalities and 56 provinces the Communist Party of the Philippines New People's Army had. These are provided on the annual level and are categorized as unaffected, threatened, less influenced or influenced. Anders (2020) uses Hidden Markov Models to estimate territorial control as unobserved latent variable derived from observed variation in rebel tactics. Higher levels of terrorism indicate tighter government control whereas higher levels of conventional warfare indicate higher levels of rebel control. Territorial control is estimated for Nigeria and Colombia on the grid cell-month level for several years and validated with different data sources. Levels of control are rebel control, disputed (closer to rebel control), disputed, disputed (closer to government control), and government control, following the classification introduced by Kalyvas (2006). Others have used government classifications of district control in the case of Nepal and several secondary sources such as newspaper reports, rebel activity and weapons caches in the case of Tajikistan to create binary indicators of district control (Ishiyama & Widmeier 2013).

2.3 Civil conflict intensity and locations of violence

National and local economic conditions have been shown to affect conflict severity. For example, downturns of a national economy increase the number of annual battle-related deaths (Chaudoin, Peskowitz & Stanton 2017). Economic inequality or grievances on the national level are also associated with more battle-related deaths (Lu & Thies 2011). However, local

economic conditions matter too. Richer locations in Liberia saw more violent events than poorer regions (Hegre, Østby & Raleigh 2009). Furthermore, lower levels of food production or poor rice and wheat harvests are associated with higher levels of killings in Indian states (Wischnath & Buhaug 2014). Lastly, the number of human rights violations in first-level administrative regions in Colombia is also positively associated with primary exports (if the region has already seen FARC violence), areas with low or negative economic development, and with previously peaceful areas which experience economic growth (Holmes, Gutiérrez De Piñeres & Curtin 2007). Thus relative deprivation and poverty at the country and regional level seem to be linked with higher numbers of battle-related deaths, or killings and human rights violations in general, on an annual level or over longer periods of time. Likewise relative deprivation and poverty on a more local level leads to more violent clashes in richer areas. This suggests that local economic conditions matter for conflict intensity and location. However, we cannot determine whether these local economic downturns or increases in conflict intensity may be the result of, or affected by, local battlefield dynamics and territorial advances.

A second group of factors are conflict and rebel group characteristics. Conventional civil wars have been found to be more severe but also shorter than irregular ones. Conventional here means that battles between two or more formidably equipped sides with access to and the ability to use heavy weaponry take place and there are relatively clear frontlines. In contrast, irregular civil wars see more guerrilla warfare by lightly armed rebels. Moreover, external government support reduces the number of battle-related deaths while external support for rebels lead to an increase (Bacells & Kalyvas 2014). A higher number of rebel groups participating in a civil conflict, coupled with the number of troops available to all sides, was shown to increase the annual number of battle-related deaths as well (Butler, Cunningham & Gates 2017). In addition, weaker rebel groups, foreign intervention and whether a conflict is internationalized are associated with higher levels of violence (Lujala 2009). Ethnic mobilization, whether a rebel group partially or fully recruits along ethnic lines, increases the likelihood of a conflict transforming to war by 92 percent compared to mobilization along other lines (Eck 2009). Likewise, ethnic homogeneity and foreign intervention led to higher levels of battle-related deaths (Lacina 2006). The importance of conventional warfare with relatively clear front lines is crucial. These frontlines can only exist when there are

also relatively clear spheres of influence and control, thus emphasizing the effect of territorial advances. Foreign interventions or support for either sides of a conflict can be regarded as a mediating or contributing factor, but they do not reduce or mitigate the importance of territorial control as a precondition for a successful insurgency. External support also increases combat ability and possibly effectiveness, but it does not substitute the need for territorial control. Indeed, foreign intervention is oftentimes only necessary once some level of territorial control by one or more challengers has been established. If the challenged state could prevent rebels from gaining territory, there would arguably be no need for outside assistance.

Disaggregated studies of civil war have looked at strategically important locations such as infrastructure and resources. For example, well-connected road network points which, once under control, can cut off access to other areas are more likely to be focal points for clashes between rebels and government forces (Hammond 2018). In addition, the location of lootable natural resources such as diamonds (Gilmore, Gleditsch, Lujala & Rød 2005), oil (Buhaug, Gates & Lujala 2009) or timber (Rustad, Rød, Larsen & Gleditsch 2008) have an impact on the levels of violence and conflict duration. Drug cultivation in conflict zones decreases the number of battle-related deaths while gemstone mining and oil and gas production in these zones lead to an increase (Lujala 2009). In addition, population density has been linked to the presence of material and human resources (Buhaug, Gates & Lujala 2009). It has also been shown that population centers emerge near resource locations or regions which are characterized by high productivity (Hegre, Østby & Raleigh 2009). There is also evidence that violent events tend to occur where population density is high but economic status is low (Buhaug, Gleditsch, Holtermann, Østby & Tollefsen 2011). Lastly, the location of ethnic group settlements affects conflict dynamics as well. The further away a settlement is from the capital city, or the closer to an international border, the more likely territorial conflict becomes (Wucherpfennig, Weidmann, Girardin, Cederman & Wimmer 2011). Thus the locations of strategically important infrastructure nodes, natural resources, and population settlements are determining factors for the location of violence. It is the active armed struggle to control and subsequently utilize these locations rather than their mere presence that increases the number of casualties.

Lastly, territorial characteristics have been argued to determine the likelihood of civil war onset and duration. Rough terrain and ruggedness

gives rebels a local advantage as it provides some protection from government forces due to relative isolation and inaccessibility (Hegre, Østby & Raleigh 2009, Tollefsen, Strand & Buhaug 2012). This is because it is more difficult for government forces to project military power and launch conventional military attacks in mountainous regions or forest areas, thus creating areas of relative safety for rebel groups (Fearon & Laitin 2003). Furthermore, state reach and capacity are higher closer to capital cities compared to regions far away from it or regions bordering neighboring countries. Especially in developing countries a state's ability to project force and effectively police its territory is much higher closer to capitals (Schutte 2015, Tollefsen & Buhaug 2015). As a result, most civil war fighting tends to take place further away from a capital city (Buhaug 2010). Thus rebels located further away from the capital enjoy some more freedom to organize and recruit, even more so if there is rough and inaccessible terrain. Rough terrain and distance to the centers of power are directly related with an absence of state control and the presence of rebel territorial control to at least some extent. It is likewise not the mere presence of mountains or forests or border regions that make them important factors for conflict severity, but the ability of rebels, or inability of governments, to control these territories and utilize them for their insurgency.

Previous studies have explained variation in the number of battle-related deaths or human rights violations over the course of a conflict (Lu & Thies 2011, Lacina 2006, Lujala 2009), in a given conflict year (Chaudoin, Peskowitz & Stanton 2017, Butler, Cunningham & Gates 2017, Eck 2009) or month (Balcells & Kalyvas 2014), or first-level administrative regions (Holmes, Gutiérrez De Piñeres & Curtin 2007, Wischnath & Buhaug 2014) per year and grid cells (Hegre, Østby & Raleigh 2009). While these studies identified economic, conflict or rebel characteristics as well as geographical factors which contribute to conflict intensity, they do not directly address the ultimate reason for the increases in intensity: the struggle over territorial control over e.g. natural resources or regions that are far away from the centers of power or difficult to access for governments. This paper seeks to fill this gap by looking at the effect of territorial advances on conflict intensity on the grid cell-month level.

2.4 Clashes, fatalities, and territorial control in civil conflicts

A civil or internal armed conflict is defined as an incompatibility about government or territory between a government and internal opposition groups with at least 25 battle-related deaths per year (Gleditsch, Wallensteen, Eriksson, Sollenberg & Strand 2002). Territorial control is of crucial importance in civil conflicts. It has been conceptualized in five categories by Kalyvas (2006): full government control, partial government control, contested, partial rebel control, and full rebel control. Territorial control enables rebel groups to recruit on a larger scale, extract resources to fund its armed struggle, and provides safe haven for rebels to regroup, organize, and plan future offensives (Weidmann 2009, Arjona 2016, Conrad et al. 2019). It also determines how rebels interact with civilians and opponent forces (Kalyvas 2006, Mampilly 2012). Gaining and maintaining control of territory is therefore a primary strategic goal of both rebels and governments. Indeed civil conflicts are oftentimes characterized by rebel groups seizing control of territory for shorter or longer periods of time. During the Sierra Leone civil war for example, the Revolutionary United Front at some point controlled over half of the country's territory and did even advance into the capital city of Freetown (HRW 1999).

The expectation in the literature is that there is no violence against non-combatants by actors in areas under their full control, i.e. no government violence against civilians in areas under full government control and no rebel violence against civilians in areas under full rebel control. However, violence against civilians by an actor is expected to be indiscriminate rather than selective in areas of partial control. Because an actor does not have the knowledge or resources to distinguish supporters or neutrals from defectors or collaborators with the enemy in areas under its partial control, they cannot target individuals but have to target larger groups instead to assert dominance and establish firm control. For example, areas under partial rebel control are expected to see more rebel violence against civilians than areas under full rebel control. Contested areas, on the other hand, are expected to see almost no selective violence but almost exclusively indiscriminate violence instead (Kalyvas 2006).

The number of clashes between government forces and rebels is by definition expected to be highest in areas under active contestation between the two opposing sides. Both sides are seeking to establish predominance

in an area and therefore fighting efforts by governments and rebels are expected to be higher compared to areas under partial or full control of either side. Fighting efforts in areas under full control are expected to be lowest while efforts in areas of partial control are expected to be between areas under full control and contested areas with regards to fighting intensity. These expectations follow the logic of violence against noncombatants in civil conflicts (Kalyvas 2006).

These expectations are derived from static status quo levels of territorial control and do not take the dynamic nature of territorial advances and momentum into account, however. Take for example recent rebel advances. I expect an immediate government reaction to rebel advances. Usually rebels hold contiguous areas of land rather than widely distributed small pockets of control. In other words, levels of territorial control are expected to cluster and these clusters are expected to be under full control in central areas and under partial rebel control or contestation further away from the areas under full control. Thus rebels advance away from areas under their full control. A government's aim will be to halt rebel advances before they establish full or partial control and engage with rebels directly after advancing. Likewise governments advancing into territory with some level of rebel control is expected to be met with immediate rebel efforts. A territorial advance, either by rebels or the government, refers to a change in territorial control by one level, e.g. from full rebel control to partial rebel control or from contested to partial government control.

Rebels advancing is a threatening scenario for governments. The territorial integrity of the country might be at risk, but at the very least the government's authority and monopoly for the legitimate use of force is challenged. As a result, if a rebel group advances into new territory a government cannot stay idle. If it does, rebels might interpret this as a sign of weakness and might subsequently attempt to increase their level of control and advance into additional areas. Therefore a government has to react and attempt to regain territorial control, or at the very least halt rebel advances, to remain the sole legitimate government of the state, both in domestic and international terms. It also has to react quickly to prevent rebels from establishing formal or informal institutions and gaining support or even trust from local populations (Mampilly 2012, Arjona 2016, Mampilly & Stewart 2021). It is therefore expected that governments engage with full force against advancing rebels. Momentum is of crucial importance in territorial battles and expansion and the government's aim is expected to

be to disrupt this momentum. Rebels, on the other hand, want to preserve this momentum and will be equally determined in their battles. As a result, the expectation is that we observe more clashes between government and rebel forces and more casualties after rebel territorial advances. It is expected that rebels likewise react to government advances. Rebels want to protect the areas under their full or partial control to remain in a position to organize and plan future offensives, and to maintain recruitment and financial sources. Rebels also want to prevent government forces advancing too close to these areas under full or partial control, thus the expectation is that they react equally quickly to government advances. As a result the number of clashes and casualties is expected to increase after government territorial advances as well. Overall the expectation is that the effect of territorial advances will be more severe for government than rebel casualties. This expectation is based on the fact that governments have more soldiers at their disposal and can blend in less in local environments than rebels can. They thus present more, and more visible, targets than rebels do. The hypotheses are as follows:

Hypothesis 1: *The number of clashes between rebels and government forces increases after territorial advances.*

Hypothesis 2: *The number of fatalities resulting from clashes between rebels and government forces increases after territorial advances.*

Hypothesis 3: *The number of government fatalities resulting from clashes between rebels and government forces increases more than the number of rebel fatalities after territorial advances.*

Turning to one-sided violence, expectations are similar to those outlined for state-based violence. There is evidence to suggest that civilians initially suffer more after rebels overtake territory (Oswald et al. 2020). Thus it appears that not only the current level of territorial control is important but also recent developments and advances. However, the reasons for increases in incidents and casualties differ between state-based and one-sided violence. For state-based violence, the creation and upkeep of momentum on the battlefield, and efforts by the opposing side to halt it, are the main reason for increases in battles and casualties. For one-sided violence, the establishment of some form of authority and control over the local population after territorial advances is the main reason for increases in violence against civilians and civilian casualties. This effect is expected

to be stronger for rebel than for government one-sided violence.² The hypothesis is as follows:

Hypothesis 4: *The number of incidents and victims of one-sided violence increases after territorial advances.*

A reasonable concern is that battle intensity, in the form of number of battles and number of fatalities, and territorial change are causally related with each other. While of course some changes in territorial control are linked to battles between government and rebel forces, this does not necessarily mean that all changes are a result of armed confrontations between rebels and the military. Indeed, in addition to the example of Afghanistan mentioned in the introduction, Daesh in Iraq and Syria in 2014 is an illustrative example. Many villages, towns and cities were effectively overrun by Daesh as a result of a combination of both momentum on its side and the fact that many local forces were both poorly trained and equipped, and not in a position to withstand an attack.³ Another factor is low morale among troops despite a huge advantage in numbers of up to 15-to-one.⁴ Furthermore, areas which see an effective change in territorial control may well be uninhabited or very thinly populated and the change in control is a result of the status of neighboring and surrounding areas. Lastly, both government and rebel forces may give up territorial control voluntarily as a form of tactical retreat in line with what Stephen Biddle calls the *modern system*, only to subsequently launch a counter-attack (Biddle 2010). In short, while battle intensity can and does have some effect on changes in territorial control, it is not the sole and necessarily strongest factor.

2.5 Country selection

I focus on the civil conflict in Nigeria between Boko Haram, and later IS to which it pledged allegiance, and the government which started in 2009. This civil conflict shows a number of desirable features for this paper's research question and design which makes it an ideal case to study. First, the vast majority of state-based and one-sided violence during the period

²Due to largely absent government one-sided violence against civilians in Nigeria in the data this hypothesis cannot be tested in this paper.

³<https://edition.cnn.com/2014/10/13/world/meast/isis-developments/index.html>, access 21 November 2022.

⁴<https://www.bbc.com/news/world-middle-east-27789770>, access 21 November 2022.

of study took place in areas of Northeast Nigeria for which we have territorial control estimates. Of the 2,098 events involving these three actors recorded between 2009 and 2017 in the UCDP Georeferenced Event Dataset, 2,062 were in the areas under consideration. Second, Boko Haram established full or partial control in a number of districts and challenged the government quite successfully for a period of time. Indeed, the Boko Haram insurgency in Nigeria started in July 2009 from Bauchi state and quickly spread to the neighbouring states of Borno, Kano and Yobe in the Northeast of the country. A joint military task force responded to a number of police killings by leaving more than 700 Boko Haram members dead and destroying its headquarters. The Nigerian government saw a threat to the state's territorial integrity and stability and felt the need to react to this threat. In 2013, the Nigerian government declared a state of emergency in the states of Yobe, Borno and Adamawa bordering Niger, Chad and Cameroon and deployed troops to deal with this lasting threat.⁵ Thus there is considerable variation in rebel and government advances over time and space.⁶

Third, Boko Haram engaged in widespread violence against civilians. It falls in the 0.98 quantile of overall civilian casualties by all conflict actors recorded in the UCDP One-sided Violence Dataset with over 10,000 killed between 1989 and 2020 (Pettersson, Davies, Deniz, Engström, Hawach, Höglbladh, Sollenberg & Öberg 2021, Eck & Hultman 2007). Fourth, Boko Haram is likewise frequently engaged in battles with the Nigerian government. It falls in the 0.88 quantile of overall battle-related deaths by all conflicts recorded between 1989 and 2020 in the UCDP Battle-related Deaths Dataset (Pettersson et al. 2021). Fifth, at least initially and prior to the insurgency, Boko Haram provided welfare handouts, food, shelter as well as job training and opportunities, community resources and a religious police akin to state-like institutions (Walker 2012). Taken together, this provides an ideal setting to test the effect of momentum derived from territorial advances on the incidence of state-based and one-sided violent events and the number of casualties since an extreme case selection, in this case on the dependent variables, serves exploratory purposes well and is designed as an open-ended entrance into a topic (Seawright & Gerring 2008, 302).

⁵<https://edition.cnn.com/2014/06/09/world/boko-haram-fast-facts/index.html> & <https://www.bbc.com/news/world-africa-13951696>, accessed 20.11.2019.

⁶See Table 2.1 in the following section with control estimates.

2.6 Data and methods

There are several dependent variables to operationalize civil conflict intensity and test the aforementioned hypotheses: the number of monthly clashes between government and rebel forces, the number of monthly acts of one-sided violence in general and by rebels specifically⁷, the number of monthly battle-related deaths, and the number of monthly government, rebel, and civilian casualties in a given 0.25 decimal degree minimum diameter hexagonal grid cell. This study uses the UCDP Georeferenced Event Data (Sundberg & Melander 2013, GED) to operationalize the dependent variables. This is a handcoded event dataset and each event is georeferenced. GED covers all countries between 1989 and 2020. It differentiates between state-based, non-state and one-sided violence. This paper focuses on two types of violence: state-based violence which is defined as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in one calendar year"⁸, and one-sided violence which is defined as "[t]he deliberate use of armed force by the government of a state or by a formally organized group against civilians which results in at least 25 deaths in a year"⁹. The variables are calculated by summarizing events and casualties per grid cell-month.

The main independent variable is territorial advances. The classification of territorial control follows Kalyvas (2006) and is divided into full and partial government control, contested, and partial and full rebel control. In numerical terms, this corresponds to 0 (rebel control), 0.25 (disputed, closer to rebels), 0.5 (disputed), 0.75 (disputed, closer to government), and 1 (government control). These estimates are provided for Northeast Nigeria from 2009 until 2017 for 943 unique 0.25 decimal degree minimum diameter hexagonal grid cells on the monthly level.¹⁰ Estimates were derived using Hidden Markov Models and variation in rebel tactics. Specifically, the estimates rest on the assumption that rebels mostly engage

⁷There were not enough acts of government one-sided violence recorded to warrant a separate dependent variable.

⁸https://www.pcr.uu.se/research/ucdp/definitions/#tocjump_8445379298458398_47, access 12.08.2021.

⁹https://www.pcr.uu.se/research/ucdp/definitions/#tocjump_8445379298458398_34, access 12.08.2021.

¹⁰Estimates were sourced directly from the replication material accompanying Anders (2020).

in conventional warfare in territory they have more control over whereas they rely mostly on terrorism when territory is under government control (Anders 2020). From these values, the variable of interest is calculated: a change by 0.25 or more from the previous ($t-1$) to the current (t) cell-month observation is coded as territorial advance. I then associate relevant GED events to the grid cells through their geolocation information.

The conceptual concern about the link between battle intensity and changes in territorial control discussed earlier is also relevant empirically. Terrorist attacks of rebels and battles of rebels with government forces are the input for Hidden Markov Models to estimate the unobserved latent feature, territorial control. For the period of time under investigation, 2009 through 2017, the vast majority of grid cell-month observations do not see any battle action. Tabulating territorial advance with the number of battles between government and rebel forces in the current month reveals that 9,673 observations saw territorial change without battles whereas only 733 observations saw both territorial change and battle action in the same month. Tabulating territorial advance with the number of battles in the previous month shows that 9,508 observations saw territorial change without battle action and only 719 saw both territorial change and battle action in the previous month. More than 90,000 observations saw neither territorial changes nor battle action. It thus appears that the estimates derived from the Hidden Markov Model reflect the conceptual discussion that territorial changes can, but do not necessarily have to, be a result of battles but a result of for example tactical retreat, effective surrender of troops without battle action, or thinly populated or uninhabited areas where we would not expect to observe any battle action.

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Full reb. control	0	0	0	168	85	155	193	22	100
Partial reb. control	0	0	0	262	173	262	351	61	152
Contested	36	31	212	296	431	426	489	406	371
Partial gov. control	36	45	217	432	503	571	596	433	411
Full gov. control	11244	11240	10887	10158	10124	9902	9687	10394	10282

TABLE 2.1: Number of cells with different territorial control levels for Nigeria (2009-2017).

Table 2.1 shows the number of cells over time under different levels of territorial control. One can observe that the number of areas under partial government control or contestation remained relatively low and stable in 2009 and 2010 but increased substantially in 2011. Since 2012 there have

been a number of areas under full rebel control, the lowest being 22 in 2016. 2014 and 2015 saw the lowest number of areas under full government control. As a result the Nigerian government and African Union joined forces to detain the Boko Haram threat through the Multinational Joint Task Force which saw 7,500 troops contributed by Chad, Nigeria, Cameroon, Niger and Benin. Indeed, 2016 saw the lowest number of areas under full or partial rebel control. In 2017, more areas were under full or partial rebel control or under contestation again, however.

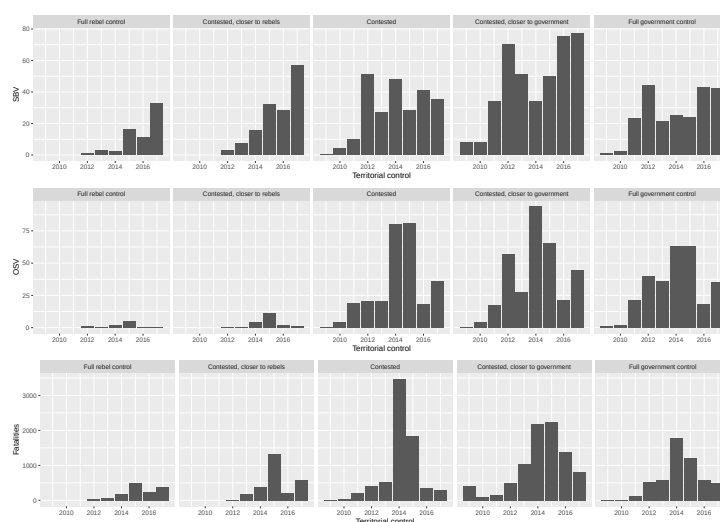


FIGURE 2.1: Histograms of state-based (SBV) and one-sided (OSV) violence and number of fatalities by level of territorial control for Nigeria (2009-2017).

Figure 2.1 illustrates variation in incidents of state-based and one-sided violence and the number of fatalities over time by levels of territorial control. There is relatively little activity in territory under full and partial rebel control, especially when looking at one-sided violence. The majority of state-based violence takes place in areas under partial government control (407), followed by contested areas (244) and areas under full government control (225). There were almost as many clashes in areas under full government control as in areas under full or partial rebel control together (209). The majority of one-sided violence takes place in areas under partial government control as well (329), followed by areas under full government control (279) and contested areas (278). There were only eight incidences of one-sided violence in rebel-held territory and only 18 in areas with partial rebel control.¹¹ Looking at overall fatalities, however, shows

¹¹Figures in the supplemental material show that the vast majority of acts of one-sided violence took place in areas under contestation, partial or full government control and was carried out by rebels.

large spikes in contested areas and areas under partial government control. Indeed, areas under partial government control saw more than 8,000 casualties followed by contested areas with 7,000 casualties. There were overall also more fatalities in areas under full government control (5,169) than in areas under full (1,283) and partial (2,608) rebel control.

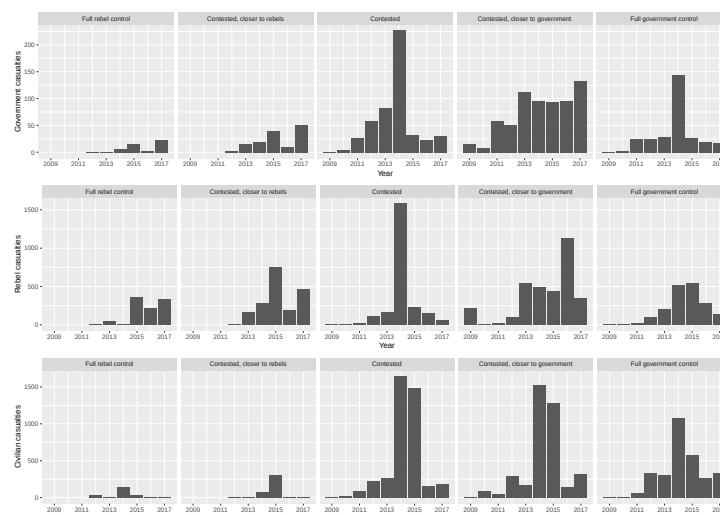


FIGURE 2.2: Histograms of numbers of government, rebel, and civilian fatalities by level of territorial control for Nigeria (2009-2017).

Figure 2.2 shows the number of government, rebel and civilian casualties over time by level of territorial control. The first thing to observe is that there were much fewer government casualties compared to rebel and civilian casualties. Over the entire period, 1,581 government forces were killed compared to 10,166 rebels and 11,352 civilians. Most government casualties happened in areas under partial government control followed by contested areas while the fewest took place in areas under full rebel control. Likewise, most rebel casualties took place in areas under partial government control followed by contested areas. Almost as many rebels died in areas under full government control (1,791) as in areas under partial rebel control (1,846). Lastly, most civilians died in areas under contestation (4,033), followed closely by areas under partial government control (3,809). Almost 3,000 died in areas under full government control while areas under full or partial rebel control saw almost 600 civilian casualties.

Figure 2.3 illustrates the number of territorial advances per year which ranges between zero and a maximum of twelve advances for one grid cell. While we can observe an overall clustering in the Northeastern border region with Chad and Cameroon, there is still some variation going

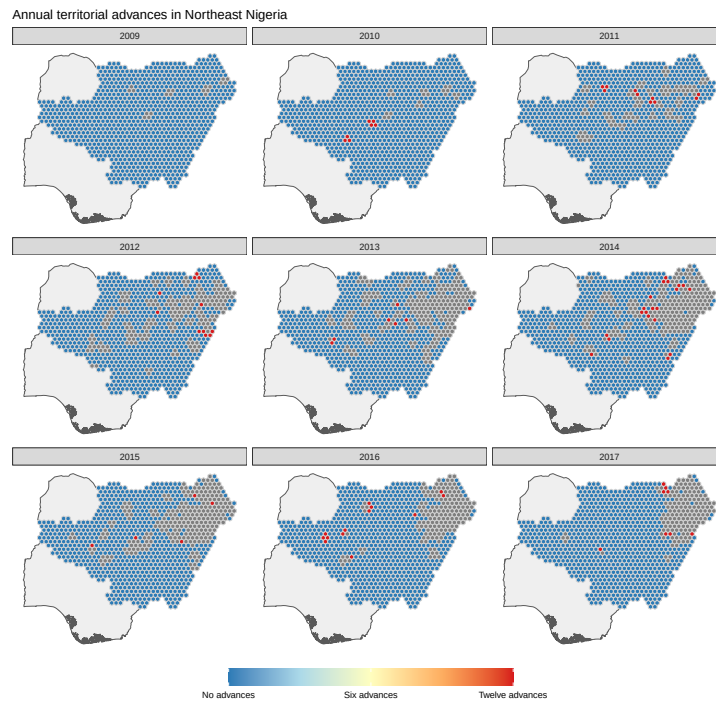


FIGURE 2.3: Map of territorial advances for each year.

more towards the geographical center of the country. One can observe the increase in grid cells affected over time, however, especially for the years 2012 through 2015. Another interesting observation is that many of the cells which saw higher numbers of territorial advances are located towards the center and not all of them are surrounded by other cells which saw many or any advances. This lends some support to the notion that there are immediate reactions to advances by the opposing side and that territorial control during civil conflicts is oftentimes patchy in reality.

I control for several other covariates which may affect the number of state-based and one-sided violence incidents and the number of casualties. State capacity is lower in areas further away from the capital (Schutte 2015, Tollefsen & Buhaug 2015). I therefore include distance to the national capital and distance to international borders. Data for national boundaries and capital locations come from CShapes (Weidmann, Kuse & Gleditsch 2010). Nighttime light emissions have been used to measure economic activity (Cederman, Weidmann & Bormann 2015, Kuhn & Weidmann 2015, Weidmann & Schutte 2017) but it has also been shown to be correlated with state capacity and quality of government such as tax revenue and public service provision (Harbers 2015). More recently, it has been argued that

nighttime light emissions can be regarded as a measure of government investment to preempt secession attempts and evidence suggests that governments invest more in secession-prone regions (Williams 2021). I thus include nighttime light emissions to account for local wealth and government reach. Nightlights data come from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) (Elvidge, Erwin, Baugh, Ziskin, Tuttle, Ghosh & Sutton 2009).

Natural resource locations are an important factor in civil conflicts. Petroleum in conflict zones has been shown to increase conflict duration (Buhaug, Gates & Lujala 2009, Lujala 2009). I include information on the location of petroleum resources as rebels are expected to seek control and secure a source of funding. Likewise the presence of gemstone mining in conflict zones has been shown to increase the number of annual battle-related deaths (Lujala 2009). Thus I also include information on gemstone locations to account for rebels aiming to seize control. Data on oil and gas field locations from Lujala, Ketil Rod & Thieme (2007) and data on gemstone deposits from Lujala (2009). There are no diamond mines or drug cultivation in Nigeria to take into account (Gilmore et al. 2005, Buhaug & Lujala 2005).

Terrain has been shown to be an important factor in civil wars as it hinders a state's ability to project force and provides rebels with natural shelter and room to organize and sustain an insurgency (Fearon & Laitin 2003, Tollefsen & Buhaug 2015). I therefore include information on mountain and forest locations to account for land cover features in favour of rebel groups. Data on forest land come from the Global Land Cover Map (Arino, Ramos Perez, Kalogirou, Bontemps, Defourny & Van Bogaert 2012) and data on mountainous areas from the United Nations Environment Programme's World Conservation Monitoring Centre (Centre 2002). Related to these geographic factors, population size is an important indicator as well as areas with higher population density provide the foundation to start and sustain an insurgency (Weidmann 2009) and locations with higher population density see more rebel violence once a conflict is ongoing (Raleigh & Hegre 2009, Daly 2012, Zhukov 2012). Thus I include population size on the grid-cell level. Information was taken from HYDE population data (Klein Goldewijk, Beusen & Janssen 2010, Klein Goldewijk, Beusen, Van Dreht & De Vos 2011, Klein Goldewijk, Beusen, Doelman & Stehfest 2017).

Exclusion of ethnic groups and their locations has also been shown to

be of importance for civil conflict onset (Cederman, Weidmann & Gleditsch 2011, Wucherpfennig et al. 2011). Information on the location of relevant ethnic groups will be included to account for the presence of political or economic inequalities. Data on excluded ethnic groups come from GeoEPR (Vogt, Bormann, Rüegger, Cederman, Hunziker & Girardin 2015, Wucherpfennig et al. 2011) and data on the number of local ethnic groups come from GREG (Weidmann, Rød & Cederman 2010). Relatedly, local economic conditions and wealth, and economic inequality more generally, are linked to civil conflict onset (Collier & Hoeffler 2004) and intensity (Hegre, Østby & Raleigh 2009, Lu & Thies 2011). I include information on gross cell product per grid cell to account for local wealth distributions. Data on gross cell product (purchasing power parity) come from the G-Econ database (Nordhaus, Azam, Corderi, Hood, Victor, Mohammed, Miltner & Weiss 2006).

I obtain all this data for PRIO GRID cells through the *xSub* R package (Zhukov, Davenport & Kostyuk 2019) and supplement them with data from the PRIO GRID yearly and static datasets (Tollefsen, Strand & Buhaug 2012) not covered by *xSub*. Nighttime lights, gross cell product and population size are provided annually and missing values within cells were linearly interpolated from past values. I then overlapped PRIO GRID cells with the smaller grid cells containing information about territorial control and conflict violence to obtain information on all the covariates for the hexagonal grid. If two or more PRIO GRID cells overlapped in one hexagonal grid I calculated the mean of the covariate values. This leads to 101,844 observations on the grid-cell month level from January 2009 through December 2017. Summary statistics for the independent variables are provided in Table 2.2.¹²

Civil conflicts have been shown to cluster over time and space, and that there is a neighborhood effect in armed conflicts (Buhaug & Gleditsch 2008). Indeed, a number of studies has looked at the phenomenon of civil conflict diffusion and contagion (Gleditsch 2007, Braithwaite 2010, Maves & Braithwaite 2013, Metternich, Minhas & Ward 2017, to name a few). Civil conflict violence and territorial control are likely spatially and temporally interdependent as well. Indeed, Lagrange Multiplier diagnostics confirm spatial dependence in the data. This makes intuitive sense since

¹²Values for distance to capital, distance to international border, and population are logged. Summary statistics for unlogged values can be found in the supplemental material.

TABLE 2.2: Summary statistics for independent variables (log)

Statistic	Mean	St. Dev.	Min	Max
Territorial advance $_{t-1 \rightarrow t}$	0.100	0.301	0	1
Distance to capital	5.802	0.613	3.438	7.095
Distance to international border	4.625	1.016	0.077	5.969
Nightlights	0.064	0.009	0.047	0.170
Petroleum	0.009	0.088	0.000	1.000
Mountains	0.117	0.206	0.000	0.993
Forest	0.035	0.113	0.000	0.763
Gemstone	0.112	0.250	0.000	1.000
Excluded ethnic groups	0.103	0.281	0.000	1.000
Population	12.364	0.799	9.189	14.894

levels of state-based or one-sided violence in one region are spatially dependent of surrounding regions and their levels of violence. Not taking spatial dependence into account leads to inefficiency and quite possibly bias (Franzese & Hays 2007, Franzese & Hays 2008). The issue of interest for this paper is outcome interdependence rather than correlated unobservables or exogenous spillovers. One unit's outcome influencing other units' outcomes is one of the paper's key arguments. As a result, a spatial-lag (of y) model is the appropriate choice to model this interdependence or contagion (Ward & Gleditsch 2018). In addition, while spatial error models imply that only unobserved or unmodeled factors lead to clustering or contagion and spatially-lagged x models imply that only observed and modeled factors lead to clustering, spatial-lag of y models impose both (Cook, Hays & Franzese 2021). It is likewise temporally dependent on previous observations of the same unit. To account for this, I add lagged dependent variables. The spatial-lag (of y) model is specified as follows with β_0 as the intercept, ρ as the spatial-lag coefficient, W as the spatial weights vector, ϕy_{t-1} as the lagged dependent variable, and the error term ϵ_t :

$$\begin{aligned}
y_t = & \rho W_t y_t + \phi y_{t-1} + \beta_0 + \beta_1(\text{Territorial advance}_{t-1 \rightarrow t}) + \\
& \beta_2(\text{National capital distance}) + \beta_3(\text{Border distance}) + \\
& \beta_4(\text{Nightlights}) + \beta_5(\text{Petroleum}) + \\
& \beta_6(\text{Mountains}) + \beta_7(\text{Forest}) + \\
& \beta_8(\text{Gemstone}) + \beta_9(\text{Excluded}) + \\
& \beta_{10}(\text{Population}) + \epsilon_t
\end{aligned}$$

Since spatial weights matrices quickly increase in size as a result of the number of observations, in my case 943 unique grid cells with monthly observations for nine full years, I had to split the analyses in two parts. First I present results for collapsing values to the grid cell-year level where my main variable of interest is the number of territorial advances in a given grid cell throughout the year. Collapsing on the grid cell-year level leaves me with 8,487 observations to analyze. This is followed by analyses for the nine individual years on the grid cell-month level where I can take territorial advances into account on the level in which they were originally measured. For every year I have 11,316 observations to analyze.¹³ In the paper I present regression results for the annual models and for one model on the grid cell-month level whereas the remaining regression and substantive effects tables can be found in the supplemental material. I use spatiotemporal autoregressive models to address interdependence and simultaneity concerns.

All analyses were done using the R statistical computing environment (R Core Team 2021). To estimate the spatial regression models I use the *spatialreg* R package (Bivand & Piras 2015, Bivand, Hauke & Kossowski 2013, Bivand, Pebesma, Gómez-Rubio & Pebesma 2013, Bivand, Millo & Piras 2021). Other R packages used to manipulate and analyze data are the *tidyverse* (Wickham, Averick, Bryan, Chang, McGowan, François, Grolemund, Hayes, Henry, Hester et al. 2019), *sf* (Pebesma 2018), *raster* (Hijmans, Van Etten, Cheng, Mattiuzzi, Sumner, Greenberg, Lamigueiro, Bevan, Racine, Shortridge et al. 2015) and *spdep* (Bivand 2006, Bivand, Altman, Anselin, Assunção, Berke, Bernat & Blanchet 2015), and *stargazer* and *texreg* to create tables (Hlavac 2022, Leifeld 2013).

¹³For analyses on the grid cell-year level it is 943 grid cells x 9 years = 8,487 observations. For analyses on the grid cell-month level 943 grid cells x 12 months = 11,316 observations.

2.7 Results

Table 2.3 presents spatial regression models for all dependent variables for the years 2009 through 2017. Two things to notice immediately is that the spatial lag parameter ρ is statistically significant across all dependent variables except government fatalities (model 5) and that the number of territorial advances is statistically significant for just two dependent variables (government and rebel fatalities, models 5 and 6). The spatial lag parameter ρ is positive when it reaches statistical significance and negative when it does not. Likewise, the number of territorial advances is positive when it reaches statistical significance whereas signs are less consistent when this significance is absent. The temporal lags for all dependent variables are statistically significant too and have the largest coefficient sizes by far. Across all dependent variables the effect is positive, indicating that with higher numbers of fatalities and battles in the previous month, higher numbers of fatalities and battles become more likely in the current month. However, coefficients from spatial regression models cannot be interpreted as easily or directly as from ordinary least squares models. More specifically, since the spatially lagged dependent variable approach is an autoregressive specification, a coefficient represents the short-run impact rather than the net effect of an independent variable (Ward & Gleditsch 2018). I will explain and provide spatial impacts below for more substantive interpretations of variable effects. What is further noteworthy is that only one other covariate reaches statistical significance at desirable levels and only for one dependent variable. Distance to the national capital has a positive effect on the number of overall fatalities in civil conflicts.

Table 2.4 provides direct, indirect, and total effects for each independent variable from model 1 for total fatalities. Estimates and corresponding p-values are provided for each variable and type of effect. Direct effects are the local effects in the spatial unit of analysis under investigation. Indirect effects are the spillover effects, the impact changes in a given spatial unit have on other spatial units. The total effects are then the sum of the direct and indirect effects and give an estimate of the overall impact of a variable change. The estimates give the average impact of a one-unit change in an independent variable on the outcome of interest across all spatial units under investigation. They thus represent the global average impact across all spatial units.¹⁴ For overall fatalities, the direct effect of

¹⁴Further details on the computation of spatial lag impacts can be found in LeSage & Pace (2009), pp. 33-42 and 114-115, and for example in LeSage & Fischer (2008).

TABLE 2.3: Spatial lag regression results

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.959*** (0.004)						
OSV (lag)		0.973*** (0.003)					
SBV (lag)			0.984*** (0.003)				
OSV rebels (lag)				0.975*** (0.003)			
Gov fatalities (lag)					0.958*** (0.003)		
Reb fatalities (lag)						0.960*** (0.003)	
Civ casualties (lag)							0.948*** (0.004)
Territorial advances $s_{t-1} \rightarrow t$	0.001 (0.001)	-0.0001 (0.0002)	0.0001 (0.0002)	-0.0003 (0.0002)	0.001*** (0.0004)	0.002*** (0.001)	0.0002 (0.001)
National capital distance	0.012* (0.006)	0.002 (0.002)	0.002 (0.001)	0.002 (0.001)	0.004 (0.003)	0.003 (0.004)	0.006 (0.005)
Border distance	0.003 (0.003)	0.001 (0.001)	0.0003 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.00001 (0.002)	0.001 (0.003)
Nightlights	0.342 (0.259)	0.050 (0.069)	0.083 (0.067)	0.029 (0.067)	0.118 (0.115)	0.047 (0.184)	0.348 (0.220)
Petroleum	-0.002 (0.024)	-0.001 (0.006)	0.0003 (0.006)	-0.001 (0.006)	0.0001 (0.011)	0.001 (0.017)	-0.001 (0.020)
Mountains	0.003 (0.013)	0.004 (0.004)	0.001 (0.003)	0.003 (0.003)	-0.0003 (0.006)	0.005 (0.009)	0.010 (0.011)
Forest	-0.010 (0.024)	-0.005 (0.007)	-0.004 (0.006)	-0.005 (0.006)	-0.003 (0.011)	-0.010 (0.017)	-0.016 (0.021)
Gemstone	-0.003 (0.009)	-0.002 (0.002)	-0.0002 (0.002)	-0.001 (0.002)	-0.002 (0.004)	-0.003 (0.006)	-0.002 (0.007)
Excluded	0.001 (0.008)	0.00002 (0.002)	0.0005 (0.002)	-0.00003 (0.002)	0.001 (0.003)	0.001 (0.006)	0.001 (0.007)
Population	0.0001 (0.003)	0.001 (0.001)	-0.0004 (0.001)	0.0004 (0.001)	-0.001 (0.001)	-0.0001 (0.002)	0.0003 (0.002)
ρ	0.03*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)	-0.00 (0.00)	0.02*** (0.00)	0.03*** (0.00)
Constant	-0.099 (0.061)	-0.025 (0.016)	-0.015 (0.016)	-0.021 (0.016)	-0.026 (0.027)	-0.020 (0.043)	-0.064 (0.052)
N	8487	8487	8487	8487	8487	8487	8487
Log Likelihood	2046.136	13242.510	13502.590	13534.910	8931.829	4974.948	3428.395
Wald Test (df = 1)	32.513***	29.039***	19.407***	34.469***	0.063	15.511***	48.730***
LR Test (df = 1)	33.012***	29.290***	19.789***	34.742***	0.065	15.733***	49.392***
AIC	-4064.273	-26457.030	-26977.180	-27041.820	-17835.660	-9921.895	-6828.791

*** p < .001; ** p < .01; * p < .05

the temporal lag of fatalities is 0.96 and the indirect effect is 0.02, amounting to a total effect of 0.98. Considering that the standard deviation of log fatalities is 0.747 with a mean of 0.159, the impact of lagged log fatalities is quite substantial. However, the impact is almost exclusively constrained to local effects. In contrast, the direct effect of distance to the national capital is 0.01 and the indirect effect is 0.00 amounting to a total effect of 0.01. Here the total effect is exclusively driven by the direct effect. Estimates for the spatial impacts of temporal lags of one-sided violence (0.97), state-based violence (0.98), rebel one-sided violence (0.98), government fatalities (0.96), rebel fatalities (0.96), and civilian fatalities (0.95) are comparable in terms of size.¹⁵ However, the substantive impact is bigger since the means and standard deviations for one-sided violence (0.039 and 0.236), state-based violence (0.048 and 0.258), rebel one-sided violence (0.037 and 0.233), government fatalities (0.039 and 0.289), rebel fatalities (0.084 and 0.527), and civilian casualties (0.094 and 0.560) are much smaller.¹⁶

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.96	0.00	0.02	0.00	0.98	0.00
Territorial advances _{$t-1 \rightarrow t$}	0.00	0.52	0.00	0.55	0.00	0.52
National capital distance	0.01	0.04	0.00	0.05	0.01	0.04
Border distance	0.00	0.41	0.00	0.42	0.00	0.41
Nightlights	0.34	0.17	0.01	0.18	0.35	0.17
Petroleum	-0.00	0.91	-0.00	0.91	-0.00	0.91
Mountains	0.00	0.82	0.00	0.83	0.00	0.82
Forest	-0.01	0.69	-0.00	0.70	-0.01	0.69
Gemstone	-0.00	0.73	-0.00	0.74	-0.00	0.73
Excluded	0.00	0.87	0.00	0.87	0.00	0.87
Population	0.00	0.98	0.00	0.98	0.00	0.98

TABLE 2.4: Direct and indirect effects on the annual level
(fatalities)

However, this approach on the annual level using the number of territorial advances across twelve months does not quite capture the initial idea of territorial advances as set out earlier. In addition to this approach on the annual level which was necessary to analyze all observations between 2009 and 2017, I present results for analyses on the grid cell-month level below. Table 2.5 shows spatial regression results for the year 2010

¹⁵Tables can be found in the supplemental material.

¹⁶Summary statistics for all dependent variables can be found in the supplemental material.

on the grid cell-month level.¹⁷ The first thing to notice is that, unlike the number of territorial advances when analyzing grid cell-years, territorial advances on the month level are statistically significant across all dependent variables. Across all models, there is a positive association between territorial advances and the dependent variable. In fact, both statistical significance and coefficient direction hold for all individual years analyzed except for 2009. In 2009, territorial advance did not reach conventional levels of statistical significance for one-sided violence and the model for rebel one-sided violence did not produce results since there was only one one-sided violence event and no rebel one-sided violence events at all. Moreover, nighttime light emissions is statistically significant in all models except for rebel fatalities and positively associated with the outcome of interest. Likewise, the temporal lags for all dependent variables are statistically significant except for rebel fatalities and positively associated with the dependent variables.¹⁸ The spatial lag parameter ρ is statistically significant in only four out of seven models, however. It does not reach conventional levels of significance for government, rebel, and civilian casualties while it does for overall fatalities. In order to get more meaningful quantities of interest, I present spatial impacts below.

Table 2.6 presents direct, indirect and total effects for overall fatalities corresponding to model 1 in Table 2.5.¹⁹ The direct effect of the temporal lag of fatalities is 0.41 while the indirect effect is -0.01, amounting to a total effect of 0.4. The total effect of nighttime light emissions is comparable with an estimate of 0.39, consisting of a direct effect of 0.4 and an indirect effect of -0.01. Turning to the variable of interest, territorial advance, the direct effect is 0.11 and the indirect effect is smaller than -0.01, accumulating in a total effect of 0.1. In this subset of observations, the standard deviation of log fatalities is 0.056 with a mean of 0.001 and a maximum of 4.394. Thus the impact of a territorial advance translates into a two standard deviation increase in log fatalities. In comparison, for the year 2014 the direct effect of a territorial advance is 0.21, the indirect effect is 0.02 amounting to a total effect of 0.23. For this particular subset of observations, the mean of log fatalities is 0.052 with a standard deviation of 0.417. Thus the impact of a territorial advance in 2014 translates into an increase

¹⁷Regression tables for the remaining years can be found in the supplemental material.

¹⁸This is likely because only one grid cell-month observation saw rebel casualties in the year 2010.

¹⁹Tables with spatial impacts for all other models and years can be found in the supplemental material.

TABLE 2.5: Spatial lag regression results (2010)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.413*** (0.017)						
OSV (lag)		0.912*** (0.009)					
SBV (lag)			0.625*** (0.010)				
OSV rebels (lag)				0.912*** (0.009)			
Gov fatalities (lag)					0.185*** (0.011)		
Reb fatalities (lag)						-0.011 (0.009)	
Civ casualties (lag)							0.412*** (0.027)
Territorial advance _{<i>t</i>-1} → <i>t</i>	0.107*** (0.006)	0.027*** (0.002)	0.034*** (0.002)	0.027*** (0.002)	0.038*** (0.003)	0.008*** (0.001)	0.088*** (0.005)
National capital distance	0.003 (0.001)	0.001 (0.0004)	0.001* (0.001)	0.001 (0.0004)	0.002* (0.001)	0.00001 (0.0002)	0.001 (0.001)
Border distance	0.001 (0.001)	0.0002 (0.0002)	0.0003 (0.0003)	0.0002 (0.0002)	0.0004 (0.0004)	0.0001 (0.0001)	0.0005 (0.001)
Nightlights	0.403*** (0.099)	0.088** (0.028)	0.113** (0.041)	0.088** (0.028)	0.142*** (0.047)	-0.009 (0.012)	0.311*** (0.089)
Petroleum	-0.0005 (0.006)	-0.0002 (0.002)	-0.0002 (0.002)	-0.0002 (0.002)	0.00004 (0.003)	0.00002 (0.001)	-0.001 (0.005)
Mountains	0.006 (0.003)	0.001 (0.001)	-0.0002 (0.001)	0.001 (0.001)	0.001 (0.002)	-0.0002 (0.0004)	0.005 (0.003)
Forest	-0.005 (0.006)	-0.0003 (0.002)	0.001 (0.002)	-0.0003 (0.002)	-0.0002 (0.003)	0.0003 (0.001)	-0.004 (0.005)
Gemstone	-0.001 (0.002)	-0.0004 (0.001)	0.0003 (0.001)	-0.0004 (0.001)	0.002 (0.001)	-0.0001 (0.0003)	-0.002 (0.002)
Excluded	0.001 (0.002)	0.0003 (0.001)	0.001 (0.001)	0.0003 (0.001)	0.0005 (0.001)	0.00003 (0.0002)	0.001 (0.002)
Population	0.001 (0.001)	0.0003 (0.0002)	0.0003 (0.001)	0.0003 (0.0002)	0.0003 (0.0004)	-0.0001 (0.0001)	0.001 (0.002)
ρ	-0.03* (0.01)	-0.02** (0.01)	-0.02* (0.01)	-0.02** (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.02 (0.01)
Constant	-0.059*** (0.016)	-0.014** (0.004)	-0.022*** (0.006)	-0.014** (0.004)	-0.025*** (0.007)	0.001 (0.002)	-0.042** (0.014)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	17071.940	31227.530	27034.430	31227.530	25632.280	40967.090	18370.890
Wald Test (df = 1)	5.872*	6.899**	3.875*	6.899**	2.210	0.199	3.042
LR Test (df = 1)	6.954**	7.796**	4.422*	7.796**	2.453	0.172	3.735
AIC	-34115.890	-62427.060	-54040.860	-62427.060	-51236.560	-81906.190	-36713.780

***p < .001; **p < .01; *p < .05

in log fatalities of about half a standard deviation. A second comparison to the year 2016 further reveals the impact of a territorial advance. The direct effect here is 0.19, compared to a direct effect of the temporal lag of fatalities of 0.22, and the indirect effect is 0.02, amounting to a total effect of 0.21. In 2016, the mean of log fatalities is 0.033 with a standard deviation of 0.294. Thus here the substantial impact of a territorial advance has a magnitude of about two thirds of a standard deviation in log fatalities. These findings provide evidence in support for hypothesis 2 that the number of fatalities increases after territorial advances.

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.41	0.00	-0.01	0.01	0.40	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.11	0.00	-0.00	0.01	0.10	0.00
National capital distance	0.00	0.06	-0.00	0.15	0.00	0.06
Border distance	0.00	0.28	-0.00	0.34	0.00	0.28
Nightlights	0.40	0.00	-0.01	0.03	0.39	0.00
Petroleum	-0.00	0.93	0.00	0.94	-0.00	0.93
Mountains	0.01	0.06	-0.00	0.15	0.01	0.06
Forest	-0.00	0.39	0.00	0.45	-0.00	0.39
Gemstone	-0.00	0.74	0.00	0.76	-0.00	0.74
Excluded	0.00	0.62	-0.00	0.65	0.00	0.62
Population	0.00	0.27	-0.00	0.34	0.00	0.27

TABLE 2.6: Direct and indirect effects on the month level
2010 (fatalities)

Looking specifically at one-sided and state-based violence, substantive effects of territorial advances are similar albeit on a smaller magnitude.²⁰ For 2010, the direct and total effects are 0.03 for both dependent variables while indirect effects are zero. In this year, the mean of log one-sided violence counts is 0.001 with a standard deviation of 0.022 and the mean for log state-based violence counts is 0.001 with a standard deviation of 0.027. Thus the substantive effect of a territorial advance corresponds to an increase in log state-based and one-sided violence events of more than one standard deviation. In comparison, in the year 2016 the direct and total effect of a territorial advance is 0.02 for log one-sided violence count and 0.06 for log state-based violence count. In 2016, the mean of log one-sided violence count is 0.003 with a standard deviation of 0.053 and the mean of log state-based violence count is 0.011 with a standard deviation of 0.096. The substantive impact is then in the magnitude of between one third and two

²⁰Tables can be found in the supplemental material.

thirds of a standard deviation of log one-sided and state-based violence counts, respectively. In contrast, for the year 2014 the mean of log one-sided violence count is 0.012 with a standard deviation of 0.108 and the mean of log state-based violence count is 0.007 with a standard deviation of 0.076. The direct effect of a territorial advance on one-sided violence is 0.05 and on state-based violence it is 0.03. Thus a territorial advance has a substantive effect of an increase of about half a standard deviation in log one-sided violence count and log state-based violence count, respectively. We find thus evidence in support of hypotheses 1 and 4 that territorial advances increase the number of clashes and of one-sided violence incidents.

Turning specifically to rebel one-sided violence, the direct and total effect of a territorial advance is 0.03 for the year 2010, 0.05 for the year 2014, and 0.02 for the year 2016. The means and standard deviations of log rebel one-sided violence count for this year are 0.001 and 0.022, 0.012 and 0.107, and 0.003 and 0.053, respectively. Thus the substantive effect of a territorial advance is an increase of about 1.5 standard deviations of log rebel one-sided violence events in 2010, about half a standard deviation in 2014, and just below half a standard deviation in 2016. Thus there is also evidence in support of the expectation that rebel one-sided violence increases after territorial advances which confirms findings for Sierra Leone in (Oswald et al. 2020).²¹

Lastly, we turn to the substantive effect of territorial advances on government, rebel and civilian casualties. Looking at government fatalities, the direct effect of a territorial advance was an increase of more than 1.5 standard deviations in 2010, about one third of a standard deviation in 2014, and about half a standard deviation in 2016. With regards to rebel fatalities, the direct effect of a territorial advance was an increase of almost 1.5 standard deviations in 2010, about one third of a standard deviation in 2014, and more than half a standard deviation in 2016. We thus find no evidence for hypothesis 3 that the impact of territorial advances is bigger for government fatalities compared to rebel fatalities. Finally, the direct effect of a territorial advance on civilian fatalities was an increase of the magnitude of almost two standard deviations in 2010 and of about half a standard in both 2014 and 2016. Thus civilians also suffer considerably as a result of territorial advances and clashes between the government and rebels.

²¹Due to the nature of the conflict, we cannot test the effect on government one-sided violence, however, because it was largely absent from the Nigerian government in the data.

2.8 Discussion and conclusion

This paper empirically tested the impact of territorial advances on state-based and one-sided violence. Building on recent advances in measuring territorial control in civil conflicts (Anders 2020), I use estimates of territorial control for 943 unique 0.25 decimal degree minimum diameter hexagonal grid cells on the monthly level in Northeast Nigeria to derive the independent variable of interest: territorial advances by either the government or rebels. Territorial control is a categorical variable indicating full or partial government control, contested control, or partial or full rebel control in line with the classification introduced by Kalyvas (2006). A territorial advance is then calculated as a change in territorial control by at least one level compared to the previous month and captures the concept of momentum in civil conflicts. Using spatial lag regression models, I find evidence for the hypotheses that territorial advances increase the number of state-based and one-sided violence incidents, and the number of government, rebel, and civilian casualties. While regression models on the grid cell-year level provide some empirical support, models for individual years on the grid cell-month level provide more robust support. However, there are important limitations to this study and avenues for future research.

First, this study only looked at one country which can be considered an extreme case: Nigeria with Boko Haram and IS as rebel groups. As outlined earlier, Nigeria is in the 0.98 quantile of overall civilian casualties by all conflict actors recorded in the UCDP One-sided Violence Dataset and in the 0.88 quantile of overall battle-related deaths in all conflicts recorded in the UCDP Battle-related Deaths Dataset. While this is a good case to test the argument, it is probably not a typical civil conflict case and substantive effects may vary for other civil conflicts. In addition, the methodology used in Anders (2020) to estimate levels of territorial control takes rebel group tactics into consideration, specifically the use of conventional warfare tactics and terrorism. Terrorism may not be as widespread in other civil conflicts as it was in Nigeria under Boko Haram and IS, and thus the same estimation strategy may not be as fruitful for other countries suffering from civil conflicts which limits the number of countries fit for testing the proposed argument.

Second, the approach to analyze individual years separately to have

the grid cell-month as unit of analysis was out of necessity and not by design. Spatial weights matrices quickly expand in size with an increasing number of spatial and temporal units. While there have been consistent results across years with regards to territorial advances, it is only a second-best solution and it raised additional questions regarding the importance of other covariates. For example, nighttime light emissions were statistically significant for almost all models in 2009 and 2010, four models in 2011, two models in 2012, but not at all in any other years. Likewise, national capital distance was significant for two models in 2009 and 2010, almost all models in 2011 and 2012, all models in 2013, none in 2014, six models in 2015, none in 2016 and two models in 2017. Similarly, population size was significant for two models in 2009, one model in 2011, five models in 2012, four models in 2013, four models in 2014, two models in 2015, three models in 2016, and six models in 2017. In addition, other covariates were only significant for specific years: excluded ethnic groups in one model in 2011, mountains in six models in 2014, forest cover in two models in 2014, gemstone in one model in 2009, and border distance in four models in 2016. For the analyses on the grid cell-year level, only national capital distance was significant for one model. Thus while we can say with some certainty that territorial advance have some effect on violent events and fatalities, it is less clear what specifically the effect of other covariates is.

Third, the spatial resolution may be considered an issue. The territorial control estimates are based on event data from UCDP GED and the Global Terrorism Database (GTD) which have geographical precision of at least second-level administrative areas. It has been shown that GED can attribute about 41 % of events to the second-level administrative region while for GTD the share is 20 % (Cook & Weidmann 2022). Likewise, the analyses in this paper only considered events that could be attributed to at least the second-level administrative region. The results are thus based on a nonrandom subset of relevant events. Issues such as reporting bias and accuracy limitations and their impact on event data which are mostly based on news reports are well documented (Drakos & Gofas 2006, Weidmann 2015, Weidmann 2016). This paper, like other studies based on event data, cannot rule out that the above mentioned issues have some effect on the results obtained.

The implications of the empirical results in this paper and the limitations outlined above open up some avenues for future research. Researchers may attempt to use the estimation strategy for territorial control outlined in Anders (2020) for one or more additional countries and seek to replicate the analyses performed in this paper to evaluate the impact of territorial advances in other civil conflict settings to test the generalizability. As outlined above, Nigeria can and should be considered an extreme case which is suitable for exploring the suspected relationship between variables (Seawright & Gerring 2008) but may not necessarily generalize to other civil conflict cases or obtain similar results. Thus confirmatory analyses in other settings are needed. Researchers may also look into for example the effect of territorial advances on protest behavior. Similar to studies looking at the effect of battles in civil wars on protest behavior (Vüllers & Krtsch 2020), it would be interesting to analyze if and under what conditions territorial advances lead to local civil resistance and protest. Lastly, advances in spatial regression models, and spatial weights matrix specifications in particular, may open up new possibilities to analyze spatial effects on a wider scale. This paper is a first step to analyze the effect of territorial advances and momentum in civil conflicts but there are various ways to improve our understanding further.

Chapter 3

Staying local: The effect of battlefield dynamics on the timing and location of terrorism in civil conflicts

Abstract

Knowing when and where terrorism occurs during civil conflicts is of both scholarly and policy importance. Previous studies have explained variation in the number of terrorist attacks by rebel group, region, and country per year and over longer periods of time and identified group, country and regime characteristics that make terrorism more likely. More specifically, rebel losses were identified to affect the timing of terrorism whereas certain administrative regions are generally more at risk than others. However, while valuable these findings do not help us explain the joint timing and location of terrorist attacks. I argue that the intensity of clashes between a government and rebels - increases in either the number of attacks or casualties - explain the timing and location of terrorism in civil conflicts. Terrorism is expected to take place in close geographical proximity to battle locations to demonstrate rebel resolve to both the government and the local population. This paper uses generalized linear mixed effects models to estimate the effect of said clashes on the timing and location of terrorism. Evidence from civil conflicts in Africa suggests that the hypothesized relationship is indeed present, and that for example distance to province capitals seems to be more important than distance to international borders or national capitals. These findings enhance our understanding of when and where terrorism occurs during civil conflicts and contribute to the literatures on disaggregated studies of civil conflicts and reactive violence in

armed conflicts more generally by showing mechanisms at the grid cell-month-level.

3.1 Introduction

Previous research provides evidence for a retaliatory, or reactive, nature of conflict events (Hegre, Østby & Raleigh 2009, Schutte & Weidmann 2011, Holtermann 2016, Beardsley, Gleditsch & Lo 2015). Studies looking at for example Iraq or other individual countries find a tit-for-tat behavior between opposing parties (Linke, Witmer & O'Loughlin 2012, Eastin & Gade 2018, Braithwaite & Johnson 2012, Papadogeorgou, Imai, Lyall & Li 2020, Jaeger & Paserman 2008, Haushofer, Biletzki & Kanwisher 2010). More recently, a number of studies have looked at the connection between terrorism and civil conflicts, and rebel use of terrorism in civil conflicts more specifically (Polo & González 2020, Asal et al. 2019, Ash 2018, Polo & Gleditsch 2016, Bakker, Hill Jr & Moore 2016, Coggins 2015, Stanton 2013, Findley & Young 2012). These studies investigated for example the timing of terrorism (Polo & González 2020) and which administrative regions tend to experience more terrorist attacks (Ash 2018). This paper aims to unify these approaches to determine both the timing and location of terrorism in civil conflicts. It is valuable to know which administrative regions tend to be preferred targets, but without any knowledge about the timing we cannot determine at which moments in time they are more at risk. Moreover, first-level administrative regions can differ vastly in size and may well be bigger than some European countries. For example, Borno state in Nigeria, one of the provinces affected by Boko Haram, is about the size of Ireland. Mali's five largest regions are all bigger than Portugal, Austria, or the Czech Republic, and the largest region, Tombouctou, is more than twice the size of Belarus, Romania, or the United Kingdom.¹ In addition, knowing under what conditions terrorist attacks are more likely in the following month is valuable but does not give us any indication where they might occur. Putting these two pieces together will help us get closer to solving this puzzle. Thus the research question of this paper is: *What explains the timing and location of terrorist attacks in civil conflicts?*

Terrorism occurred in 73 per cent of civil conflicts between 1970 and 2004 (Findley & Young 2012). Scholars have only recently started to look at terrorism as part of wider violent campaigns rather than as an isolated phenomenon. Studies looking at terrorism in civil conflicts (Polo & González 2020, Asal et al. 2019, Ash 2018, Polo & Gleditsch 2016, Bakker,

¹https://commons.wikimedia.org/wiki/Atlas_of_first-level_administrative_divisions, access 18.02.2022.

Hill Jr & Moore 2016, Coggins 2015, Stanton 2013) have explained variation in the number of terrorist attacks in a country, or by a rebel group in a country or region, per month, year or over longer periods of time. They identify group, country and regime characteristics which make groups more likely to use terrorism and regions more prone to terrorism. Polo & González (2020) identify rebel losses as important factor for the timing of terrorist attacks on the monthly level but the design does not allow to take spatial dynamics into account and thus leaves room to explain both the timing and location of terrorism. Likewise, Ash (2018) identifies administrative regions at risk but does not give insights into the timing of attacks. Thus taking both spatial and temporal conflict dynamics into account while changing the spatial unit of analysis to the grid cell can bring us closer to explaining both the timing and location of terrorism in civil conflicts.

I argue that the amount and intensity of battles, and the amount of government and rebel casualties, are the key to explain the timing and location of terrorism in civil conflicts, thus building on and extending previous work (Ash 2018, Polo & González 2020, Kibris 2021). Governments, or rebels, increase the conflict intensity to test the opposing side's resolve and potentially alter the course of the conflict in their favour in the form of an increase in the number or severity of attacks. It can thus be considered a form of signaling. Insurgents have exhausted their tactics in regular warfare fighting conventional opponents - the military and police. Such a signal of resolve pushes them to decide whether to expand their repertoire towards terrorism or not. I expect a strategic interaction between a government and rebels. It is a signaling game about actors' resolve in civil conflict, and these events and attacks are their means of communication. Previous studies have been restricted to group, region and country characteristics on the annual or monthly level to explain which groups and administrative regions are more prone to terrorism which is insufficient to show this interaction which depends on both spatial and temporal dynamics. To overcome this limitation I use disaggregated data on the grid cell-month level and generalized linear mixed effect models to show this interaction and demonstrate that variation in the timing and location of terrorism in civil conflicts is systematically influenced by such events.

Why should we look at terrorism in civil conflicts and not simply one-sided violence? One-sided violence as defined by the Uppsala Conflict

Data Program (UCDP) is direct and deliberate lethal violence against civilians (Eck & Hultman 2007). Terrorism is a, depending on the definition used much smaller, subset of one-sided violence. In addition, attacks can be classified as terrorist if there are no fatalities and would not be included in UCDP as one-sided violence events. Furthermore, terrorism is commonly associated with the intention to send a message to a wider audience beyond the immediate victims, in most cases the government, and to instil fear in the population (Crenshaw 1981, McCormick 2003, Cronin 2009, Hoffman 2006, Stanton 2016). Indeed terrorism is argued to be a form of communication or signaling (Kydd & Walter 2006), and it is directed towards both a government and the population. Terrorism is thus designed to influence the government of a state and not the immediate victims and witnesses of attacks (Fortna 2015, Polo & González 2020). One-sided violence, in contrast, is designed to establish control and force cooperation of the local population, for example to extract resources, and thus aims at the victims and witnesses of attacks (Kalyvas 2006, Wood 2014, Polo & González 2020). It is thus important to look at terrorism in civil conflicts since one-sided violence is a much broader category of civilian targeting (Fortna, Lotito & Rubin 2018, Fortna, Lotito & Rubin 2020) and terrorism has different underlying intentions and a wider target audience. In order to illustrate what difference the definition makes, the analyses will be carried out with differently operationalized dependent variables taking target characteristics into account. These different targets of terrorist attacks reflect the intended severity or shock level which corresponds to signaling and conveying messages (Conrad & Greene 2015). Building on recent advances in attributing terrorist attacks to recognized rebel groups as defined by UCDP, this paper combines information from the UCDP Georeferenced Event Dataset and the Global Terrorism Database to look specifically at actors which are in an active armed struggle against a government meeting the UCDP threshold of 25 annual battle-related deaths (Fortna, Lotito & Rubin 2020).

This paper makes several contributions to the literature. To the best of my knowledge, this is the first study which investigates the effect of conflict dynamics and intensity on the timing *and* location of terrorism in civil conflicts. Previous studies have looked either at country-wide or first level administrative regions on the annual or monthly level to explain either the timing or the location of terrorism in civil conflicts. By disaggregating the unit of analysis to grid cells, this study contributes to our understanding

of local battle dynamics on rebel tactics and illuminates which areas tend to be more affected by terrorism than others. Second, it differentiates terrorism by target choice or shock levels. With regards to terrorism as signaling mechanism, this approach captures the intentions of rebels better than casualty counts. Differentiating between infrastructure, combatants and government, and civilian targets allows us to infer what kind of message rebels want to send, since the choice of target determines the shock level a group is aiming for. There is a qualitative difference between attacking a water or power plant and attacking a shopping mall, and rebels choose strategically when to strike at which kind of target. The paper proceeds as follows: First it reviews the literature on terrorism in civil conflict. I then present a theory on the occurrence of terrorism which is followed by a discussion about the expected timing and location of terrorism in civil conflicts connected to this theory. After describing the data and methods, I present empirical in-sample and out-of-sample results and quantities of interest. I conclude by discussing the implications and limitations of this study and avenues for future research.

3.2 Terrorism in civil conflicts

States suffering from violent political instability or political collapse and emerging anarchy are more likely to experience both domestic and international terrorist attacks and show a higher probability of producing international terrorism (Coggins 2015). In civil wars, weaker groups are more likely to resort to terrorism whereas those which are better equipped carry out conventional attacks (Polo & Gleditsch 2016). Religious groups tend to focus on "soft" civilian targets whereas those with more diverse followers tend to attack "hard" official targets. Lastly, more repressive governments with a history of violence and greater media freedom have the largest substantive effects. Through greater media freedom attacks will be reported and the background of the underlying conflict will be outlined to a broader public (Polo & Gleditsch 2016). State repression points to government actions as a predictor of terrorist attacks while media freedom appears to have a multiplier effect.

Terrorism is most likely in civil wars with a democratic government and when a government and rebels represent different religious strands (Fortna 2015). Rebels challenging democratic governments in civil wars

use small-scale bombs to attack civilian targets in 80 % of cases as democracies are believed to be sensitive to civilian casualties. Groups aiming for broad civilian support - revolutionary insurgencies with nonreligious political objectives - are less likely to attack targets which cause civilian casualties than rebel groups with exclusionary political goals and a narrow constituency - separatist insurgencies and revolutionary insurgencies with religious goals (Stanton 2013). The dependent variable is binary and captures whether terrorism did or did not occur between 1989 and 2010. Thus a more fine-grained approach will allow to test effects more thoroughly.

Focussing on terrorism in dissident environments, government coercion, violent and nonviolent acts of dissent, international conflict, contestation, participation, civil liberties, physical quality of life and population size increase the number of terrorist attacks. Increasing the number of veto players and the size of the coercive bureaucracy leads to fewer attacks (Bakker, Hill Jr & Moore 2016). Almost all of these factors point to ongoing civil conflict as strong predictor of terrorism. In addition, a recent study has looked at variation in terrorism across administrative regions in civil war countries. It found that relative deprivation, ongoing armed conflict, capital city status, and attacks by other rebel groups make terrorism more likely (Ash 2018). While this approach exploited spatial variation more than previous scholarship it is still restricted to annual indicators and to first-level administration regions, and cannot explain the timing of attacks and more precise locations. Funding structures may determine the use of terrorism by rebels as well. Groups which rely on civilian support are more cautious than those which rely on lootable resources of foreign support (Fortna, Lotito & Rubin 2018).

Terrorism in civil wars can also be considered a reaction to government actions. Repressive or punitive government tactics, including police and military operations, tend to be associated with subsequent terrorism incidence whereas more conciliatory tactics do not show a similar association (Asal et al. 2019). Terrorism in civil wars can also be regarded as a mobilization tool. This approach assumes that rebels are seeking local support while engaging in battles with the government. As a result, rebels use terrorism after battlefield losses to both provoke a government overreaction and to exploit in-group out-group dynamics in order to mobilize and recruit. These battlefield losses determine the timing of terrorist attacks, conditional on the likelihood of mobilization success (Polo & González 2020). Both these studies point to a reactive nature in the use of terrorism by

rebels.

Previous studies have explained variation in the number of terrorist attacks of a rebel group (Polo & Gleditsch 2016), in a country (Bakker, Hill Jr & Moore 2016, Coggins 2015), or first-level administrative region (Ash 2018) per year or month (Asal et al. 2019, Polo & González 2020) and whether a rebel group used small-scale bombs against civilian targets within a longer time frame (Stanton 2013). They explain which groups are more likely to use terrorism, and their timing, and which administrative regions are more prone to terrorism. However, they are not able to take civil conflict dynamics and processes in a both spatially and temporally disaggregated level into account and are therefore not sufficient to capture the aforementioned strategic interaction and specific events leading to the use of terrorist attacks and their timing and location. An approach on the grid cell-month level exploits variation across time and space more thoroughly to illuminate these dynamics.

3.3 Rebel use of terrorism

Internal armed conflict is defined as an incompatibility about government or territory between a government and internal opposition groups with at least 25 battle-related deaths per year (Gleditsch et al. 2002). Terrorism is defined as the "deliberate creation and exploitation of fear through violence or the threat of violence in the pursuit of political change" (Hoffman 2006, 40), or social change (Enders & Sandler 2011, 4), by a subnational actor. It is directed toward a specific target audience and conducted by either an organization, individuals or a small group of individuals, and usually targets civilians (Ganor 2002, Hoffman 2006, Enders & Sandler 2011).

The literature commonly draws a distinction between domestic and international or transnational terrorism. International or transnational terrorism is usually defined as attacks in which at least two of the nationalities of attackers, victims, or the location differ and is a topic of wide scholarly interest (George 2018, Helbling & Meierrieks 2020, Marineau, Pascoe, Braithwaite, Findley & Young 2020, to name a few recent studies). Domestic terrorism, with examples such as the ETA or the IRA, has initially been largely overlooked while transnational terrorism garnered more scholarly interest (Sánchez-Cuenca & De la Calle 2009). In more recent years, however, domestic terrorism has likewise received widespread attention among researchers (Ghatak, Gold & Prins 2019, Krieger & Meierrieks

2019, Piazza 2020, to name a few). However, much like definitions of terrorism and terrorist groups in general are not universally agreed upon (Sánchez-Cuenca & De la Calle 2009, Phillips 2015), there is also some discussion about what specifically constitutes domestic terrorism (Berkebile 2017). To circumvent this issue, I exclusively look at terrorist attacks carried out by recognized rebel groups which are party to civil conflicts with a government according to the Uppsala Conflict Data Program (Fortna, Lotito & Rubin 2020). This ensures that only relevant terrorist attacks are analyzed which are attributable to named rebel groups and which are part of a wider armed struggle rather than for example lone-wolf attacks or attacks by unknown perpetrators.

Foundational studies argued that "a significant difference exists between *preconditions*, factors that set the stage for terrorism over the long run, and *precipitants*, specific events that immediately precede the occurrence of terrorism" (Crenshaw 1981, 381). These *precipitants* are, more often than not, unexpected and unusual use of force by a government (Crenshaw 1981, 384). I argue that *precipitants* are the key to explain the occurrence of terrorism in civil conflicts. These are signs of resolve by any party to a conflict facing mounting pressure. *Precipitants* here are increases in the number or severity of actions against governments or rebels, and the population they represent. Specifically, I look at the number of clashes between government and rebel forces and the amount of government, rebel, and civilian casualties resulting from these battles.

Preconditions in a civil conflict are the structural factors specific to a country and conflict. These are for example distances to natural resources, international borders or a capital city, GDP per capita, or population size. *Precipitants* are relative to structural conditions. To account for this, intensity of government actions in terms of number and severity of attacks is used to separate preconditions from precipitants. For example, in a civil conflict which features large-scale government operations regularly, one additional operation will not have the same impact compared to a civil conflict which has not or seldom seen comparable operations. Spikes in conflict intensity over time are expected to precede the occurrence of terrorism. Recent scholarship has demonstrated the importance of short-term events in addition to structural factors to explain the onset of interstate conflicts (Chadefaux 2014). This project builds on this line of scholarship by analyzing the impact of short-term increases in the number and lethality of battles on the decision of insurgents to use terrorism in civil

conflicts.

A government tests rebels' resolve, and the population they represent, to test how far it can go, to indicate how far it is willing to go, to undermine rebel morale, and ideally to accelerate its victory. Civil conflicts are usually about self-determination, secession, or regime change; a state's territorial integrity and sovereignty, and possibly a government's survival are at stake. Given these high stakes a government may be willing to do whatever it takes to win (Merari 1993, 236-237); a recent example is Syria. Governments experiencing civil conflicts therefore have an incentive to increase conflict intensity and potentially change the course of the conflict in its favour. In the case of no reaction from the rebels, the government has no reason to refrain from continued intensification against them and the wider population they represent.

Why would governments increase conflict intensity if it may result in terrorist attacks? A government's authority is challenged and control over its territory contested. Indeed it may have already lost full control over some areas which happens frequently during civil conflicts since territorial control or influence are fluid concepts which vary over time and space (Anders 2020, Rubin 2020). In addition, both governments and rebels tend to be more indiscriminate, i.e. more focused on large-scale targeting of civilians, the further away they are from their own centers of power (Schutte 2017). This is linked to the "control-collaboration" model which states that indiscriminate violence against civilians is a function of territorial control and the need to enforce collaboration and prevent defection among the local population. Highly contested areas and areas under firm government or rebel control are expected to see less indiscriminate but more selective violence against civilians whereas areas which are only under partial government or rebel control, and thus under more moderate contestation, are expected to experience the highest levels of indiscriminate violence because actors lack information about, and capacity over, the local population to punish defections more selectively (Kalyvas 2006, Kalyvas & Kocher 2009, Kalyvas 2012). Thus both governments and rebels are willing to increase conflict intensity to achieve their goals.

Insurgents in turn switch to terrorism to send a signal to both the government and the wider population about their willingness to continue their armed struggle, and thus their resolve and capacity to fight. The conflict intensified to an extent that rebels cannot meet with regular means of

guerrilla warfare. Rebels have an incentive to respond to conflict intensification because not doing so would signal weakness and a government would want to take advantage of this and increase their attack rates even more if they believe an end to the armed conflict, and rebel defeat, is near. In the best case scenario, conflict intensity will decrease again at least in the short term. The worst case scenario would arguably be identical, or at the very least similar, to the scenario with no rebel response: continuously high conflict intensity.

Why should insurgents switch to terrorism in particular? The group is fighting against military and police forces, and is perhaps also targeting government personnel. If insurgents are still determined to fight they have to expand their repertoire of tactics. Options other than terrorism would be for example acts of sabotage, or attacking infrastructure or telecommunications. However, these can be repaired, as can other objects sabotaged. Likewise, buildings can be rebuilt. Lives of civilians cannot be recovered. I argue that attacking civilian targets is more costly for governments independent of regime type in line with the provocation strategy of terrorism linked to disproportionate government responses (Kydd & Walter 2006, Python, Brandsch & Tskhay 2017). A government has to adequately protect parts of the population not yet sympathetic towards the insurgents. If it does not, the government's inability or inaction to prevent terrorism will likely lead to at best less support for the government and at worst radicalization of parts of the population. Police and military forces, the conventional opponent of insurgents in civil conflicts, have already been on the target list to no avail. The natural extension of this list points to civilians to hurt the government and attract recruits. In addition, rebels want to use the signaling aspect of terrorist attacks to communicate with both the government and the wider population to convey that they are still determined to fight.

3.4 Timing and location of terrorism in civil conflicts

Existing work strongly suggests spatial and temporal linkages of conflict events in civil conflicts (Lyall 2009, Hegre, Østby & Raleigh 2009, Schutte & Weidmann 2011). For example, it has been argued that relative rebel

strength determines the location of local insurgency onsets, such that relatively weak rebel groups tend to start local insurgency in inaccessible areas, in areas with preexisting ties to the local population, and in areas nearby ongoing rebel activity (Holtermann 2016). In addition, relative rebel strength and ethnic ties determine whether fighting is geographically limited or more widespread. Weaker rebels without strong ethnic ties tend to lack control over local territory and are therefore forced to engage with the government in more varied locations rather than in relatively established rebel strongholds (Beardsley, Gleditsch & Lo 2015). Weather conditions can also lead to conflict events being postponed or accelerated (Carter & Veale 2015). Thus local conditions matter for conflict events.

There is also evidence to suggest a tit-for-tat nature in conflict events. During the counterinsurgency in Iraq, there was a retaliatory link between coalition- and rebel-initiated conflict events. This effect is moderated by local religious majorities and economic wealth, such that there is stronger evidence for reactive rebel violence in majority Sunni and Shi'a areas and in nonurban and Sunni poor regions (Linke, Witmer & O'Loughlin 2012). Similarly in Iraq, it has been argued that the intensity of counterinsurgency operations determines future insurgent attacks, with low to moderately intense counterinsurgency operations leading to increases in insurgent attacks while it is the opposite for high intensity operations. In these instances, insurgents can signal strength and resolve and establish momentum (Eastin & Gade 2018). Another study found similar results for reactive violence in close vicinity, and additionally found a moderate increase in counterinsurgency operations near locations of insurgent violence (Braithwaite & Johnson 2012). Also in Iraq, increases in daily coalition airstrikes for prolonged periods of time lead to more insurgent attacks across the country and within the capital, and these attacks can be as far as 400 kilometers away (Papadogeorgou et al. 2020). Studies in different contexts found similar evidence for a retaliatory nature between opponents in internal armed conflicts (Jaeger & Paserman 2008, Haushofer, Biletzki & Kanwisher 2010).

Recent research argued that this strand of the literature tends to overlook the effect of rebel losses on the capacity to retaliate (Kibris 2021). Rebel losses in the form of rebel casualties may occur of course in intense battles which can ultimately be considered rebel victories against a government. However, given that the number of rebels is almost always smaller than the number of government forces, absolute losses are

important to consider. Absolute losses are more indicative of how harmful battles are to rebel groups, because they convey both the reduction of fighters and material losses in terms of resources such as weaponry and territory (Polo & González 2020). It thus minimizes what has been called organizational capability: the ability to launch successful combat operations against the opponent (Kibris 2021). This also highlights why both battles and casualties should be taken into account: it makes a qualitative difference whether ten battles in one month lead to 10 or 500 casualties. The number of battles and casualties thus capture two distinct dimensions of conflict intensity, and both are important to consider. Indeed, there is evidence for a spatiotemporal dimension in civil conflict battles and casualties and spatial spillovers. Government losses were indicative of future battles nearby the locations where the government suffered these losses whereas battles with rebel casualties see no such effect (Kibris 2021). In contrast, rebel losses have been identified as crucial factor in determining the timing of terrorism in civil conflicts. Terrorism can be regarded as a mobilization tool in times of need, specifically after a rebel group suffers losses and seeks to increase civilian support. Thus the timing of terrorism in civil conflicts depends on battlefield dynamics and losses (Polo & González 2020). Previous research generally highlighted that both rebel losses and a lack of government losses make rebel violence against civilians more likely (Hultman 2007, Wood 2014, Nyseth Brehm, Robinson & Saraswati 2021). Therefore, rebel losses on the battlefield tend to have no effect on the timing and location of future battles with the government, but they tend to have an effect on the timing of future terrorist attacks by these rebel groups.

Other studies look at violence against civilians and whether there is a retaliatory or reactive nature (Lyall 2009, Raleigh 2012, Schutte & Donnay 2014, Oswald et al. 2020). While some studies find no evidence for indiscriminate government violence against civilians leading to a subsequent increase in insurgent violence (Lyall 2009), others find that it leads to increased civilian collaboration with insurgents (Kocher, Pepinsky & Kalyvas 2011). It has also been argued that the spatial and temporal distribution of violence against civilians is linked less to retaliation or punishment and more to revealing information and competition with opposing rebel groups (Raleigh 2012). There is nevertheless evidence to suggest that rebels initially increase violence against civilians immediately after taking territorial control to establish control over the civilian population as well

(Oswald et al. 2020). Still, a spiralling tit-for-tat between competing actors and their patterns of civilian targeting do occur and violence against civilians by one actor can lead to subsequent violence against civilians by opposing actors (Fielding & Shortland 2012, Raleigh & Choi 2017, Nyseth Brehm, Robinson & Saraswati 2021). Other studies find similar evidence and additionally argue that increases in population density and geographical spread of conflict activity are associated with more violence against civilians (Lis, Spagat & Lee 2021). However, there is also evidence for diversionary rebel violence against civilians during state military offensives to distract government forces and create a need for them to disperse geographically (Holtermann 2019). There are thus reactive elements between battlefield dynamics and violence against civilians too.

Turning to the location of terrorism in civil conflicts, first level administrative regions which contain the capital city and which are relatively deprived tend to see more terrorist attacks. Both a punishment and a destabilization mechanism are present here, such that attacks in the capital can be regarded as government punishments and attacks in relatively deprived areas are intended to additionally destabilize already fragile regions (Ash 2018). This links to more general patterns of indiscriminate violence against civilians which is most likely close to capital cities and in remote regions (Schutte 2017). Indeed, both regional and national capitals tend to see more indiscriminate rebel violence against civilians. Rebels want to coerce elites, intimidate the local population, and persuade an international audience by threatening or targeting citizens of other countries, each of which is designed to put pressure on the government (Koren 2017). However, while national and provincial capitals seem to be more at risk than other cities, relative deprivation on the administrative regions level leaves some variation to be explained since these regions can easily be larger than some European countries. Therefore, a more spatially disaggregated approach at the grid cell-level is used in this paper to better capture and exploit spatial variation in violence and terrorism in particular.

Instead of the quantity of terrorism, this paper investigates the quality of terrorism (Conrad & Greene 2015, Polo 2020). This means that the focus is on target choice rather than the number of casualties. Terrorism is a notoriously difficult concept to define, with some definitions restricting targets to unarmed civilians while others exclude attacks on for example police and military forces or government personnel (Sánchez-Cuenca &

De la Calle 2009, Phillips 2015). In addition, rebel groups in civil conflict are already engaged in battles such that the intention behind terrorism is deemed more important than the number of casualties. To circumvent issues about one definition, I differentiate between attacks on infrastructure, combatants and government, and civilians. Infrastructure covers airports and aircraft, food and water supply, ports and maritime facilities, telecommunication, transportation other than aviation, and utilities. Combatants and government cover general and diplomatic government personnel, police and military forces, terrorists and nonstate militias, and violent political parties. Civilians cover businesses, educational institutions, journalists and media, nongovernmental organizations, private citizens and property, and tourists. Attacks on infrastructure are the least shocking and attacks on civilians are the most shocking, with combatants and government representing the intermediate shock level. The choice of more shocking targets creates the perception that a group is stronger or more effective than it actually is, examples being al Qaeda and 9/11 or al-Shabaab and the Westgate shopping mall attack. More shocking attacks also garner more media attention and create publicity (Conrad & Greene 2015). This, combined with a possibly heavy-handed government reaction, serves the purpose to increase support and recruitment in parts of the population while coercing the population as a whole (Kydd & Walter 2006, Lake 2002, Conrad & Greene 2015). It does, however, risk popular backlash from parts of the population (Kalyvas 2006). Still, given the widespread use of terrorism in civil conflicts the coercive nature seems to reflect decision-making in many rebel groups.

It is important here to differentiate terrorism from other forms of violence. As mentioned earlier, terrorism is a concerted effort to create and exploit fear via the threat or actual use of violence with the aim for social or political change (Hoffman 2006, Enders & Sandler 2011). Traditionally it has been outside a context of legitimate warfare which makes it distinct from clashes between government and rebel forces which UCDP categorizes as "normal" warfare. One way to think about it is that clashes are open encounters whereas terrorist attacks are "covered" encounters. In the case of terrorism against combatants and government, the targets may overlap with the targets of clashes but the nature of the encounters is different. Examples include the 1983 Beirut barracks bombing on US forces or the USS Cole bombing in 2000. In contrast, one-sided violence refers to violence against unarmed civilians (Eck & Hultman 2007). It is commonly

intended to coerce a local population into cooperation and establish control (Kalyvas 2006, Wood 2014, Polo & González 2020). In contrast, terrorism is intended to influence a government into for example making concessions or heavy-handed responses (Fortna 2015, Polo & González 2020). While especially in the case of terrorism against civilians the targets may overlap with one-sided violence, they have different intentions and target audiences. Lastly, both clashes and one-sided violence require casualties while terrorism does not. Terrorism and clashes and terrorism and one-sided violence are thus distinguishable from each other.

Relating battlefield dynamics to terrorism target choice yields distinct hypotheses to test. The main audience for all terrorism targets is the civilian population. It is most directly influenced by acts of sabotage and by attacks against civilians, and the receiver of information derived from attacks on infrastructure (a signal of government inability to prevent sabotage), on combatants and the government (a signal of rebel strength and government/opposing actors' weakness) and civilians (a signal of coercion and intimidation). After rebel losses, rebels want to punish the civilian population, and more specifically suspected informants, to prevent future information leaks and successful government operations (Holtermann 2021). I therefore expect terrorism against civilians to increase in the vicinity of battles after rebel losses. In addition, I expect terrorism against infrastructure to increase as well. However, not in the vicinity of battles, assuming these areas are of interest to rebel groups, but in or near the centers of power instead. These centers of power are the national and provincial capitals. I expect a negative relationship between rebel losses and terrorism against combatants and government personnel in line with previous research (Kibris 2021). The corresponding hypotheses are:

Hypothesis 1: *Terrorism against any target becomes more likely in close geographical proximity to clashes, and in or near national and provincial capitals.*

Hypothesis 2: *Terrorism against combatants and government becomes less likely in close geographical proximity to clashes with rebel losses, and in or near national and provincial capitals.*

Hypothesis 3: *Terrorism against civilians becomes more likely after clashes with rebel losses in close geographical proximity to these clashes.*

After government losses, I expect a decrease in terrorism against civilians because there is no need to send a signal of government weakness and also no need for coercion. The battle outcomes speak for themselves. However, there is a desire to send a signal about government inability to further convince the population that a rebel group is the better alternative. I therefore expect an increase in terrorism against infrastructure. Likewise I expect an increase in terrorism against combatants and government personnel. Rebels are in a position of relative strength and momentum is on their side, thus continued attacks against other combatants and the government have the aim to uphold this momentum and make further gains. The corresponding hypotheses are:

Hypothesis 4: *Terrorism against civilians becomes less likely both in close vicinity to battles and in or near national and provincial capitals after clashes with government losses.*

Hypothesis 5: *Terrorism against combatants and government personnel becomes more likely after clashes with government losses both in close geographical proximity to these clash and in or near national and provincial capitals.*

One issue to address is the possibility of reverse causality and how independent measures of terrorist attacks and battlefield losses are from each other. We have to keep in mind that this paper looks at terrorism in the context of active civil conflict, thus battles are the norm in such armed conflicts. In contrast, terrorist attacks during civil conflict are not the norm and vary greatly between conflicts and groups (Polo & González 2020). Previous research has shown that terrorism in civil conflicts can be regarded first and foremost as a mobilization tool after battlefield losses, and that there is reduced rebel capacity to engage in open battles (Polo & González 2020, Kibris 2021). Terrorism in the context of civil conflicts does not serve the purpose of increased escalation but to attract recruits, coerce governments into making concessions, and draw support away from the government. From a government perspective, open battles or clashes provide more actionable intelligence to work with to plan future government operations than terrorist attacks due to their more clandestine nature. In other words, open battles reveal more information than terrorist attacks. As a result, it is more likely that a government responds militarily to battles than to terrorist attacks in a civil conflict context.

3.5 Data and methods

To test the theoretical expectations outlined above, I use geographically and temporally disaggregated data on terrorist attacks and battles between governments and rebels. Inference based on precise spatial and temporal dimensions faces the modifiable areal unit problem (MAUP). The MAUP reflects the fact that event counts will depend on the choice of spatial window used to aggregate events (Openshaw 1979, Cressie 1996). As a result, one cannot be certain that conclusions drawn are not an artifact of the specific space-time window used to capture subsequent instances of terrorism. One way to mitigate this problem is to rely on artificial but constant spatial units such as provided by PRIO-GRID rather than on subnational boundaries which may be sensitive to political decisions and locations of for example ethnic group settlements, civil war outbreaks or concentrations of local wealth (Tollefsen, Strand & Buhaug 2012). It thus helps to both reduce endogeneity concerns and overcome issues such as changing national and subnational borders. The paper focuses on terrorism in civil conflicts in Africa. Africa is commonly regarded as representing typical civil conflicts cases and can therefore be considered both a representative sample of all civil conflicts and a most-likely scenario for testing theoretical expectations surrounding civil conflict dynamics (Vüllers & Krtsch 2020). Rebel groups in civil conflicts based in Africa also provide considerable variation in the use of terrorism and a general increase in the occurrence of terrorism over time has been observed (Thomas 2014). Observations are restricted to countries and years in active conflict between 1989 and 2013 according to the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al. 2002, Pettersson et al. 2021). Thus Africa is an appropriate choice to test the hypotheses outlined above.

The dependent variable is the occurrence of terrorist attacks in civil conflict countries per PRIO-GRID cell-month. Apart from the general terrorism occurrence, other dependent variables distinguish between three categories of terrorism following Conrad & Greene (2015) to categorize target severity. This concept is subdivided into maximum (civilians), intermediate (combatants and government), and minimum (infrastructure) severity and there are three separate variables to capture each severity level. Data for the dependent variables come from the Global Terrorism Database (LaFree & Dugan 2007, GTD). It contains information on more than handcoded 190,000 domestic and international attacks between 1970

and 2018 with geolocation. I focus on deliberate and direct attacks by non-state actors as scores of terrorist attacks in civil conflicts. I then filter events using the link data from the Terrorism in Armed Conflict project which ensures that only recognized rebel groups in the UCDP Georeferenced Event Dataset are left (Fortna, Lotito & Rubin 2020). I also filter events which cannot be attributed to at least the second order administrative region. The remaining GTD events are then associated to PRIO-GRID cells using their latitude and longitude information.

Data for the main independent variables, number and intensity of clashes, come from the UCDP Georeferenced Event Data (Sundberg & Melander 2013, GED). This is a handcoded event dataset and each event is georeferenced and attributed to PRIO-GRID cells. GED covers all countries between 1989 and 2019. It differentiates between state-based, non-state and one-sided violence. The focus of this paper is on state-based violence between a government and a recognized rebel group which results in at least 25 annual battle-related deaths. Like for GTD, I keep events which can be attributed to at least second order administrative regions. Intensity of clashes is operationalized in several ways. The main independent variables are the number of clashes and rebel and government casualties while I also include the number of civilian casualties as a result of battles between a government and rebels. Combining GED and GTD events leaves 21,803 observations of terrorist attacks and clashes between rebel groups and government forces for Africa from 1989 to 2013.² Aggregating events to the cell-month level generates 11,145 unique observations. Of these, 5,451 saw one or more terrorist attacks and 7,277 saw one or more clashes between rebels and a government. Summary statistics are provided in Table 3.1.

It is important to discuss the possibility of empirical overlap between measuring clashes, losses and terrorism. Clashes are taken from UCDP GED and include only events in the context of "normal" warfare with led to one or more casualties. Rebel and government casualties are the fatalities resulting from these clashes. In contrast, terrorist attacks are taken from GTD which includes events that are intentional, entail some level of

²Data beyond 2013 were not included in the Terrorism in Armed Conflict project. While link data could have been adjusted such that years after 2013 could have been included, it would not have captured newly established rebel groups in civil conflicts and would thus have led to an incomplete dataset. Future research might seek to fill this gap and reproduce analyses performed here.

TABLE 3.1: Summary statistics for dependent and main independent variables

Statistic	Mean	St. Dev.	Min	Max
Terror	0.489	0.500	0	1
Terror (min)	0.053	0.223	0	1
Terror (int)	0.247	0.431	0	1
Terror (max)	0.244	0.430	0	1
Clashes	1.095	1.800	0	32
Rebel casualties	4.901	51.667	0	5,000
Government casualties	11.464	198.531	0	10,029

violence or immediate threat of violence, and are executed by a subnational actor. In addition, two of three criteria have to met: 1) the aim has to be of political, economic, religious, or social nature, 2) there has to be evidence that the aim was to intimidate, or send a message, to a larger audience beyond the immediate victim(s) of the attack, and 3) it must be outside a legitimate warfare context according to international humanitarian law. The latter two points, one of which has to be met in order for a terrorist attack to be included, are crucial. The two criteria separate terrorist attacks from clashes between government and rebel forces. The aim of an open battle or clash, for example to gain territory or to diminish opponent forces, is of a military nature and thus part of a legitimate warfare context. Thus GTD events meeting this criterion should not have overlap with GED events. In contrast, terrorist attacks are designed to send a message to a wider audience. The examples of the Beirut barracks and USS Cole bombings had an audience well beyond the immediate victims and were designed to pressure a government into making concessions. Battles, on the other hand, are not designed for a government to make concessions but for a rebel group to advance and to the size of opposing forces. The two examples above also did not have aims of a military but of a political nature. As a result, the losses resulting from battles are also distinct from terrorist attacks and its victims.

Terrorism occurred in about half the observations at the grid cell-month level which saw battle events. However, attacks against infrastructure are relatively rare compared to attacks against combatants and government or attacks against civilians, which occurred about equally often. Descriptive statistics for the main independent variables reveal high skewness when looking at the means, standard deviations and maximum values.

In addition, the maximum values for rebel and government casualties indicate high skewness. As a result, I will logtransform these, and all other numerical covariates outlined below, for subsequent analyses. The maximum numbers for terrorist attacks per grid cell-month in general, attacks against infrastructure, combatants and government personnel, and civilians, are 42, 42, 30 and 19, respectively. Thus some cell-months saw on average about one or more attacks per day. The average number of clashes is about one, with a maximum of 32 and an interquartile range of 1, indicating that most cell-months experience a relatively low number of clashes. The mean number of government casualties is more than twice as large as the mean number of rebel casualties, but the medians and interquartile ranges are comparable indicating again the influence of some unusually intense events and months. Figure 3.1 shows the geographical spread of civil conflicts and terrorist occurrences in civil conflicts in Africa.³

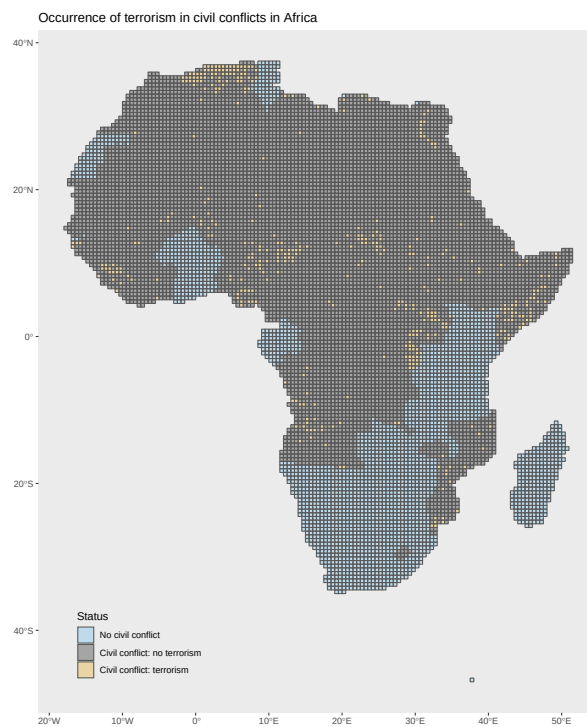


FIGURE 3.1: Geographical distribution of active civil conflicts and terrorism occurrences. Observations were collapsed on the grid cell.

I include several other covariates which may affect the occurrence of terrorist attacks and the number of clashes and fatalities. State capacity

³Observations were collapsed on the grid cell to create this plot. Similar plots terrorism with minimum, intermediate, and maximum severity can be found in the supplemental material.

is generally considered to be highest in and around a capital city and decreases with increasing distance to the capital (Schutte 2015, Tollefsen & Buhaug 2015). Variables indicating the distance to the national capital and international borders are included using CShapes data (Weidmann, Kuse & Gleditsch 2010) and distance to nearest provincial capital data come from GGIS⁴. Another indicator associated with state capacity in the form of taxation capacity and provision of public services but also economic activity is nighttime light emissions (Cederman, Weidmann & Bormann 2015, Harbers 2015, Kuhn & Weidmann 2015, Weidmann & Schutte 2017). Recent work also argued that it can be regarded as proxy for government investment in regions prone to secession (Williams 2021). Calibrated mean nighttime light emissions are therefore included using data from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) (Elvidge et al. 2009).

The location of natural resources in countries experiencing civil conflict may affect the timing and location of rebel attacks as well. This includes petroleum, gemstone, oil and gas, and diamonds and gold. All of these resources can be utilized by rebel groups to finance their armed struggle (Walsh et al. 2018) and may help them extend civil conflict duration (Conrad et al. 2019). Thus more intense fighting might take place as governments might allocate more resources to secure and defend these locations whereas rebels have an incentive to take control of these locations. Indeed, gemstone mining locations in conflict zones are associated with higher numbers of annual battle-related deaths (Lujala 2009). Areas containing gold and gemstones productions see increased conflict intensity (Balestri 2012). Balestri (2012) used an original dataset containing the locations of gold resources which is used in this paper as well. GEM-DATA are used to gemstone locations and come from Lujala (2009). If conflict zones contain petroleum locations civil conflicts tend to last longer (Buhaug, Gates & Lujala 2009, Lujala 2009). Data on oil and gas field locations are provided in PETRODATA (Lujala, Ketil Rod & Thieme 2007). Diamonds, especially secondary diamonds, are associated with civil war onset (Lujala, Gleditsch & Gilmore 2005). Data on primary and secondary diamond locations come from DIADATA (Gilmore et al. 2005). Lastly, drug cultivation in conflict zones is associated with lower levels of conflict severity (Lujala 2009). Data for coca bushes, opium poppies and cannabis

⁴<https://webgis.wr.usgs.gov/globalgis/datasets.htm>, retrieved through the xSub R package (Zhukov, Davenport & Kostyuk 2019).

locations come from DRUGDATA (Buhaug & Lujala 2005).

Rough terrain is also a crucial aspect to civil wars. Mountains terrain or forests make it easier for rebel groups to hide, organize, and sustain their armed struggle, and more difficult for governments to project power (Fearon & Laitin 2003, Tollefsen & Buhaug 2015). The analysis therefore accounts for mountain and forest locations to incorporate geographic features favouring rebel groups. Forestland data come from the Global Land Cover Map (Arino et al. 2012) and mountainous terrain data come from the United Nations Environment Programme's World Conservation Monitoring Centre (Centre 2002). Related to terrain, drought has been associated with civil conflict incidence (von Uexkull 2014) and local geographical patterns of violence (De Juan 2015). I therefore include the Standardized Precipitation Evapotranspiration Index (SPEI). SPEI is a drought indicator which takes precipitation and potential evaporation into account and captures whether a region, here a grid cell, receives enough water to satisfy its water usage. Data come from AfroGrid.⁵ Lastly, ethnic group locations and whether they are politically and economically excluded or included is a decisive factor for civil war onset (Cederman, Weidmann & Gleditsch 2011, Wucherpfennig et al. 2011). The analyses therefore accounts for the presence of relevant ethnic groups which may face political or economic inequalities. Geo-referencing Ethnic Power Relations (GeoEPR) provides data on excluded ethnic groups and I include a variable indicating the number of excluded groups.

Lower levels of local wealth and economic well-being are associated with both civil war onset and outbreak (Collier & Hoeffler 2004, Buhaug et al. 2011) and intensity (Hegre, Østby & Raleigh 2009). I therefore include gross cell product per grid cell information to take local wealth into account. Data come from the G-Econ database (Nordhaus et al. 2006). Population size is an important feature as well. Areas with higher levels of population density oftentimes serve as starting point for insurgencies as they provide opportunities to recruit (Weidmann 2009). These areas also tend to see higher levels of rebel violence during a conflict (Raleigh & Hegre 2009, Daly 2012, Zhukov 2012). I therefore account for population size per grid cell using HYDE population data (Klein Goldewijk, Beusen & Janssen 2010, Klein Goldewijk et al. 2011, Klein Goldewijk et al. 2017). Lastly, road density affects conflict onset as well, with low density in remote regions making separatist conflicts more likely while urban regions

⁵<https://doi.org/10.7910/DVN/LDI5TK>.

with more developed road networks are associated with governmental conflicts (Buhaug & Rød 2006). In addition, road networks and distances to roads have been shown to have an effect on the spread and location of rebel violence (Zhukov 2012, Hammond 2018). Road density data come from the Digital Chart of the World project (Danko 1991). Summary statistics for all covariates are provided in Table 3.2 below. Continuous covariates are presented in their original format but are logtransformed for subsequent analyses.⁶

The unit of analysis is the PRIO-GRID cell-month. These cells are artificial but equally sized and permanent grid cells which have an edge length of 50 km at the equator (Tollefsen, Strand & Buhaug 2012). I retrieve PRIO-GRID data, and covariates on elevation, forest cover, number of ethnic groups and petrol fields, distance to provincial capitals, road density, GDP and nighttime light emissions using the *xSub* R package (Zhukov, Davenport & Kostyuk 2019). This is complemented by static and annual data for additional variables from PRIO-GRID. After constructing the PRIO-GRID frame for all countries in Africa which experienced a civil conflict according to UCDP, I add the aforementioned information from UCDP GED and GTD to individual cell-months. This provides 1,149,162 unique observations to analyze. I randomly split the data 70:30 into training and test data such that both datasets contain roughly the same share of dependent variable realizations. Regression tables and predicted probabilities represent results using the training data which contain 804,414 observations. Out-of-sample validation is performed with the remaining 344,748 observations. Some variables such as population size, road density, nighttime lights emissions or GDP are not available for the entire time period and I use the k-nearest neighbors algorithm to impute missing values.

Civil conflicts tend to cluster over time and space, and neighborhood effects in armed conflicts are common (Buhaug & Gleditsch 2008). On a subnational level, battle events tend to be spatially and temporally clustered as well (Buhaug & Rød 2006, Aas Rustad, Buhaug, Falch & Gates 2011). Not accounting for these factors will lead to inefficiencies and quite possibly biased results. All models include a temporal lag variable lagging the dependent variable by one month to account for temporal autocorrelation. In addition, models include a spatial lag variable which indicates whether terrorism occurred in a neighboring cell during the same month

⁶Correlation plots of the variables used in the analyses and additional visualizations of covariates in the training and test data can be found in the supplemental material.

TABLE 3.2: Summary statistics for covariates

Statistic	Mean	St. Dev.	Min	Max
Distance to capital	731.611	429.709	3.986	1,947.954
Distance to international border	172.956	144.792	0.029	667.959
Distance to province capital	259.581	216.546	0.000	1,234.060
Diamonds (primary)	0.002	0.044	0	1
Diamonds (secondary)	0.011	0.106	0	1
Drugs	0.022	0.147	0	1
Excluded ethnic groups	0.477	0.667	0	5
Forest	0.041	0.113	0.000	0.964
Urban	0.064	0.503	0.000	19.796
Nightlights sum	906.058	5,091.653	0	171,328
Gemstone	0.004	0.064	0	1
GDP	0.122	0.511	0.000	17.625
Population sum	72,568.420	201,828.500	0.000	8,761,952.000
Mountains	0.138	0.258	0.000	1.000
Petroleum	0.051	0.221	0	1
Road density	0.070	0.084	0.00000	1.576

to account for spatial diffusion of terrorism. To test the hypothesized relationships I use generalized linear mixed effects models. The observations on the monthly level are nested in grid cells which are nested in countries. Thus a three-level random intercept model is appropriate to capture this dynamic. This model enables examining spatial and temporal variation in terrorism while addressing dependence within countries and grid cells over time. Random intercepts account for systematic differences in terrorism occurrence between countries and cells while the slopes, or coefficients, are fixed and assumed constant across all countries and cells (Gelman & Hill 2007). The regression equation for the full model, and the dependent variable occurrence of terrorism⁷, with random intercepts α_j and α_k is as follows:

⁷Changing the dependent variable changes the temporal and spatial lags accordingly.

$$\begin{aligned}
 \text{Terror}_i &\sim \text{Binomial}(n = 1, \text{prob}_{\text{Terror}=1} = \hat{P}) \\
 \log \left[\frac{\hat{P}}{1 - \hat{P}} \right] &= \alpha_{j[i],k[i]} + \beta_1(\text{Rebel casualties}) + \\
 &\quad \beta_2(\text{Clashes}) + \beta_3(\text{Government casualties}) + \\
 &\quad \beta_4(\text{Civilian casualties}) + \beta_5(\text{Terror (temporal lag)}) + \\
 &\quad \beta_6(\text{Distance to international border}) + \beta_7(\text{Distance to province capital}) + \\
 &\quad \beta_8(\text{Road density}) + \beta_9(\text{Mountains}) + \\
 &\quad \beta_{10}(\text{Drought index}) + \beta_{11}(\text{Gemstone}) + \\
 &\quad \beta_{12}(\text{Drugs}) + \beta_{13}(\text{Petroleum}) + \\
 &\quad \beta_{14}(\text{Diamonds (primary)}) + \beta_{15}(\text{Diamonds (secondary)}) + \\
 &\quad \beta_{16}(\text{Nightlights}) + \beta_{17}(\text{GDP}) + \\
 &\quad \beta_{18}(\text{Population size}) + \beta_{19}(\text{Excluded ethnic groups}) + \\
 &\quad \beta_{20}(\text{Terror (spatial lag)}) \\
 \alpha_j &\sim N \left(\gamma_0^\alpha + \gamma_1^\alpha(\text{Distance to capital}) + \gamma_2^\alpha(\text{Forest}) + \gamma_3^\alpha(\text{Urban}), \sigma_{\alpha_j}^2 \right) \\
 &\quad \text{for grid cell } j = 1, \dots, J \\
 \alpha_k &\sim N \left(\mu_{\alpha_k}, \sigma_{\alpha_k}^2 \right) \\
 &\quad \text{for country } k = 1, \dots, K
 \end{aligned}$$

Analyses were done using the R statistical computing environment (R Core Team 2021) including packages such as the *tidyverse* for data manipulation (Wickham et al. 2019), *recipes* from *tidymodels* to impute missing data (Kuhn & Wickham 2021), *lme4* for fitting linear hierarchical models (Bates, Mächler, Bolker, Walker et al. 2015), *lmerTest* to obtain additional metrics (Kuznetsova, Brockhoff & Christensen 2017), *stargazer* to create tables (Hlavac 2022) and *broom.mixed*⁸ to generate custom regression table output, *ggeffects*, *marginalEffects*, and *merTools* to visualize results and calculate quantities of interest (Lüdtke 2018, Arel-Bundock 2022, Knowles & Frederick 2020), *pROC* to obtain and plot area under the curve metrics (Robin, Turck, Hainard, Tiberti, Lisacek, Sanchez & Müller 2011) and *cvms* to generate the confusion matrices and other performance metrics (Jeyaraman, Olsen & Wambugu 2019, Olsen & Zachariae 2020).⁹

⁸<https://github.com/bbolker/broom.mixed>.

⁹In addition, Stata (StataCorp 2021) was used for finding spatial neighbors.

3.6 Results

Table 3.3 shows results for the full models for the four dependent variables.¹⁰ The number of clashes, temporal lags of the dependent variables, and distance to provincial capitals are statistically significant in all models. In substantive terms, a one standard deviation increase in the number of clashes increases the adjusted prediction for terrorism in model 1 by 0.07. In comparison, a one standard deviation increase in distance to the province capital decreases the adjusted prediction by 0.59.¹¹ In addition, distance to international borders, nighttime light emissions, and population size reach conventional levels of statistical significance as well in all models. For model 1, a one standard deviation increase in distance to international borders leads to a change in adjusted predictions by -0.34, a one standard deviation increase in nighttime light emissions leads to a change in adjusted predictions by 0.43, and a one standard deviation increase in population size leads to a change in adjusted predictions of 1.08. All the above mentioned estimates have the same sign across models. There is thus strong evidence for hypothesis 1 that terrorism against any target increases as a result of an increase in clashes. There is also evidence for hypotheses 2 that terrorism against combatants and government personnel becomes less likely after rebel losses and for hypothesis 5 that terrorism against combatants and government personnel becomes more likely after government losses, confirming previous research findings (Kibris 2021). There is, however, no evidence for hypothesis 3 which says that terrorism against civilians becomes more likely after rebel losses. Thus this finding of previous research cannot be confirmed in this setting (Holtermann 2021). There is also no evidence for hypothesis 5 that terrorism against civilians becomes less likely after government losses. The relationship, while positive, does not reach conventional levels of statistical significance.

¹⁰Additional regression tables with different model specifications can be found in the supplemental material. The full models are displayed here and used for calculating quantities of interest as they had the lowest log likelihood and AIC values. It only had the lowest BIC value for one out of four dependent variables, however, compared to more parsimonious model specifications.

¹¹Tables displaying all marginal effects for all models and independent variables can be found in the supplemental material. These marginal effects are contrasts computed with *marginaleffects*, which are defined as "[t]he difference between two adjusted predictions, calculated for meaningfully different regressor values (e.g., College graduates vs. Others)" (Arel-Bundock 2022). The contrasts reported in the paper are statistically significant.

TABLE 3.3: Generalized linear mixed effects regression results

	Terror Model 1	Terror (min) Model 2	Terror (int) Model 3	Terror (max) Model 4
Rebel casualties	−0.183 (0.103)	0.278 (0.224)	−0.531*** (0.145)	0.184 (0.115)
Clashes	3.676*** (0.209)	2.078*** (0.458)	3.998*** (0.259)	2.628*** (0.249)
Government casualties	0.192 (0.113)	0.326 (0.250)	0.361** (0.132)	0.094 (0.145)
Terror temporal lag	2.431*** (0.144)			
Terror (min) temporal lag		2.011** (0.630)		
Terror (int) temporal lag			2.655*** (0.235)	
Terror (max) temporal lag				2.306*** (0.211)
National capital distance	0.221** (0.085)	0.217 (0.188)	0.286** (0.109)	0.153 (0.101)
Border distance	−0.131** (0.048)	−0.282* (0.116)	−0.162* (0.064)	−0.142* (0.059)
Province capital distance	−0.338*** (0.080)	−0.651** (0.202)	−0.427*** (0.105)	−0.370*** (0.098)
Road density	1.328* (0.636)	0.873 (1.551)	0.279 (0.845)	1.939** (0.736)
Drought index	0.116** (0.044)	0.119 (0.142)	0.032 (0.069)	0.132* (0.057)
Petroleum	0.125 (0.213)	0.587 (0.525)	−0.973* (0.411)	0.541* (0.253)
Nightlights	0.148*** (0.025)	0.150* (0.065)	0.177*** (0.036)	0.136*** (0.031)
Population	0.459*** (0.062)	0.410** (0.145)	0.464*** (0.088)	0.435*** (0.077)
Excluded	0.378*** (0.107)	0.208 (0.279)	0.463** (0.150)	0.242 (0.136)
Terror spatial lag	0.025 (0.135)			
Terror (min) spatial lag		−1.443 (0.827)		
Terror (int) spatial lag			−0.358 (0.251)	
Terror (max) spatial lag				−0.346 (0.217)
Constant	−12.805*** (1.098)	−12.177*** (2.401)	−13.606*** (1.493)	−12.393*** (1.330)
Number of countries	32	32	32	32
Number of grid cells	7955	7955	7955	7955
sd(country)	1.028	0	1.142	0.95
sd(grid cell)	0.963	1.492	0.81	1.032
N	804414	804414	804414	804414
Log Likelihood	−3462.879	−453.261	−1622.957	−2240.251
AIC	6977.758	958.522	3297.914	4532.501
BIC	7279.303	1260.067	3599.458	4834.046

***p < .001; **p < .01; *p < .05

Some variables were omitted. Full tables can be found in the supplemental material.

Interestingly, the spatial lag of any of the dependent variables does not reach conventional levels of statistical significance and has a positive sign for the broad definition of terrorism and negative signs for all more specific definitions. Thus there does not seem to be an element of spatial diffusion, or neighborhood effects, for any type of terrorism. Other variables which did not contribute significantly to any of the models presented in Table 3.3 are the number of civilian casualties as a result of battles between government and rebel forces, GDP, and spatial factors such as forest and mountains cover, urban areas, and the presence of gemstone, drug cultivation, and primary and secondary diamonds.

While impact in terms of standard deviations was outlined above, Figure B.15 visualizes the effect of the number of clashes and distance to the provincial capital based on simulation using *merTools*. It illustrates nicely the impact of the number of clashes for different levels of intensity and the general decreasing trend the further away a grid cell is from the province capital. Rugs on the bottom of the plot show data points. For lower levels of conflict intensity, the probability of terrorism is much lower compared to higher levels of conflict intensity. Likewise, the negative effect of distance to the province capital is much more steep for higher levels of conflict intensity.

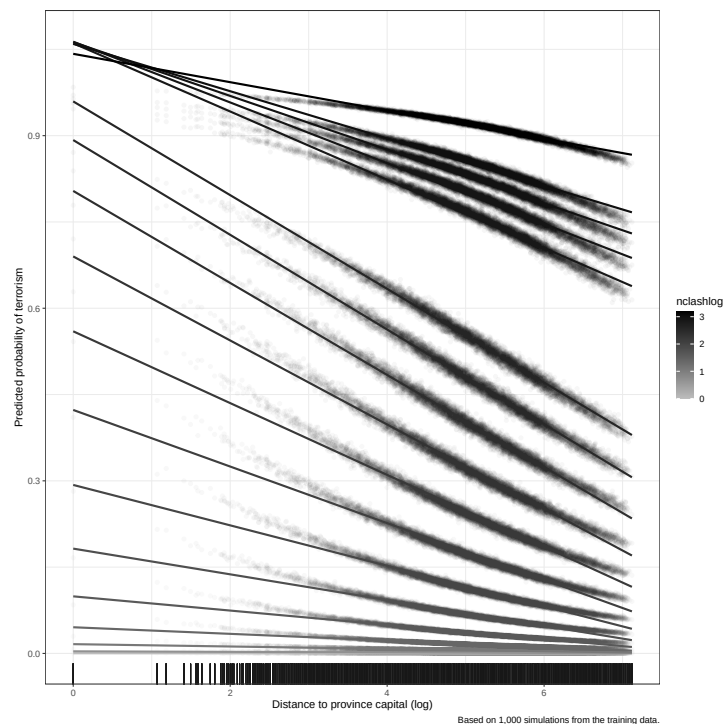


FIGURE 3.2: Substantive effects of distance to province capital and number of battles for model 1.

Other variables only seem to have an effect for a particular type of targets. For example, both rebel and government casualties only impact terrorist attacks on combatants and the government but not attacks against civilians or infrastructure, or indeed the general definition of terrorist attacks. While rebel casualties have a negative effect, government casualties have a positive effect. The result is intuitive, provides evidence for hypothesis 2 that terrorism against combatants and governments becomes less likely after rebel losses, and confirms previous research which looked at conflict diffusion in Turkey (Kibris 2021). Once rebels successfully target security and government personnel they want to uphold the momentum and continue attacking them in the nearby area. However, if rebels suffer losses their ability to fight is at least temporarily reduced and there is a need to regroup, leading to a reduction of future clashes in the vicinity.

Similarly, distance to the national capital only affects terrorism against combatants and the government and terrorism broadly defined. The further away from a national capital, the more likely it is that rebels target other combatants and government forces. Distance to the capital has no effect on terrorist attacks against infrastructure and civilians, however. This speaks for the argument that state capacity diminishes with rising distance to the center of power which makes combatants and government personnel a relatively easier and less guarded target (Schutte 2015, Tollefsen & Buhaug 2015).

Both road density and the drought index only impact terrorism broadly defined and terrorist attacks against civilians. Road density speaks for the idea of conflict diffusion via roads (Zhukov 2012) but future research should look into why this ostensibly only affects terrorist attacks against civilians in civil conflicts but not against combatants and government personnel, especially given the considerable estimate size. Likewise, future research should possibly look into the effect of droughts on terrorism against civilian targets. At first glance, it might provide evidence for the effect of droughts leading to food insecurity. This in turn leads to civilians being more willing to defend their scarce food resources and rebels preemptively targeting civilians to obtain their food supplies (Bagozzi, Koren & Mukherjee 2017). However, the estimate size of the drought index is relatively small and the research design does not allow to establish a causal link so future research should look into this connection more closely.

The presence of oil and gas fields only affects terrorist attacks against combatants and government personnel, and civilians. Interestingly, it has

a negative effect on attacks combatants and government personnel but a positive effect on attacks against civilians. Similar to increased violence against civilians near diamond mines in Sierra Leone (Oswald et al. 2020), this may provide evidence to suggest that rebels coerce civilians in the form of terrorist attacks for the purpose of forced labor to extract natural resources. However, given that this analysis has found no evidence for any other types of natural resources having an effect on terrorism in any form in civil conflicts, and given the relative small effect size while failing to reach desirable levels of statistical significance, this finding should not be overinterpreted.

Excluded relevant ethnic groups only affect terrorism broadly defined and attacks against combatants and government personnel. The presence of excluded ethnic groups increases the probability of both these forms of violence with comparable effect sizes. It makes intuitive sense that rebel groups which presumably represent these excluded groups, do not target infrastructure and civilians upon which they rely but instead on other combatants and government personnel. It seems reasonable to assume that the statistical significance for terrorism broadly defined is driven by attacks against combatants and government personnel.

Turning to variables which are statistically significant across all dependent variables, the number of clashes stands out in terms of effect size and provides evidence for the conflict intensity hypothesis. The more clashes there are between government and rebel forces, the more likely it is to observe terrorism of any kind in the vicinity. In addition, distance to borders and to province capitals have a consistently negative effect on the occurrence of terrorism in any form. However, distance to international borders does not reach desirable levels of statistical significance and the effect sizes are considerably smaller compared to distance to provincial capitals. Nighttime light emissions and population size likewise have consistently positive effects on the occurrence of terrorism. Attacks of any form tend to take place in economically active or residential areas in order to achieve their intended effects beyond the immediate victims. Estimate sizes for both variables are comparable across the different dependent variables, suggesting that the logic applies no matter the form of terrorism.

Lastly, lagged dependent variables are statistically significant and obtain large estimate sizes across all dependent variables too. Areas which saw any kind of terrorism in the previous month are more likely to experience respective form terrorism in the current month. Given this strong

empirical finding, it is surprising that there is no geographical spillover effect in the form of spatial lags of the dependent variables. This suggests that terrorism of any kind is by and large a relatively local affair. This is further corroborated by the fact that only distance to the provincial capital reaches desirable levels of statistical significance compared to distances to both national capitals and international borders. Rebels seem to use terrorism of any kind closer to local rather than national centers of power, and there do not seem to be local spillovers of terrorism of any kind.

To illustrate substantive effects for different levels of random effects, I use *ggeffects*. Marginal effects are calculated for selected countries to illustrate differences. Figure B.16 shows predicted probabilities for Mali, Sierra Leone, Nigeria, Chad, Somalia, Djibouti, Ethiopia, Algeria and Sudan. For each civil conflict, predicted probabilities for terrorism are displayed as a function of the number of clashes and for first, third, fourth quartile values of distance to the provincial capital. In the left panel, one can see immediately the different levels of probabilities for Mali, Chad and Ethiopia. The probability starts rising much earlier and reaches overall higher levels in Mali compared to Chad while Ethiopia has the lowest probability among the nine countries. Likewise, countries like Somalia or Nigeria show higher probabilities for terrorism in their civil conflicts than Sudan or Djibouti.

While the evidence presented above is based purely on in-sample data, an overreliance and sole focus on statistical significance and effect sizes may hide the problem of overfitting and contribute to finding variables which may fit the data at hand well but are of limited importance when using the model for unseen data (Ward, Greenhill & Bakke 2010, Schrodtt 2014). To avoid this issue, I initially left out 30% of all observations for out-of-sample tests. I split the data along the dependent variables such that both training and test data have about the same share of terrorism occurrences. Areas under the receiver-operator curve are generally large for both data partitions, ranging between 0.93 to 0.98 for training data and 0.93 and 0.96 for test data.¹² However, the vast majority of observations does not see occurrences of any type of terrorism. Indeed, terrorism in civil conflicts on the grid cell-month level is a very rare event. As a result, accuracy and specificity values of 1 or 0.999 are driven by correctly

¹²ROC curves, confusion matrices, and further out-of-sample metrics can be found in the supplemental material.

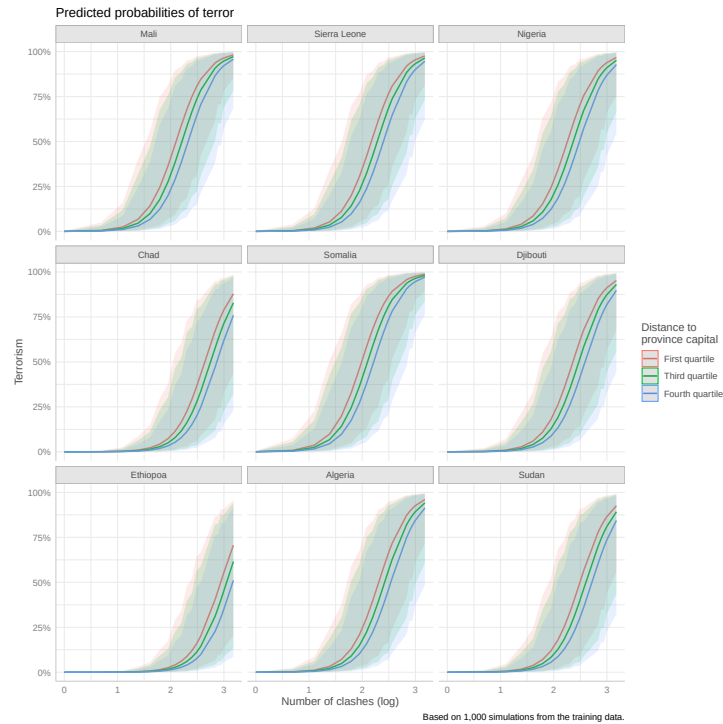


FIGURE 3.3: Substantive effects of distance to province capital and number of battles for model 1 for different countries.

predicting the absence of terrorism of any kind for all models. This is reflected in sensitivity scores ranging from 0.06 to 0.11, which convey the number of relevant observations that were correctly classified or the completeness of the predictions and how many were missed. In contrast to standard accuracy, balanced accuracy is the average of recall, or sensitivity, obtained on each class, thus taking imbalances in the data into account which led to the accuracy rate of 1. It ranges from 0, which would indicate random performance, to 1, which would mean perfect performance. The balanced accuracy ranges from 0.51 to 0.55.¹³ Thus the models are very good in predicting absences of terrorism while the predictive performance for correctly classifying terrorist occurrences of any kind is below desirable levels. We do not seem to be in a position, with the models presented here, to meaningfully predict terrorism in civil conflicts on the grid cell-month level.

¹³The values presented here and in the supplemental material are based on a cutoff of 0.5. Changing these cutoffs to either 0.9 or 0.1 do not alter the conclusions drawn here.

3.7 Discussion and conclusion

This paper investigated the effects of battlefield dynamics on the timing and location of terrorism in civil conflicts. Previous research looked at the timing and location of terrorism in civil conflicts separately, thus the aim of this paper was to build upon these studies and analyze the timing and location jointly. I analyzed terrorism in civil conflicts in Africa between 1989 and 2013 on the grid cell-month level using generalized linear multilevel models including both spatial and temporal lags of the dependent variables. Terrorism was specified in four different ways: making no distinction between targets and terrorist attacks targeting infrastructure (minimum severity), combatants and government (intermediate severity), and civilians (maximum severity), respectively. I found that the number of clashes and distance to province capital are consistently among the strongest predictors of terrorism in civil conflicts across all terrorism specifications. Higher intensity in the form of higher numbers of clashes increases the probability of terrorism in civil conflicts. In contrast, the further the distance to province capitals, the less likely terrorism becomes. Predicted probabilities illustrated the marginal effects of these and other covariates. In addition, temporal lags of the dependent variables have a large substantive effect as well. If a grid cell saw terrorism in the previous month, it is much more likely to see terrorism again in the current month.

While regression results and predicted probabilities showed satisfying results, out-of-sample validation painted a less satisfying picture. Whereas the models obtained very good results in terms of accuracy and specificity, this was largely driven by correctly predicting absences of terrorism in any form. Indeed the vast majority of observations on the grid cell-month level saw no terrorism during the periods under investigation in both the training and test set. Balanced accuracies of around 0.5 and sensitivity values ranging from 0.02 to 0.11 indicate that the models are not particularly fit for predicting these rare events. There are a number of possible reasons for this. For example, I only included terrorist events which can be attributed to known actors in UCDP datasets. However, a substantial amount of events in the GTD are not attributed to actors (Fortna, Lotito & Rubin 2020). Thus among those events included in GTD, there might well be relevant attacks that cannot be conclusively attributed to known actors. In addition, due to reporting bias not all relevant events are included which is not only an issue for GTD but any data collection effort

based on media reports (Drakos & Gofas 2006, Weidmann 2015, Dugan & Distler 2016, Weidmann 2016). A further data related issue is that I only include terrorist events that can be reasonably accurately attributed geographically to the second order administrative region. This decision further restricts the subset of events taken into account since only about 20% of observations in GTD can be attributed to this or an even lower unit (Cook & Weidmann 2022). There are thus inherent limitations in the data on the dependent variables that likely affect the results obtained.

Other issues that have to be taken into account are the period of time and the area under investigation. Following Fortna, Lotito & Rubin (2020), I restrict the time frame to 2013 to be able to obtain more reliable matches between actors in GTD and UCDP GED. This comes at the cost of omitting six years of observations for terrorism in civil conflicts, including for example Libya, Nigeria, Cameroon or Mali. Thus additional and more recent years of observations may help to provide a fuller picture of the phenomenon of terrorism in civil conflicts. Moreover, while Africa is commonly considered typical and representative of civil wars (Thomas 2014, Vüllers & Krtsch 2020), there is evidence to suggest that civil war onsets in for example Africa have different reasons, and baseline risks, than those in the Middle East or Asia (Dixon 2009). Indeed, more recently there has been criticism about the focus on studying civil wars in for example Africa or the Middle East and the lack of studies on civil wars in Asia despite their prevalence (Brenner & Han 2022). There might thus be systematic differences between Africa and other regions of the world which this study cannot account for. In addition, the Syrian civil war and the rise and fall of IS in several countries are for example not part of this study, or temporary flare-ups in other countries such as Turkey starting in 2014. Thus future research may endeavor to confirm findings of this paper by extending the temporal and geographical focus.

Another possible limitation is the use of a generalized linear mixed effects with spatial lags rather than spatial regression models with spatial weights matrices. However, the spatial lags, which indicate whether there was terrorism in any of the adjacent grid cells, in these models did not reach statistical significance at conventional levels. While this is an indication that there may be no spatial element to terrorism in civil conflicts, future research may look more closely into this spatial aspect using spatial regression models (Ward & Gleditsch 2018). The choice of grid cell-months as unit of analysis and the resulting number of observations precluded the

use of spatial regression models due to limitations about the use and computation of spatial weights matrices. Despite these limitations and shortcomings, the paper made a valuable contribution to the study of terrorism in civil conflicts by jointly analyzing the timing and location of terrorism to enhance our understanding of local conflict dynamics and outlined several avenues for future research.

Chapter 4

Margin of (t)error: Predicting terrorism in civil conflicts for theory building and improvement

Abstract

Theories are expected to be able to both explain and predict well. However, many papers are based solely on explanatory power and in-sample evaluation and we cannot judge how well different variables can deal with new data. Terrorism in civil conflicts has seen studies explaining variation in the number and occurrences of terrorist attacks by rebel group, region, and country per month, year and over longer periods of time. They identify group, country and regime characteristics that make terrorism more likely. However, these measures are based on statistical significance and predicted probabilities and their predictive performance is yet to be evaluated. This study fills this gap by testing the predictive power of existing indicators identified in the literature to explain the occurrence of terrorism against soft and hard targets per month by known rebel groups. Random forests are used in combination with interpretable machine learning techniques to illustrate findings intuitively and to go beyond standard measures of accuracy, precision and recall. The empirical evidence suggests that while some variables have very high predictive power, other previously identified explanatory factors appear to be of limited predictive value. These findings and additional interaction effects discovered in the data have important implications for future research. Data-driven theory building and refinement is thus a valuable addition to the research process for the study of terrorism in civil conflicts and beyond.

4.1 Introduction

Terrorism has been a frequently studied subject ever since 9/11. Still, almost two decades later we know relatively little about motivations and causes, not least because the concept itself remains ambiguous and different definitions lead to different conclusions and implications (Sanchez-Cuenca 2014). The study of terrorism has oftentimes been subdivided into studying transnational and domestic terrorism (Sánchez-Cuenca & De la Calle 2009, Enders, Sandler & Gaibulloev 2011, Piazza 2011). In addition, the use of terrorism in civil conflicts has recently received scholarly attention as well. Terrorism occurred in 73 per cent of civil conflicts between 1970 and 2004 (Findley & Young 2012). Studies have explained variation in the number of terrorist attacks in a country, or by a rebel group in a country or region, per month, year or over longer periods of time (Polo & González 2020, Asal et al. 2019, Ash 2018, Fortna, Lotito & Rubin 2018, Polo & Gleditsch 2016, Bakker, Hill Jr & Moore 2016, Coggins 2015, Stanton 2013). They identify group, country and regime characteristics which make groups more likely to use terrorism and regions more prone to terrorism. However, these studies are based on null hypothesis significance testing which may generate misleading results (Ward, Greenhill & Bakke 2010). Indeed, the literature on state repression provides evidence that testing the predictive performance of variables helps to both test theoretical expectations using out-of-sample validation and create new research agendas thus advancing our understanding and the discipline more generally (Hill Jr & Jones 2014). Focusing on predictive power using random forests and cross-validation, this paper seeks to identify which variables drive the success of predictive models as a form of data-driven theory testing and improvement to take stock and outline avenues for future research. Thus the research question of this paper is: *Which factors predict the incidence of terrorist attacks by rebel groups in civil conflicts?*

Whether and under what conditions terrorism can be seen in civil wars has important policy and research implications. Terrorism is, subject to the definition used, a subset of the more general violence against civilians concept. Unlike one-sided violence against civilians as defined by the Uppsala Conflict Data Program, terrorism does not require casualties (Eck & Hultman 2007). Indeed, the general expectation is that terrorism is more about the message it sends to the larger population and a government than

about the immediate victims of an attack. Among the main aims of terrorism are to intimidate the population and to send a signal to this population and the government (Crenshaw 1981, McCormick 2003, Cronin 2009, Hoffman 2006, Kydd & Walter 2006, Stanton 2016). Meanwhile, one-sided violence is used to coerce a local population into cooperation and to establish control, and has thus the victims and witnesses of attacks as audience (Kalyvas 2006, Wood 2014, Polo & González 2020). There is thus no perfect overlap between terrorism and violence against civilians since there are different intentions behind these two tactics rebels can choose from which is what makes studying terrorism in civil conflicts so important (Fortna, Lotito & Rubin 2018, Fortna, Lotito & Rubin 2022). Indeed, the recent release of a new data set combining terrorism with armed conflict data is evidence for the continued interest in, and importance of, the subject (Fortna, Lotito & Rubin 2022). As a result, it is imperative to test the theoretical expectations derived in the literature by evaluating the predictive performance of variables identified as determinants of terrorism in civil wars. It will help to enhance our understanding about if and under what conditions rebel groups decide to use terrorism by determining which variables are more or less important to identify avenues for future research bringing us closer to a unified theory of rebel use of terrorism.

Effect sizes alone are not necessarily good or reliable indicators of how well variables explain variation in outcomes (Ward, Greenhill & Bakke 2010, Lo, Chernoff, Zheng & Lo 2015). Forecasting is also useful to avoid model overfitting and to balance against overreliance on measures of statistical significance. Thus prediction can be regarded as a tool to build, test and improve theories by evaluating the power of individual variables or entire models (Hegre, Metternich, Nygård & Wucherpfennig 2017, Beger, Morgan & Ward 2021). Predictions as such do not require assumptions of causality, but predictions with at least plausible causal claims tend to be stronger. Thus variables which are claimed to be causal should be able to predict well too (Ward & Beger 2017). Predicting for example civil war onset and incidence (Muchlinski, Siroky, He & Kocher 2016, Blair & Sambanis 2020), and the role of theory in predicting these (Beger, Morgan & Ward 2021, Blair & Sambanis 2021), or changes in conflict intensity (Hegre, Allansson, Basedau, Colaresi, Croicu, Fjelde, Hoyles, Hultman, Höglbladh, Jansen et al. 2019, Hegre, Bell, Colaresi, Croicu, Hoyles, Jansen, Leis, Lindqvist-McGowan, Randahl, Rød et al. 2021) have received more attention recently. To the best of my knowledge this has not been the

case for particular tactics or types of violence in civil conflicts on a wider geographical scale.¹ This paper will begin to fill this gap by predicting the incidence of terrorism against hard and soft targets by rebel groups in civil conflicts to test and refine existing theoretical claims and work towards a unified theory of rebel use of terrorism. This is also important because there is still little consensus about the root causes of terrorism (Sandler 2014) and prediction and out-of-sample validation can help to identify variables which make terrorism in civil conflicts more or less likely and by extension help refine existing theories and expectations.

The paper thus makes several contributions. First, it uses a machine learning algorithm and introduces out-of-sample validation to the study of terrorism in civil conflicts thereby extending the modeling approaches used in previous studies. Second, it takes stock of relative variable importances and visualizes variable effects. This is important for our theoretical understanding of terrorism in civil conflicts and serves both theory testing and building. Third, by identifying the relative importance of variables and exploring interaction effects in the data, the paper seeks to establish the foundation for a unified theory for the use of terrorism in civil conflicts by recognized rebel groups. To illustrate the importance of data-driven theory building and improvement, I use replication data from a recent paper (Polo & González 2020). I chose this dataset because it is, to the best of my knowledge, the only published paper about terrorism in civil wars by known rebel groups with monthly rather than annual observations as unit of analysis which also provides a number of relevant variables. It is thus not a duplication study (King 1995) but instead a mixture of verification and extension (Janz & Freese 2021). The aim is not to critique a particular paper, methodology, or findings, but to move the literature forward by using a different empirical approach and assessing the relative importance and effects of individual variables and combinations of these variables to identify and present avenues for future research. It thus falls

¹A few studies have used random forests to predict for example local violence in Libya (Blair, Blattman & Hartman 2017) or Colombia and Indonesia (Bazzi, Blair, Blattman, Dube, Gudgeon & Peck 2022) and state repression on a global level (Hill Jr & Jones 2014). Other studies used machine learning algorithms either in rather specific cases such as transnational terrorism or in a general fashion without distinctions between targets, perpetrators, or attacks types (Python, Bender, Nandi, Hancock, Arambepola, Brand-sch & Lucas 2021, Huamaní, Alicia & Roman-Gonzalez 2020, Guo 2019, Basuchoudhary & Bang 2018, Ding, Ge, Jiang, Fu & Hao 2017, Gelpi & Avdan 2018, Desmarais & Cranmer 2013, Enders, Liu & Prodan 2009) while the focus in this paper is on terrorism in civil conflicts by known rebel groups. There has also been research using predictive modeling for genocide and politicide onset for example (Goldsmith, Butcher, Semenovitch & Sowmya 2013, Goldsmith & Butcher 2018).

in the same category as the empirical evaluation of explanations for state repression by Hill Jr & Jones (2014) which tests the predictive power of variables identified by null hypothesis significance testing.

The paper is structured as follows: first I will outline key theoretical claims in the literature and empirical findings. I will then describe the added value of prediction for theory building and evaluation with the example of civil war onset and incidence and why it is important to use out-of-sample validation for tactics and other types of violence too. A description of the data is followed by the evaluation of predictive performance of explanatory variables using random forests (Breiman 2001a). Tree-based methods are used because they have become more popular in political science recently and they are intuitive compared to other machine learning algorithms such as neural networks. Issues of transparency and interpretability oftentimes surround machine learning (Athey 2017). I therefore use interpretable machine learning techniques to produce intuitive and meaningful quantities of interest (Molnar 2020). Findings suggest that success of the models is mostly driven by a small number of variables such as democracy, time since the last attack, GDP and population size. There are also interesting findings with regards to interaction effects such as for example democracy and religious groups, indicating that religious groups are less likely to use terrorism against hard targets when facing a democratic opponent. The paper concludes with a discussion and the implications of these results and data-driven theory building and outlines several avenues for future research.

4.2 Terrorism in civil conflicts

Factors influencing terrorism in civil conflicts can be categorized in state or government and rebel group features. States which are on the verge of becoming a failed state are more likely to suffer from terrorism. This includes the collapse of government institutions and political systems, intense political instability, emerging anarchy, and involvement in international conflicts (Coggins 2015, Bakker, Hill Jr & Moore 2016). States with democratic institutions are more likely to experience terrorism as well. This relates to the rebel belief that democracies are more sensitive to civilian casualties and as a result easier to persuade and more likely to give in to demands (Stanton 2013, Fortna 2015). Related to democracy, higher levels of media freedom are associated with more terrorist attacks (Polo & Gleditsch 2016).

Factors such as political contestation and participation and civil liberties are likewise related to increases in terrorist attacks in dissident environments (Bakker, Hill Jr & Moore 2016). Lastly, capital cities are more likely to be targets of terrorism and ongoing armed conflict in regions is an indicator of increased terrorism risk too (Ash 2018). Thus state institutions and state fragility are related to the likelihood of terrorism in civil conflicts.

Governments with a history of violence and repression are more likely to suffer from terrorism (Polo & Gleditsch 2016). Indeed, government coercion and limited respect for physical integrity rights make terrorism in dissident environments more likely too. Similarly, violent and nonviolent acts of resistance are linked to increased numbers of terrorist attacks. However, the larger the number of political veto players and the larger the size of the coercive bureaucracy, the less likely terrorism gets (Bakker, Hill Jr & Moore 2016). There is also evidence that police and military operations, as opposed to more conciliatory approaches to accommodate rebel demands, increase the probability of terrorism (Asal et al. 2019). These arguments relate to a reactive or retaliatory nature of terrorism with rebels seeking to punish a government for repressive or punitive actions. Moreover, different religious beliefs among a government and a rebel group makes terrorism much more likely (Fortna 2015). Lastly, relatively deprived regions are also more likely to experience terrorism (Ash 2018) which may speak for government neglect as a factor explaining terrorism.

Weaker rebel groups are more likely to use terrorism whereas stronger groups tend to engage in more conventional warfare (Polo & Gleditsch 2016). This relates to terrorism as being a weapon of the weak (Crenshaw 1981, Merari 1993). It has also been argued that religious groups are more likely to attack civilian targets while groups with a more diverse followership are more likely to attack more official targets. Civilian targets here are classified as soft while official targets such as government personnel are classified as hard (Polo & Gleditsch 2016). Groups which seek broad civilian support, including groups seeking regime change and non-religious goals, are less likely to commit attacks with civilian casualties. In contrast, rebels with more exclusionary goals and those seeking support from specific groups in the population, commonly secessionist or separatist movements or revolutionary organizations with religious objectives, are more likely to attack targets which cause more civilian casualties (Stanton 2013). How rebels finance their armed struggle matters too. If rebels rely on lootable resources rather than local civilian support

to sustain their insurgency, they are more likely to use terrorism. External financial support likewise increases the probability of terrorism but not significantly (Fortna, Lotito & Rubin 2018). Lastly, rebel losses on the battlefield make terrorism as mobilization tool more likely. This mobilization works through provoking a government overreaction and exploiting out-group antagonism (Polo & González 2020). Lastly, rebel group competition makes terrorism more likely too (Ash 2018). There are thus specific characteristics that make the use of terrorism more likely for some groups than for others.

Previous studies have explained variation in the number and occurrence of terrorist attacks for different units of analysis. Explanatory variables used are on the country-, group-, group-region-year and group-conflict-month level and explain which groups are more likely to use terrorism and which administrative regions are more prone to terrorism. However, these studies were based on null hypothesis significance tests and predicted probabilities which gives no indication of how well these variables and models perform with unseen data. Thus we cannot determine with confidence how valuable or important the different identified variables are and ultimately how well the theories are able to predict. This paper seeks to fill this gap by using random forests and out-of-sample cross-validation, calculating relative variable importances, visualizing variable effects, and exploring interaction effects to provide the foundation for a unified theory of rebel use of terrorism in civil conflicts.

4.3 Machine learning, prediction and theory building

While there was some initial divide between what Breiman called the data modeling and algorithmic modeling cultures (Breiman 2001*b*), it has become increasingly more widespread to integrate and combine explanation and prediction approaches in social science research (Hofman, Sharma & Watts 2017, Hofman et al. 2021, ?). The use of prediction and machine learning models has been advocated to build better models in the social and political sciences and to boost external validity (Schrodtt 2014, Hindman 2015, Cranmer & Desmarais 2017, Fariss & Jones 2018). The added value is that prediction improves insight into model fit, provides a benchmarking tool to evaluate the necessary level of model complexity,

and can help to generate insights into complex models (Verhagen 2022). Using predictions generated from machine learning models also improves policy advice since it can pair empirical results and policy more closely (Athey & Imbens 2019). It further allows scrutinizing estimated models and boosts model transparency (Greenhill, Ward & Sacks 2011). Prediction also improves model specification by avoiding overfitting and providing the ability to make models more parsimonious and, because it is data-driven, for estimating models that reflect nature more accurately and include oftentimes unknown patterns in the data (Cranmer & Desmarais 2017).

Machine learning algorithms are argued to be better alternatives to ordinary least squares and logistic or probit regression models because they tend to be better at quantifying uncertainty and producing more accurate out-of-sample predictions. Thus relatively simple machine learning models such as tree-based algorithms have been advocated for theory building and hypothesis testing. Tree-based algorithms such as random forests continuously split the data into two groups by the best-predicting variable(s) and typically outperform regression models, especially when nonlinearities and interactions are at play. They are less sensitive to outliers and it is also easier to communicate the relative importance of different variables. In combination with out-of-sample validation, this leads to overall more robust and reliable empirical findings to make theoretical claims (Hindman 2015).

Prediction is a common feature in political science, for example forecasting election results.² Using machine learning algorithms to predict conflict is likewise becoming more common. For interstate conflicts, it has been shown that machine learning models such as neural networks are able to recognize complex patterns and structures while out-of-sample forecasts avoid the problem of overfitting to predict new militarized interstate disputes (Schrodt 1991, Beck, King & Zeng 2000). Similarly, it has been shown that random forests, and AdaBoosted and gradient boosted trees, improve predictions of civil war onset compared to logistic regression models (Muchlinski et al. 2016, Colaresi & Mahmood 2017, Neunhoeffer & Sternberg 2019, Wang 2019). It has further been shown in the civil war literature that an overreliance on statistical significance in the study of civil war onset led to a neglect of predictive performance. By evaluating

²See for example Stoetzer, Neunhoeffer, Gschwend, Munzert & Sternberg (2019), Wang, Rothschild, Goel & Gelman (2015), Norpoth & Gschwend (2010), or Lewis-Beck (2005).

the predictive power of two influential civil war onset models (Fearon & Laitin 2003, Collier & Hoeffler 2004) it was demonstrated that the inclusion of some statistically significant variables actually reduced predictive performance. This is likely due to model misspecifications and the fact that statistical significance does not necessarily translate into predictive power (Ward, Greenhill & Bakke 2010, Lo et al. 2015). Indeed more recently a distinction has been drawn between statistical and practical or substantive significance (Gross 2015) and calls to redefine or abandon statistical significance garnered widespread attention (Benjamin, Berger, Johannesson, Nosek, Wagenmakers, Berk, Bollen, Brembs, Brown, Camerer et al. 2018, McShane, Gal, Gelman, Robert & Tackett 2019). Prediction thus helps to identify variables which may obtain statistical significance but actually decrease the ability to predict, and vice versa helps to identify which variables increase our ability to predict but may fail to reach conventional levels of statistical significance.

Lastly, theories are designed to be able to make causal claims and ultimately to predict. Thus prediction is considered necessary by some researchers to give causal claims validity, and predictions derived from credible causal claims tend to be stronger. In general, overfitting, meaning a model specification that fits in-sample data very well and picks up noise and idiosyncrasies present in the data, can be a problem and out-of-sample tests provide one safeguard against it. Prediction is also useful to determine substantive effects and their relative importance (Ward & Beger 2017). This paper will use variable importance calculations and accumulated local effects as quantities of interest to determine these substantive effects and importances. For all these reasons, machine learning models, and tree-based algorithms in particular, and out-of-sample validation are valuable tools for data-driven theory building and improvement which should not be neglected.

This paper is thus an exercise in the evaluation of postulated hypothesis and conjectures as argued for the study of international relations and world politics (Ward 2016, Ward 2017). It is also an exercise to provide the foundation for a unified theory of rebel terrorism in civil conflicts allowing the right level of abstraction which is crucial for good theory to be "intellectually interesting, empirically generative, or practically successful" (Healy 2017, 118). The goal is to establish a foundation for a unified theory for rebel use of terrorism in civil conflicts and outline avenues for

future research. In order to do this, the paper takes stock of variables identified, uses random forests and interpretable machine learning techniques to visualize relative variable importance and relative effects of these variables to combine data-driven approaches with traditional theory building. Detection of interaction synergies is further used to outline avenues for future research to come closer to this unified theory.

4.4 Data and methods

Data from Polo & González (2020) are used as it is the most granular and provide a number of the above mentioned variables.³ It contains information about 205 rebel groups in the Middle East, Asia and Africa between 1989 and 2009 on the rebel group-conflict-month level. The data combine information about rebel groups which are present in both the Global Terrorism Database (LaFree & Dugan 2007) and the UCDP Georeferenced Event Dataset (Sundberg & Melander 2013). The procedure of how matching of rebel groups in the two data sets is done so that only groups which are present in both are left while avoiding duplicate events is explained in Polo & Gleditsch (2016). Overall there are 6,642 observations of 47 variables. Removing missing data to perform the analyses leaves 4,928 observations. This is divided into 3,691 observations for training the model and 1,237 observations for out-of-sample testing by splitting the data at the third quantile of the date variable.

I look at two distinct dependent variables: a dichotomous variable indicating whether a conflict has seen one or more terrorist attacks on a soft or hard target in a given month. Hard and official targets are general and diplomatic government personnel, police forces, transportation, telecommunications and utilities as well as food and water supply points, maritime targets, and airports and aircrafts (excluding hijacking). Soft targets are businesses, educational institutions, journalists and media, private citizens and property, religious figures and institutions, tourists, and other

³It is important to briefly note the difference between the analyses in this paper and the analyses in Polo & González (2020). The models in Polo & González (2020) included the variables relative government losses (lag), rebel group competition, rebel centralized leadership, external support rebel groups, conflict intensification, territorial conflict, democracy, GDP (log), and time since last attack (normal, squared, and cubed), plus repression (PTS 2-5 year moving average), relative rebel losses (lag), and the interaction between the two to test the first hypothesis, and out-group antagonism, relative rebel losses (lag), and the interaction of the two to test the second hypothesis. Remaining variables were used as alternative independent variables in the supplemental material. In this analysis, *all* variables are used.

targets such as ambulances or refugee camps (Polo & Gleditsch 2016). About one third of the observations is a case of hard terrorism while less than one quarter of cases are categorized as soft terrorism.

There are a number of independent variables or features considered. The main variables reflect government repression and battle losses. One operationalization of government repression is using the Political Terror Scale, PTS (Wood & Gibney 2010). This 5 point scale indicates the level of government repression in a particular country and year with higher values indicating higher levels and lower levels indicating less repression. The scores are hand-coded based on human rights reports provided by Amnesty International and the US State Department. A four-year moving average is used to capture the effect of repression over time. Another operationalization is using respect for physical integrity rights (Fariss 2014). The main difference is that while PTS is based on reports and requires human coders, respect for physical integrity rights is estimated as a latent variable based on binary and event measures of repression reflecting changes in government accountability for violations of physical integrity rights.

The role of ethnicity has been a longstanding subject of interest in civil wars. It has been found that exclusion of politically relevant ethnic groups contributes to civil war duration once violent conflict has started (Wucherpfennig, Metternich, Cederman & Gleditsch 2012). It is likewise plausible that rebel groups are more likely to target members of other ethnic groups. The data thus include variables which capture whether a rebel group claims to exclusively fight on behalf of a specific ethnic group, and whether there is direct or indirect evidence for it, whether it recruits from a specific ethnic group, and whether a rebel group is supported by at least half of the members of a specific ethnic group. In addition, out-group antagonism is a dichotomous variable indicating whether a rebel group has any of the abovementioned ties to an ethnic or religious group in society. Data for ethnic ties come from ACD2EPR (Wucherpfennig et al. 2012) and coding of religious groups by Polo & González (2020).

There are a number of rebel group-related factors which may affect the use of terrorism. To capture the possible reactive nature of terrorism in response to battle dynamics, the data include variables for both rebel and government losses in relation to their overall troop sizes. Relative rebel and government losses are calculated using information about casualties and troop sizes. Rebel and government troop sizes are derived from

Wood (2014) and complemented with information from the UCDP Conflict Encyclopedia. Data on rebel and government losses come from the UCDP Georeferenced Event Dataset (Sundberg & Melander 2013). The variables are lagged by one month. There is an additional variable indicating whether a rebel group suffered any casualties at all in the previous month. Moreover, a history of civilian victimization may indicate a general willingness to target civilians on the rebel side and can be considered another measure for repression on the government side. There are thus several variables capturing the amount of rebel and government one-sided violence against civilians (Eck & Hultman 2007). It is important to note the difference between rebel terrorism against soft targets and rebel one-sided violence against civilians: one-sided violence against civilians is designed to influence a local population to cooperate and to establish some level of control whereas terrorist attacks against soft targets is designed to influence the government to make concessions and the wider population to attract recruits and draw support away from the government (Kalyvas 2006, Wood 2014, Polo & González 2020). While the targets are civilian for both concepts, they are conceptually distinct from each other because the individual attacks have different underlying intentions, aims, and target audiences. It is further plausible that the presence of competing rebel groups increases the likelihood of terrorism (Wood & Kathman 2015). There is thus a variable which captures the number of rebel groups involved in the same conflict. In addition, the internal structure of rebel groups is important as the level of leadership control over its rank and file may affect the prevalence of terrorism (Abrahms & Potter 2015). Furthermore, there is also evidence that weaker groups tend to use terrorism more often than stronger groups since stronger groups can engage more in conventional warfare (Polo & Gleditsch 2016). The data thus include information from the nonstate actor dataset to differentiate between strong leaderships and internal factionalizations and between weak and strong rebels (Cunningham, Skrede Gleditsch & Salehyan 2009, Cunningham, Gleditsch & Salehyan 2013). In addition, rebel groups which receive external support may be more inclined to use terrorism because they are less reliant on civilian support. I therefore include a variable which captures whether a group receives external support (Högbladh, Pettersson & Themnér 2011). Ideology and religion may affect the decision to use terrorism too (Polo & Gleditsch 2016). Variables capturing whether groups are religious or ethnoreligious account for this possibility. Territorial control

may also influence whether groups use terrorism (De la Calle & Sánchez-Cuenca 2012). A binary variable thus captures whether a particular rebel group controls territory. Lastly, time since the last terrorist attack is included to account for the fact that groups which use terrorism may tend to do so on a regular and frequent basis. The data also include the squared and cubed time since the last terrorist attack to account for nonlinear temporal dynamics (Carter & Signorino 2010).

Conflict- and country-related features may affect the likelihood of terrorism too. First, conflict intensification captures the change in battle-related deaths compared to the previous month. Continuous intensification may affect the decision to use terrorism in addition to, or alongside, more conventional warfare. Second, territorial conflict indicates whether a conflict is about secession or self-determination and may affect the decision to use terrorism. Rebels in conflicts over territory rather than government may be more likely to use terrorism since they do not seek legitimacy across the entire population. Third, GDP per capita reflects development and generally low levels of GDP are linked with higher levels of violence. Fourth, population size is linked to conflict since it increases both the recruitment and target pool for rebel groups. Fifth, democracy has long been associated with terrorism. There is thus a binary indicator for democracy (Vreeland 2008). Lastly, leadership change may influence conflict dynamics too, changing incentive structures for both the government and rebel groups. A binary variable captures whether there was a recent change in leadership with data coming from CHISOLS (Mattes, Leeds & Matsumura 2016).

To train the data and generate predictions I use random forests to evaluate and illustrate predictive performance of the above mentioned variables (Breiman 2001a).⁴ Random forests have been used more frequently in conflict research as well, for example to predict civil war onsets (Muchlinski et al. 2016, Blair & Sambanis 2020), changes in conflict intensity (Hegre et al. 2019), types of local violence (Blair, Blattman & Hartman 2017), local violence in Indonesia and Colombia (Bazzi et al. 2022), and to test the predictive power of measures associated with state repression (Hill Jr & Jones 2014). I use random forests for classifying the incidence of terrorism

⁴I chose to refrain from using ensemble methods to keep the focus on variable importance and predictive performance using fairly well known and intuitive yet powerful machine learning methods. The focus of this paper is on variable importance and theory building rather than achieving higher predictive performance using for example ensemble Bayesian model averaging (Montgomery & Nyhan 2010, Montgomery, Hollenbach & Ward 2012, Beger, Dorff & Ward 2016).

against hard and soft targets. All predictors except binary variables were centered and scaled prior to analyses.

Random forests grow a number of independent decision trees on bootstrapped samples of the training data and predictors. Decision trees are flexible models which split the data into subsets according to variable values which produce different outcome values. Recursive binary splitting begins at the top of the tree and splits the space of predictors to minimize prediction error. The random forest averages the predictions produced by all the independent decision trees grown to improve predictive performance (Breiman 2001a). Variance and extra trees⁵ split rules are tested and 1,000 trees grown for each model. This procedure is repeated five times with ten-fold cross-validation. The metric of interest to select the best models is the area under the receiver-operator-curve (ROC) for classification tasks. I use permutation as measure of feature importance. Permutation importance randomly permutes values of a feature and measures the resulting error increase (Altmann, Tološi, Sander & Lengauer 2010).⁶ Furthermore, interpretable machine learning techniques such as accumulated local effects alongside variable importance will be used to both illustrate results more intuitively and highlight feature effects (Molnar 2020).

All analyses were done in the R statistical computing environment (R Core Team 2021). Random forests are trained using the *caret* and *ranger* packages and quantities of interest were calculated and visualized using the *iml* package (Kuhn 2008, Wright & Ziegler 2017, Molnar, Casalicchio & Bischl 2018). Other packages used include the *tidyverse* for data manipulation and visualization (Wickham et al. 2019), *pROC* to obtain and plot area under the curve metrics (Robin et al. 2011) and *cvms* to generate the confusion matrices and other performance metrics (Jeyaraman, Olsen & Wambugu 2019, Olsen & Zachariae 2020).

⁵Extra trees refers to extremely randomized trees (Geurts, Ernst & Wehenkel 2006). This means that random split points are drawn from a uniform distribution ranging from the minimum to maximum covariate values for continuous variables. For categorical variables the union of two subsets, a random subset of all covariate values in the current node and a second subset of all covariate values not in the current node, which generates the best score is selected as the split.

⁶Another option would have been impurity instead of permutation. Impurity refers to Gini importance and calculates feature importance as the number of splits which include a particular feature divided by the number of samples the feature splits. However, it tends to be biased towards variables with many possible split points and while recent advances have mitigated this bias to some extent (Nembrini, König & Wright 2018), I still opt for the computationally less efficient but less biased permutation method.

4.5 Results

After briefly presenting performance metrics, I will discuss variable importance, present accumulated local effects for the nine most important variables, present interaction strength plots and subsequently accumulated local effects plots for selected pairings of variables with high interaction strengths. This will help determine which variables, and combinations of variables, are important for model performance from a data-driven point of view and will be paired with theoretical considerations to discuss avenues for future research. I will do this first for terrorism against hard targets, followed by a section on terrorism against soft targets.

4.5.1 Incidence of terrorism against hard targets

The ROC metric is 0.956 for the training data and 0.813 for the test data. The final model has nine random predictor variables and extra trees as split rule with a minimum node size of 20. The out-of-bag prediction error (Brier score) is 0.143.⁷ The focus, however, is less on how well these models predict terrorism in civil conflicts, which is decent, and more on which variables are particularly important for the prediction success and in what way. This is not to say that variables ranking relatively low are unimportant, but the high ranking variables are the ones ultimately driving the success of the models.

Figure 4.1 shows variable importance based on permutation. Democracy is the most important feature by far. The connection between terrorism and democracy in general has been of scholarly and policy interest for decades (Schmid 1992, Weinberg & Eubank 1998, Eubank & Weinberg 2001, Chenoweth 2013) and we will return to this in the discussion section. Democracy is followed by time since the last terrorist attack. Past violence as important factor is a common finding in the political violence literature. There have been for example a number of studies seeking to explain the fact that many countries see civil wars recurring (Berg 2020, Rudloff & Findley 2016, Zeigler 2016). These two features are followed by GDP per capita and population size. There also seem to be rebel groups which are inherently more likely to make use of terrorist attacks against hard targets than others. Other features of relative importance are time since the last

⁷Tuning parameter search plots, confusion matrices, ROC plots and further performance metrics are provided in the supplemental material.

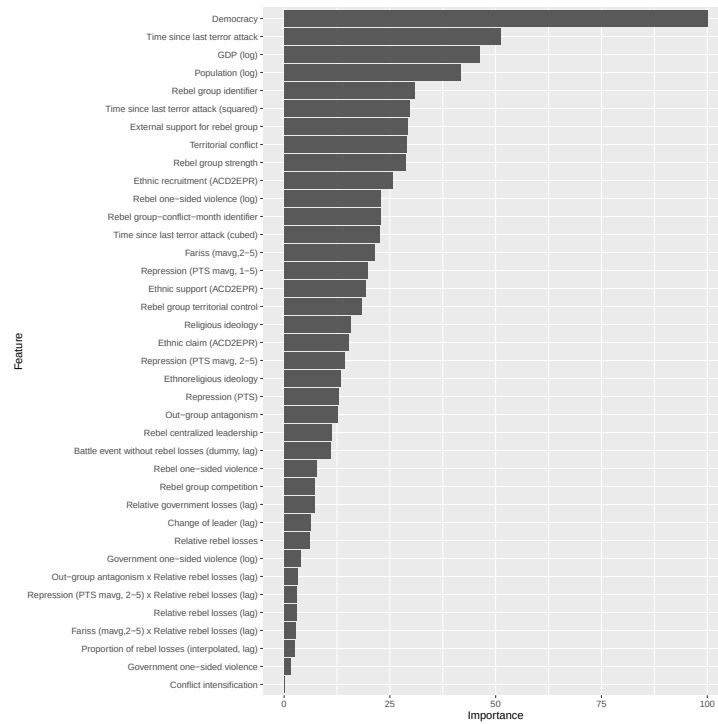


FIGURE 4.1: Variable importance for monthly terrorist incidence against hard targets.

terrorist attack squared, external rebel support, territorial conflict, rebel group strength, and ethnic recruitment.

In addition to ethnic recruitment, which captures whether there is an active recruitment process along ethnic lines present, ethnic support ranks relatively highly too. This captures whether a rebel group has support of at least 50percent of an ethnic group (Wucherpfennig et al. 2012). Interestingly, variables relating to both government and rebel losses are among the least important features to predict the monthly incidence of terrorism against hard targets. Likewise, measures of one-sided violence and violence against civilians by the government are among the least important features whereas rebel violence against civilians seems to be more important. Measures of repression, however, rank moderately highly, both in terms of political terror (PTS) and physical integrity rights (Fariss). Lastly, conflict intensification is the least important feature in this setting.

Effects of the nine most important variables are illustrated through accumulated local effects (ALE) plots to make them more interpretable and intuitive. ALE plots visualize how features affect the prediction of a machine learning model on average. They are a faster and unbiased alternative to partial dependence plots which tend to show bias when a feature

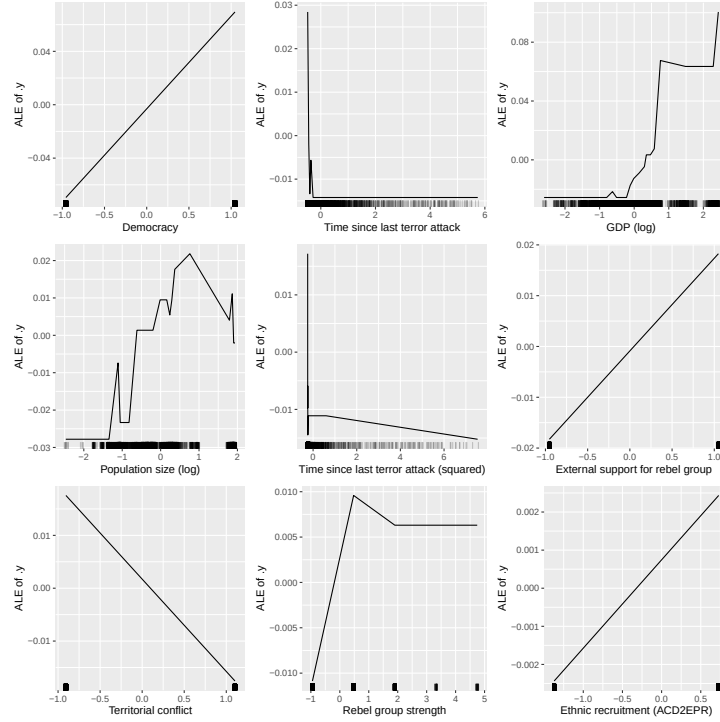


FIGURE 4.2: Accumulated local effects for important features for terrorist incidence (permutation).

and the outcome are correlated (Apley & Zhu 2020).⁸ ALE plots show feature distributions in the form of rugs indicating data points on the x-axis and plots are centered at zero. The ALE value at each point on the curve is the difference to the mean prediction of the model. In other words, it is the relative effect of changing a specific feature on the prediction conditional on a given value of that feature. It isolates the effect of one feature by altering values of this feature to calculate the effective change on model predictions (Molnar 2020). ALE plots for the nine most important features are shown in Figure 4.2.

Democracy as the most important feature shows a positive relationship with terrorist incidence. It increases the average prediction by about five percent. This lends support for theories suggesting that democracies are

⁸A partial dependence plot visualizes the marginal effect one or more features have on model predictions (Friedman 2001). It is able to visualize linear, monotonic, or more complex relationships between the outcome and the selected feature(s) (Molnar 2020). It thus illustrates how one or more features change the average prediction. The relationship between the feature(s) and the outcome is causal in the model but it does not necessarily indicate a causal relationship in the real world (Zhao & Hastie 2021). However, this direct interpretation is only plausible if the assumption that the features are independent holds. If features are correlated, for example urban and population size or density, we may create unrealistic new data points since we would average over the marginal distribution of population size and would thus take high population values into consideration for a low value of urban (Molnar 2020).

more popular terrorism targets as they are expected to be more vulnerable to (civilian) casualties (Stanton 2013, Fortna 2015). Time since the last attack, both regular and squared, has the largest effect in small intervals, increasing the average prediction by about three percent. Thus most groups tend to use terrorism regularly rather than sporadically or in a more selective way. The longer a group has not used terrorism against hard targets, the less likely the group becomes to revive this tactic. GDP per capita indicates that the effect is largest in comparatively wealthy countries and even negative in comparatively poorer countries. At intermediate levels of GDP it does not change the average prediction considerably but there is a sharp jump to about six or seven percent increases while at the highest levels of GDP in the data, average predictions increase by 10 percent. In contrast, population size has the largest impact in countries with moderate population sizes but there appears to be a nonlinear effect. However, the steep decline observed may be driven by the absence of data points in this range and the effects are only about one or two percent changes in average predictions.

External rebel group support increases the average prediction of terrorism against hard targets by two percent. This points to previous suggestions in the literature that groups which are more reliant on local support tend to use terrorism less while groups obtaining external support and are thus less reliant on local support are more likely to use terrorism (Fortna, Lotito & Rubin 2018). Conflict about territory points to the importance of what type of conflict is fought. It changes the average prediction by two percent. This is in line with previous findings about in-group and out-group dynamics arguing that for example groups with more inclusive audiences are less likely to use terrorism, and refrain more from high casualty attacks, than groups with more narrowly defined audiences (Polo & Gleditsch 2016, Stanton 2013). Thus groups aiming for regime change or territorial independence, and thus having to seek support and legitimacy from wider parts of the population and the international community, are less likely to use terrorism. This also links to the fact that external public opinion decreases if rebel groups use terrorism (Arves, Cunningham & McCulloch 2019). Rebel group strength indicates that weaker rebel groups are more likely to use terrorism than both very weak and relatively stronger groups. This runs somewhat contrary to the common perception that terrorism is a weapon of the weak (Crenshaw 1981, Merari 1993). However, the change in average predictions is moderate at one percent.

Lastly, ethnic recruitment makes terrorism more likely too. The change in average predictions is almost negligible, however. Still, this likewise points to in-group dynamics having an effect on the choice of whether to use terrorism or not.

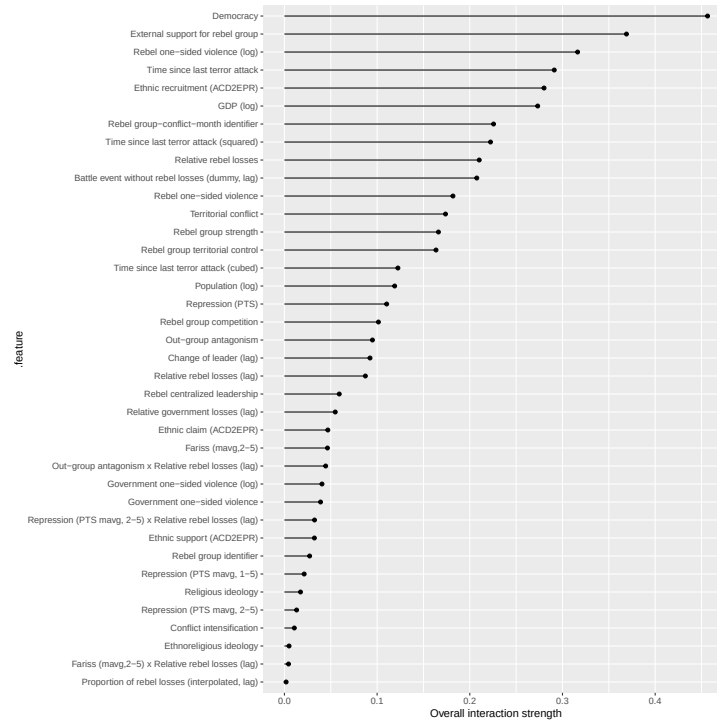


FIGURE 4.3: Variable interaction strengths for monthly terrorist incidence (permutation).

Now that we have established which variables drive the success of the model, I look at individual interaction strengths of the variables included. Interactions between features are measured via decomposition of the prediction function. It is estimated via Friedman's H-statistic which measures how much of the variation of the prediction depends on the interaction of the features and ranges between 0 (no interaction) and 1. An interaction plot shows the potential a variable has to be part of an interaction term but it does not necessarily follow that the two variables with the highest scores are part of a common interaction term. Likewise it does not tell us what the interaction effect looks like. I focus on variables with an H-statistic of 0.2 or higher which is an arbitrary but reasonable threshold given interactions strengths detected in the data.

Figure 4.3 suggests to look more closely at democracy, external support, rebel one-sided violence against civilians, time since the last terrorist attack against hard targets, ethnic recruitment, GDP per capita, time since the last terrorist attack (squared), relative rebel losses, and battle events

without rebel losses. Interaction plots looking at these variables individually to identify possible and reasonable interaction terms are in the supplemental material. Instead, accumulated local effects (ALE) plots for selected variables are displayed below to illustrate these possible interaction effects. It is important to note here that the interpretation of interaction effects is slightly different from interpreting the effect of an individual feature. Instead, it illustrates second-order effects of the combination of the two features. This means that ALE plots of interaction effects only show the additional effect of the interaction without taking the main effects of the individual features, i.e. the effects displayed in Figure 4.2 for the nine most important features, into account (Apley & Zhu 2020, Molnar 2020).

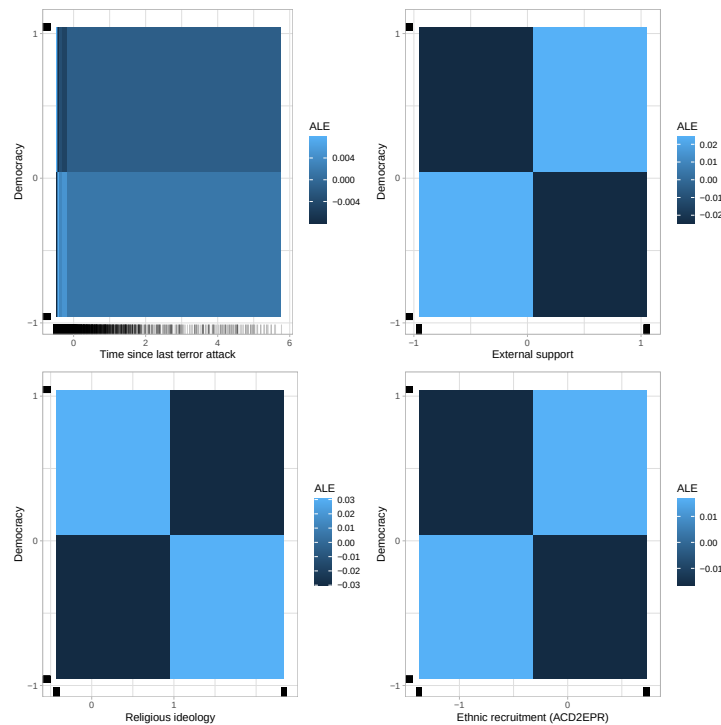


FIGURE 4.4: Interaction effects for terrorist incidence (permutation): Democracy.

Figure 4.4 illustrates the effect of democracy interacted with the four relevant features it had sizable interaction strengths with: time since the last terror attack, external support, religious ideology, and ethnic recruitment. Democracy was the most important feature for predicting terrorism against hard targets. What the four plots have in common is that democracy has a positive effect on the probability of terrorism, indicated by the shading of the color getting lighter in the upper part of the plots. Looking at the interaction of terrorism and time since the last terror attack, it appears that the effect of democracy is only present if a rebel group uses

terrorism on a regular basis rather than sporadically or occasionally. This is an important finding: it indicates that if democracies tend to be the opponents in civil conflicts, terrorism against hard targets on a regular basis is much more likely compared to nondemocracies. The added effect of the interaction to the individual effects is relatively small, however, with around one percent. The interaction of democracy and external support likewise shows that the effect of external support only sets in with the switch from nondemocracy to democracy. The additional combined effect of democracy and external support is a 2.5 percent increase in the average prediction of terrorism against hard targets whereas there is negative effect of external support with regards to nondemocracies. It is important to remember here that democracies have a higher baseline risk as demonstrated in Figure 4.2. Turning to religious ideology, the plot on the lower left shows that it has a dampening effect on the average prediction of terrorism against hard targets. If a nonreligious group faces a democracy the average prediction decreases by three percent whereas it increases by three percent against nondemocracies. Notice that religious ideology did not rank highly in terms of variable importance, thus it does not trump democracy in terms of importance but it does have a substantive effect in combination with democracy. Lastly, ethnic recruitment in combination with democracy changes the average prediction by around two percent.

Turning to external support as one further example of this data-driven approach, I look at interaction effects with population size, rebel group strength, repression (PTS), and ethnic support as those were the features with the highest interaction strengths.⁹ At lower levels of population size, the average prediction of terrorism against hard targets is decreased which quickly increases for intermediate levels of population size only to decrease again slightly for larger levels. These effect change the average predictions by around two percent. The effect for rebel group strength in interaction with external support is strongest for stronger rebel groups with external support, and almost identical for weaker groups no matter whether they receive external support or not. The effects are very marginal, however. Repression (PTS) interacted with external support has its largest effect for lower levels of repression; a repression level of 2 (out of 5) in combination with external support shows a one percent change of the average prediction of terrorism against hard targets whereas the absence

⁹Interaction strength plots and several more ALE plots can be found in the supplemental material.

of external support increases the average prediction slightly at higher levels of repression. Lastly, the interaction of external support and ethnic support has its biggest impact in the presence of external but absence of ethnic support. The effect is below one percent, however. One further interesting aspect are interaction effects of relative rebel losses and rebel group strength.¹⁰ Relative rebel losses interacted with rebel group strength have no effect at all for low and intermediate levels of losses, but show increases of 40 to 50 percent for rebel groups which are not very weak for high levels of losses. However, given the relatively few data points on these high levels of relative rebel losses, this finding should not be overestimated.

4.5.2 Incidence of soft terrorism

The ROC metric is 0.948 for the training data and 0.799 for the test data. The tuning parameters to maximize the area under the curve are eight randomly selected predictors with a minimum node size of 25 and splitting by extra trees. The out-of-bag prediction error (Brier score) is 0.127.¹¹

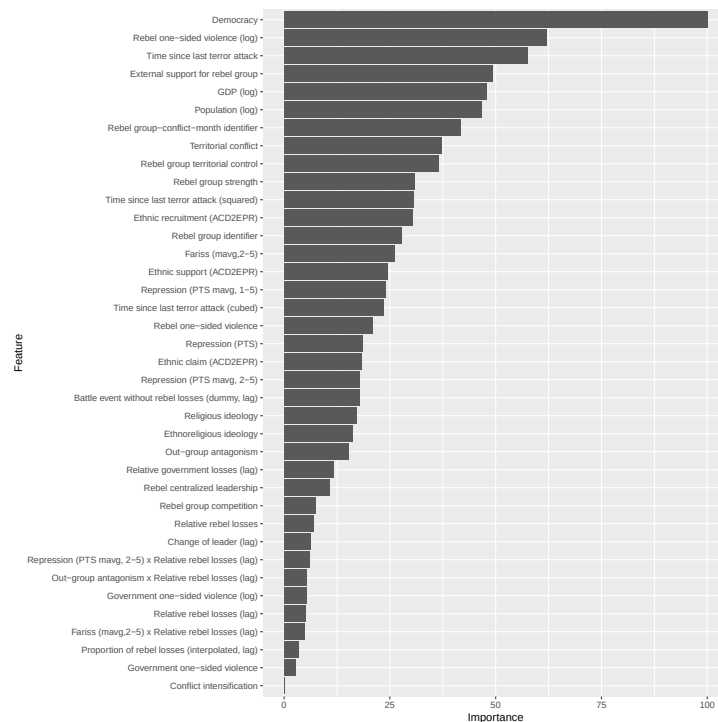


FIGURE 4.5: Variable importance for monthly soft terrorist incidence (permutation).

¹⁰ALE plots are in the supplemental material.

¹¹Tuning parameter search plots, confusion matrices, and ROC plots can be found in the supplemental material.

Figure 4.5 shows variable importance by permutation for the monthly incidence of terrorism against soft targets. Democracy is again the most important feature by far. The fact that this dummy variable seems to be equally important for terrorist attacks against both hard and soft targets will be discussed in detail in the following section. Democracy is followed by rebel one-sided violence against civilians. Rebels which target civilians more often in general are also more likely or inclined to target soft targets, which do include private citizens and property, with terrorist attacks. Time since the last attack is, like with terrorism against hard targets, of great importance and the effect will be visualized below. This is followed by external support for a rebel group. It ranks more highly for terrorism against soft targets compared to hard targets. GDP per capita and population size, also comparable to terrorism against hard targets, rank relatively highly. Other variables worth mentioning are territorial conflict, rebel group territorial control, and rebel group strength. The mentioned features are illustrated with ALE plots below to visualize their substantive effects.

However, it is equally interesting to note which features did not contribute (as) much to the success of the models. Ethnicity does not seem to be a driving factor in the decision to attack soft targets. While some of the features such as ethnic recruitment and support rank relatively highly, none of the ethnicity-related variables are among the ten most important features. Likewise, no measure of repression is among the ten most important features. The most important feature relating to rebel losses is the variable indicating that there were no rebel losses at all, while relative rebel losses, current, lagged, or in combination with other variables are among the least important features driving the success of the model. Other low-ranking features relate to government one-sided violence against civilians and overall conflict intensification. Thus it appears that ethnicity, repression, rebel losses and government violence against civilians are secondary, if not tertiary, in rebel decision-making to use terrorism against soft targets but future research should seek to confirm this notion. Lastly, while previous research found that rebel group competition leads to an increase in civilian victimization (Wood & Kathman 2015), there is not much evidence in this data-driven approach that such competition drives terrorism against soft targets.

ALE plots for the nine most important features are shown in Figure 4.6. Rebel groups facing a democratic opponent makes soft terrorist incidences

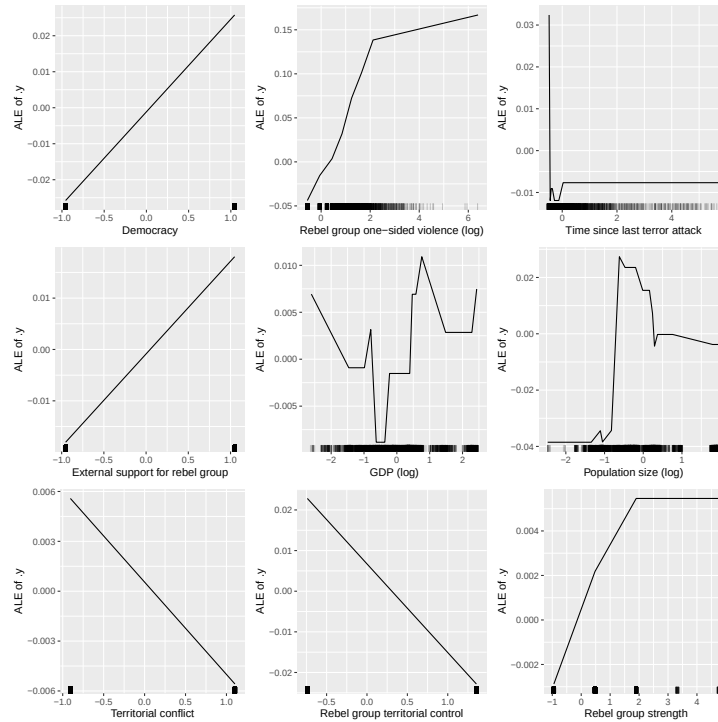


FIGURE 4.6: Accumulated local effects for important features for soft terrorist incidence (permutation).

more likely. It increases the average prediction by about two percent. Likewise rebel groups with a history of civilian victimization are more likely to attack soft targets as well. The effect is more substantial and relatively quickly leads to an increase in the average prediction of ten and more percent while the effect increases steadily but less sharply after. Time since the last attack has its strongest effect for groups which use terrorism regularly. Once a few months without soft terrorist incidences have passed, it gets less likely that groups attack soft targets again and the average prediction decreases. Similar to attacking hard targets, external support for a rebel group has a positive effect on attacking soft targets. The increase of the average prediction is about two percent and comparable to terrorism against hard targets.

The most striking difference in terms of effect can be observed for GDP per capita. While for terrorism against hard targets, the effect was initially negative and increased or remained on the same level for higher levels of GDP, there is a more complex effect on terrorism against soft targets. Whereas initially for very low levels of GDP, the average prediction increases, for intermediate levels of GDP the average prediction decreases

only to increase again for higher levels of GDP with both positive and negative spikes in between. However, the substantive effect is almost negligible with a maximum effect of about one percent while it reached up to ten percent increases in the average prediction for hard targets. The effect of population size is similar to attacks against soft targets, reaching a maximum of an increase of the average prediction of below three percent. It is noteworthy that the effect on terrorism against soft targets is negative and decreases the average prediction by about four percent for low and very low levels of population size while there is next to no effect for high and very high levels of population size.

Rebel territorial control and conflict over territory decrease the average prediction for soft terrorism incidence. As for terrorism against hard targets, territorial conflict likely leads to rebel groups refraining from high casualty attacks, especially against civilians, because they want to seek support and legitimacy from a wider part of the population and the international community more generally (Stanton 2013, Polo & Gleditsch 2016, Arves, Cunningham & McCulloch 2019). However, the effect of conflict over territory does not change the average prediction by even one percent so the substantive effect seems almost negligible. The effect of rebel group territorial control is more substantive and decreases the average prediction by about two percent. The effect of rebel group strength is similar to terrorism against hard targets but the substantive effect is smaller. The average prediction decreases for very weak groups but increases for any other level of group strength. However, the substantive effect in percentage points is smaller than plus or minus one.

Figure 4.7 shows interaction strengths for all variables. Taking an H-statistic of 0.2 or higher as a cutoff again, it suggests looking at several different variables more closely, and many more compared to terrorism against hard targets. Increasing the cutoff for the H-statistic to 0.3 would make this difference even more pronounced. Without overinterpreting this fact too much, it does suggest that rebel group decisions attacking soft targets are more layered or complex compared to attacking hard targets. Another way of interpreting this is that attacks against hard targets seem to be more straightforward whereas more, and more different, considerations have to be taken into account by rebels when it comes to attacks against soft targets. Such an interpretation does make intuitive sense, however, since for example government personnel and police forces as hard targets do represent the enemy and are thus natural targets in

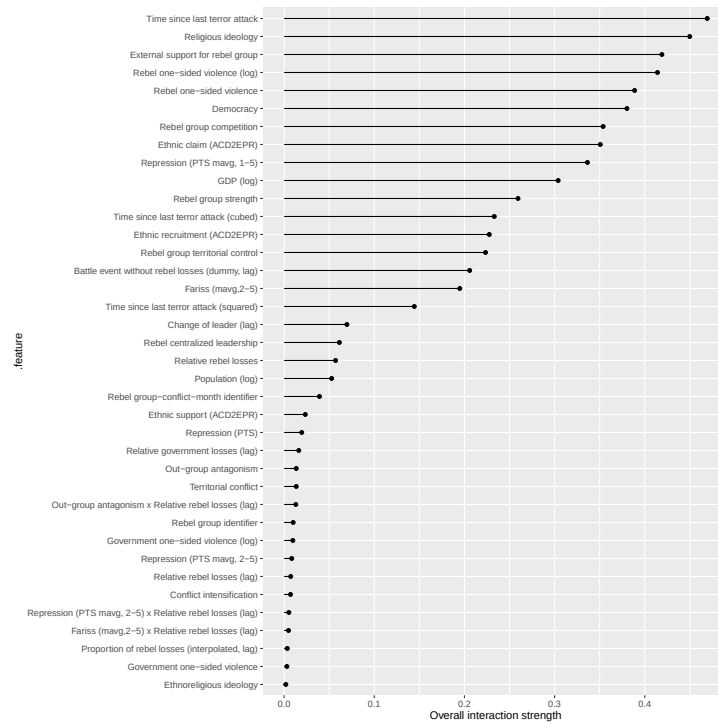


FIGURE 4.7: Variable interaction strengths for monthly soft terrorist incidence (permutation).

civil conflicts. This topic will be discussed in more detail in the following section. Features I will look more closely into are time since the last terror attack (normal and cubed), religious ideology, external support for a rebel group, rebel one-sided violence (normal and logged), democracy, rebel group competition, ethnic claims and recruitment of rebel groups, repression (PTS and Fariss moving average), GDP per capita, rebel group strength, rebel group territorial control, and battles without rebel losses. Plots for individual variables are provided in the supplemental material.

Figure 4.8 visualizes interaction effects between rebel one-sided violence and the first four variables with high interaction strength: democracy, GDP per capita, out-group antagonism, and external support for a rebel group, respectively. The first thing to notice is that rebel one-sided violence only has a positive effect in nondemocracies and a negative effect in democracies, increasing or decreasing the average prediction by about two percent. However, for most data points for rebel one-sided violence the increase of the average prediction is slightly lower than that. Looking at GDP the effect is generally negative for relatively low levels and increases to changes to the average prediction of 20 percent or more. The effect is larger for very large levels of rebel one-sided violence but again

with relatively few actual data points. Out-group antagonism has a positive effect but the changes to the average prediction are very marginal at levels well below one percent. Lastly, external support has a negative effect in combination with rebel one-sided violence, indicating that if rebels are not reliant on local support, they become less likely to target civilians to establish control and coerce them into cooperation.

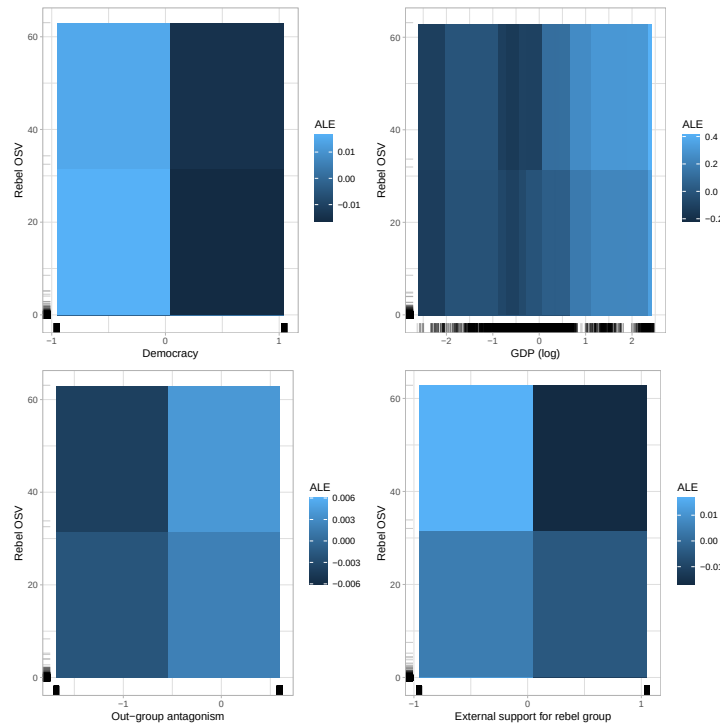


FIGURE 4.8: Interaction effects for monthly soft terrorist incidence (permutation): Rebel one-sided violence.

Compared to terrorism against hard targets, where democracy in interaction with other features reached effects of four percent and more on the average prediction, the effect on its own and in interaction with other variables is less pronounced when predicting terrorism against soft targets while still being the most important feature.¹² For example, in interaction with external support for a rebel group, the average prediction of terrorism against soft targets increases by one percent. The interaction with territorial conflict produces a negative change for the average prediction by less than one percent. The effect is only positive if the opponent is a democracy and it is not a territorial conflict or if the opponent is non-democratic and the conflict is about territory. The interaction effect with ethnic support, in contrast, increases the average prediction slightly if the

¹²The ALE plot for democracy and other variables can be found in the supplemental material.

opponent is democratic and there is ethnic support whereas the average prediction decreases if the opponent is democratic and there is no ethnic support or if the opponent is nondemocratic and there is ethnic support. Just to reiterate: the numbers displayed in these plots and in the supplemental material only convey the additional effect arising from the interaction and do not take the substantive effects of the individual components of the interaction term into account.

4.6 Discussion and agenda for future research

What the above analyses have shown is that democracy is by far the most important feature when predicting terrorism against both hard and soft targets. However, democracy is mostly used as a binary indicator. In this paper, i.e. in Polo & González (2020) but also in Fortna, Lotito & Rubin (2018), the X-Polity measure proposed by Vreeland (2008) is used which is based on the Polity IV index (Marshall, Gurr, Davenport & Jaggers 2002) but removes components related to civil war. These components capture political participation which leaves a democracy variable based on executive characteristics and constraints. In contrast, Polo & Gleditsch (2016) use a dummy variable indicating whether a country has a polity score of 7 or more and a separate variable measuring media freedom. Coggins (2015) uses the Polity 2 score but also includes dummy variables capturing government effectiveness, rule of law, and control of corruption. Fortna (2015) uses a dummy variable indicating a polity score of 6 or higher. Stanton (2013) differentiates between democracies, with a score of 6 or higher, autocracies, with a score of -6 or lower, and countries falling in between as anocracies, thus including the anocracy category that Vreeland (2008) argued to be linked to civil war. Bakker, Hill Jr & Moore (2016) use various variables measuring political institutions in the form of contestation, participation, veto players, freedom of association/press/religion/speech, and size of the coercive bureaucracy, all of which substantively affect terrorism in dissident environments. It is noteworthy that they focus on dissident environments rather than civil wars, however. Asal et al. (2019) use a Quality of Government variable which combines Polity with Freedom House with a range from 0 to 10. It is thus the only study looking at terrorism in civil conflicts which uses a continuous variable.

However, we are still largely left guessing which democratic characteristics specifically affect the probability of terrorism in civil conflicts against both hard and soft targets. Democracy has long been linked to terrorism (Chenoweth 2013). The literature on terrorism has for example looked at human rights provisions in the form of different types of minority discrimination (Piazza 2011, Piazza 2012) or respect for physical integrity rights (Walsh & Piazza 2010). Physical integrity rights were included in this paper and were not found to be of high relative importance, however. Looking into different forms of minority discrimination might be a fruitful avenue for future research. The fundamental puzzle we are left with is: if categorical variables indicate that a country is a democracy, then why do we see terrorism in civil conflicts and indeed a civil conflict in the first place? Future research should thus seek to disentangle more what specific aspects of democracy, or the lack thereof, are driving this importance of democracy with regards to terrorism in civil wars. Another possible avenue would be to look at the variables introduced in dissident environments (Bakker, Hill Jr & Moore 2016) but in a civil war context instead. As of now we know that democracies are at higher risk but we do not quite know why. Democracies are expected to be more sensitive to (civilian) casualties, but this does not explain why there is a civil conflict in the first place and why some democracies in civil conflict are more prone to terrorism than others.

Another main takeaway from the analyses in this paper is that battle dynamics in the form of government and rebel losses are among the least important features driving the success of the models. This is surprising given recent findings in the literature (Polo & González 2020, Kibris 2021) highlighting the importance of such losses on the spread and evolution of violence in civil wars. Future research should look more closely into this to determine whether feature importances calculated in this paper can be reproduced using different machine learning algorithms. Permutation importance was introduced for random forests (Breiman 2001a, Breiman 2001b) and recently further developed to be model-agnostic (Fisher, Rudin & Dominici 2019). Thus comparable feature importance calculations can be performed for different machine learning algorithms in the future.¹³ Another concept that ranked surprisingly low in terms of importance are different measures of government repression. Future research should thus

¹³See also for example Wei, Lu & Song (2015) for a comprehensive overview of different variable importance analyses.

look more closely into both battlefield dynamics and government repression to reproduce the findings of this paper.

In addition to democracy, other variables found to be relatively more important for predicting terrorism against both hard and soft targets are time since the last terror attack (both normal and squared), GDP per capita, population size, territorial conflict, rebel group strength, ethnic recruitment, and external support. All these variables have similar effects on the probability of terrorism against both hard and soft targets. Two variables which rank higher for terrorism against soft targets are rebel one-sided violence and territorial control. The fact that rebel groups which deliberately target and kill civilians more frequently are also more likely to target soft targets is not surprising and makes intuitive sense, but it does not bring us any closer to determine *why* a group is more likely to target civilians in general. Future research should thus explore whether factors explaining rebel one-sided violence against civilians are by and large identical to factors explaining terrorism against civilian targets or whether there are some variables that actually separate the two concepts. There is, however, a good reason for why territorial control ranks relatively highly. Both territorial control and territorial conflict reduce the probability of terrorism against soft targets. Thus groups seeking regime change appear to be overall less likely to target civilians, be it in the form of deliberate killings or terrorist tactics. This may be evidence for the finding that terrorism is less likely if rebel groups want to be perceived as legitimate to establish themselves as acceptable ruling party both domestically and internationally (Arves, Cunningham & McCulloch 2019). Still, at this stage we cannot satisfactorily determine why some groups attack both hard and soft targets with terrorist tactics while others do not.

Lastly, the exploration of accumulated local effects and interaction effects using partial dependencies was a worthwhile endeavor. ALE plots in particular help to illustrate nonlinear and nonmonotonic relationships for both continuous variables as illustrated for population size and GDP per capita and categorical variables such as rebel group strength. ALE plots could thus also be used to visualize the suspected nonlinear relationship between a continuous democracy variable and terrorism against hard and soft targets in civil conflicts as a starting point to determine which more specific democratic characteristics, or lack thereof, are the driving factor behind the importance of democracy. This will depend on the type of

democracy index used, however. With regards to exploring interaction effects, sizable effects were detected for democracy, external support, and GDP per capita but also some interesting effects regarding relative rebel losses and the absence of rebel losses related to terrorism against hard targets and democracy and rebel one-sided violence related to terrorism against soft targets. Future research might thus explore these interactions more to determine whether there are good theoretical reasons for the effects we observe with this data-driven approach. Especially the large effects of democracy should be further investigated and linked to more detailed analyses of which aspects of democracy in particular drive these effects.

4.7 Conclusion

This paper has taken stock of commonly used independent variables explaining terrorism in civil conflicts and assessed their relative importance and effects when determining what makes rebel groups in civil conflicts more or less likely to use terrorism against hard and soft targets. Using available data on 205 rebel groups in the Middle East, Asia, and Africa between 1989 and 2009 on the rebel group-conflict-month level and random forests with 1,000 trees, I divided the data into training and test sets to determine variable importances and cross-validate these results. Predictive performance metrics were appropriate but not the main focus of this paper. Instead, the focus was on relative feature importance and feature effects using interpretable machine learning approaches. Feature importance was determined using permutation and feature effects were calculated and visualized using accumulated local effects plots. In addition, interaction strengths were calculated for all features included and for those specifically which had reasonably high interaction strengths and selected interaction effects were visualized using accumulated local effects plots. The aim of this paper was to introduce a data-driven approach for theory building, testing, and refinement as a complement to more traditional theory building to serve theory improvement. After all, theories should not only be able to explain but also to predict well (Ward & Beger 2017). One aim of this paper is to provide a foundation for a unified theory of rebel use of terrorism in civil conflicts. By establishing which features are relatively more important and illustrating the effects visually, this foundation

is set and avenues for future research have been outlined to come closer to this unified theory.

This paper is not without its own limitations, however. One point future research should address is the limited time frame until 2009 by expanding it to include more recent civil conflicts which featured terrorism. Conflicts missing in the data are for example Boko Haram in Nigeria and the Islamic State in Syria and Iraq and the many other countries it has been involved in which saw widespread use of terrorist tactics. It is also based on one machine learning algorithm, random forests. Future research might seek to improve predictive performance by using different machine learning algorithms and ensemble methods. However, this should still be undertaken with a focus on feature importance and effects. The aim should not be to derive so-called black box models which achieve high predictive performance without knowing how specifically this performance is reached. Instead, in order to be able to formulate credible theories of rebel use of terrorism in civil conflicts, researchers should focus on transparent and interpretable models to determine feature importance and effects. This paper had the modest aim to start this process and to outline ways to get to such a unified theory. The data-driven approach to theory building and improvement used here can and should be extended to other areas of political science research as well to complement more traditional approaches of theory building.

Chapter 5

Conclusion

5.1 Findings

This thesis provides answers to important social science questions of scholarly and substantive relevance. What explains the timing and location of state-based and one-sided violence in civil conflicts? Using recent advances in measuring local levels of territorial control on the monthly level, it was shown that territorial advances explain the timing and location of clashes between a government and rebels, of one-sided violence against civilians, and their intensity in the form of government, rebel, and civilian casualties. These estimates were derived for the civil conflict in Nigeria between the government and Boko Haram and the Islamic State between 2009 and 2017 at the grid cell-month level. Spatial regression models were an appropriate choice to model spatially and temporally dependent outcomes, and the substantive effects indicate an average impact of territorial advances of 0.5 to 1.5 standard deviations in the outcome of interest.

When and where do rebels use terrorism in civil conflicts? Using disaggregated data at the grid cell-month level for civil conflicts in Africa between 1989 and 2013, it was shown that the number of clashes and distance to a provincial capital were the most important determinants for the timing and location of terrorism. This was consistent across different specifications of the dependent variable: terrorism in general, terrorism against infrastructure, against combatants and government, and against civilians. The use of multilevel models was appropriate as indicated by the differing baseline risks for terrorism for different countries such as Nigeria, Mali, Somalia and Sudan. Predicted probabilities illustrated the importance of these factors. Out-of-sample validation showed that terrorism is a rare event in civil conflicts in Africa which makes it difficult to predict accurately, however.

Which factors predict terrorism in civil conflicts? Previous studies were restricted to explanatory approaches and various linear regression models which can produce misleading results. This thesis has used random forests as one example of a tree-based machine learning algorithm to utilize out-of-sample validation as a form of theory testing and improvement. Relative variable importances, substantive effects in the form of accumulated local effects and partial dependencies, and exploratory interaction strength calculations in the data were used to test how well different variables are able to predict terrorism in civil conflicts, how important they are for the model to be successful, and what the relationships with the outcome of interest look like specifically. Differentiating between terrorism against hard and soft targets, the study found that while some variables are of crucial importance, others have limited predictive power. Among the most important variables were democracy, time since the last attack, GDP per capita and population size. Of seemingly less importance are relative government and rebel losses and measures of government repression. Factors more important for terrorism against soft targets are territorial conflicts and control, suggesting that rebels who seek secession engage less in civilian victimization. It thus provides a foundation for a unified theory of rebel use of terrorism in civil conflicts upon which future research can build to come closer to this unified theory.

5.2 Implications

This thesis also has important research implications in terms of measurement and modeling and the study of political violence in general. Chapter 2 illustrated the importance of making use of new measurement strategies to answer substantive questions of interest. Oftentimes newly derived and innovative measures remain unused rather than seeking to validate and actively incorporating them into new research. Science and research are cumulative processes and we should build upon previous work not just in terms of theories and variables but also in terms of new and innovative data sources for measures for which we lack directly observable data. The chapter also illustrates the importance of dynamic processes in civil conflicts and territorial advances and control in particular. Territorial advances and control can thus be utilized in the study of other forms of political violence too. It further illustrates that spatially and temporally dependent outcomes should be modeled accordingly to avoid inefficiencies

and biased results (Franzese & Hays 2007, Franzese & Hays 2008, Cook, Hays & Franzese 2021).

Chapter 3 illustrated the importance of a multilevel modeling approach. Multilevel models are an extremely useful yet vastly underutilized modeling approach despite some advocating for it fervently for a long time (Gelman & Hill 2007). Different probabilities for terrorism in different countries, and the difference in the level of predictors to reach these probabilities, illustrate this importance. It also illustrates the importance of out-of-sample validation to put the empirical findings in perspective. The combination of multilevel modeling and out-of-sample prediction should thus be used more often in cross-sectional time-series studies of political violence in general.

Chapter 4 illustrated the importance of data-driven theory building and improvement as a complement to more traditional theory building approaches. After all, a theory should be able to both explain and predict well. Holding out data to test the models with unseen data is a valuable strategy which has been advocated by some for years (Ward, Greenhill & Bakke 2010). In addition, it illustrated the importance of diversifying empirical modeling options researchers can choose from beyond a variety of linear regression models which are still the standard in empirical political science (Schrodt 2014). Indeed, some argue that machine learning algorithms, and tree-based algorithms such as random forests in particular, should be part of any empirical modeling exercise alongside lasso or ridge regressions (Hindman 2015). At a minimum, calls to integrate explanation and prediction more in the social sciences are warranted in order to obtain more reliable and robust results (Hofman et al. 2021).

5.3 Future research

This thesis also opens up various avenues for future research. Chapter 2 illustrates the importance of territorial advances for the civil conflict in Nigeria between the government and Boko Haram and the Islamic State. Future research may seek to replicate both estimating territorial control and the effect of territorial advances in other civil conflicts to confirm findings of this exploratory study. In addition, results for one-sided violence against civilians were driven by widespread civilian victimization of Boko Haram and the Islamic State while there was very little government one-sided violence. Thus future research should seek to investigate the effect

of territorial advances on government violence against civilians. In addition, advances in spatial regression models, and spatial weights matrix specifications in particular, which are in progress right now will enable cross-national time-series analyses to allow testing the generalizability of the empirical findings provided in this chapter.

Chapter 3 illustrated the importance of local conflict dynamics and conceptual and definitional issues surrounding terrorism. Future research may seek to replicate the results obtained for Africa for civil conflicts in other regions, in particular Asia. There is some criticism in the literature that there is too much focus on civil conflicts in Africa and the Middle East which may obfuscate our understanding of conflict dynamics by neglecting other areas in the world in which civil conflicts are prevalent. Moreover, future research may seek to reproduce the analyses in this chapter for a longer time frame since many important conflicts which saw frequent terrorist attacks were not (fully) part of the period under investigation. This includes for example Libya, Nigeria, Cameroon, Mali and Turkey. Lastly, while this study included a spatial lag which did not reach statistical significance at conventional levels, future research may still seek to use spatial regression models to analyze the timing and location of terrorism in civil conflicts, once spatial weights matrices have been further optimized to be able to handle larger amounts of observations.

Chapter 4 illustrated the importance of incorporating both explanation and prediction in social science research to obtain more reliable and robust results by using machine learning algorithms and out-of-sample validation. The focus of this chapter was less on high predictive performance and more on transparency and interpretability to determine which variables drive the success of models and in what way. Future research may seek to increase predictive performance by using different machine learning algorithms or ensemble models as long as it can still be determined which variables are more important than others so that we come closer to a unified theory of rebel use of terrorism in civil conflicts. Recent advances in estimating variable importances for machine learning algorithms which are not tree-based open up a wide range of algorithms to choose from. Moreover, future research may seek to reproduce the results of this chapter after extending the time frame under investigation. Data were limited to 2009 and thus many important civil conflicts which saw widespread use of

terrorism remained missing. These include Boko Haram in Nigeria, the Islamic State in the various countries it was active, and many others. Importantly, it opened up avenues for future research as a result of the variables found to be most important. In particular, binary measures of democracy tend to be widely used and are found to be important predictors, but this does not provide an answer for why democracies are particularly popular targets and why some democracies in civil conflict suffer from terrorism while others do not. Future research should thus dissect which aspect(s) of democracy in particular, or the lack thereof, make democracies a popular target of terrorism.

Appendix A

Supplemental information for: Caught up in the moment: The effect of changes in territorial control on the timing, location and intensity of state-based and one-sided violence in civil conflicts

A.1 Overview

This supplemental material provides additional information about the data and models. Descriptive statistics, additional maps, and correlation plots for the independent variables are in the first section. The second section provides additional regression tables for linear regression models. The third section provides additional regression tables for spatial regression models.

A.2 Descriptives

A.2.1 Dependent variables

Summary statistics month level

TABLE A.1: Summary statistics for dependent variables on month level (log)

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	101,844	0.025	0.272	0.000	6.649
OSV	101,844	0.005	0.070	0.000	2.485
SBV	101,844	0.006	0.076	0.000	2.398
OSV rebels	101,844	0.005	0.069	0.000	2.485
Gov fatalities	101,844	0.004	0.088	0.000	3.970
Reb fatalities	101,844	0.011	0.177	0.000	6.545
Civ casualties	101,844	0.013	0.195	0.000	6.404

TABLE A.2: Summary statistics for dependent variables on month level

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	101,844	0.243	5.381	0	771
OSV	101,844	0.009	0.143	0	11
SBV	101,844	0.011	0.154	0	10
OSV rebels	101,844	0.009	0.141	0	11
Gov fatalities	101,844	0.016	0.532	0	52
Reb fatalities	101,844	0.100	3.411	0	695
Civ casualties	101,844	0.111	3.140	0	603

Summary statistics annual level

TABLE A.3: Summary statistics for dependent variables on annual level (log)

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	8,487	0.159	0.747	0.000	7.207
OSV	8,487	0.039	0.236	0.000	3.951
SBV	8,487	0.048	0.258	0.000	4.205
OSV rebels	8,487	0.037	0.233	0.000	3.932
Gov fatalities	8,487	0.039	0.289	0.000	4.290
Reb fatalities	8,487	0.084	0.527	0.000	6.557
Civ casualties	8,487	0.094	0.560	0.000	6.711

TABLE A.4: Summary statistics for dependent variables on annual level

Statistic	N	Mean	St. Dev.	Min	Max
Fatalities	8,487	2.911	28.745	0	1,348
OSV	8,487	0.107	1.139	0	51
SBV	8,487	0.128	1.208	0	66
OSV rebels	8,487	0.104	1.116	0	50
Gov fatalities	8,487	0.186	2.216	0	72
Reb fatalities	8,487	1.198	13.986	0	703
Civ casualties	8,487	1.338	16.420	0	820

Maps of dependent variables by year

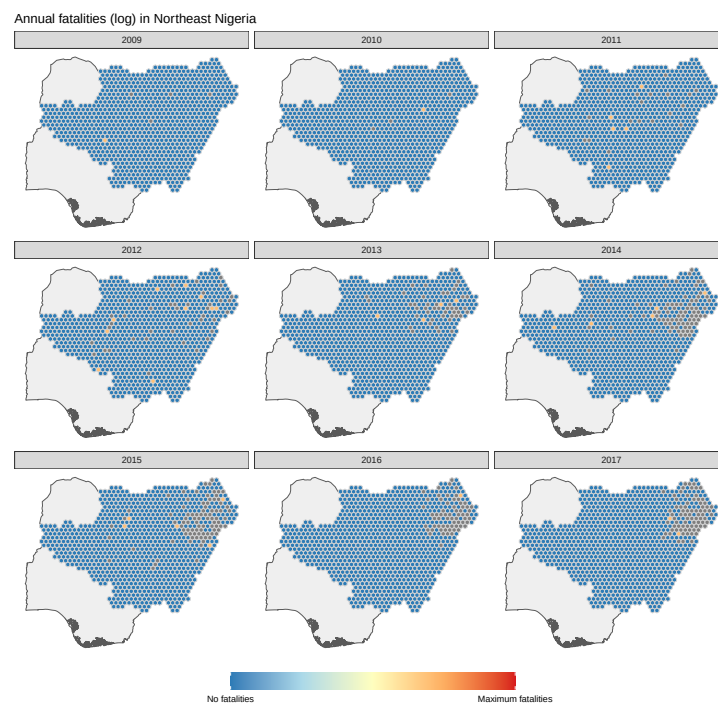


FIGURE A.1: Map of fatalities for each year.

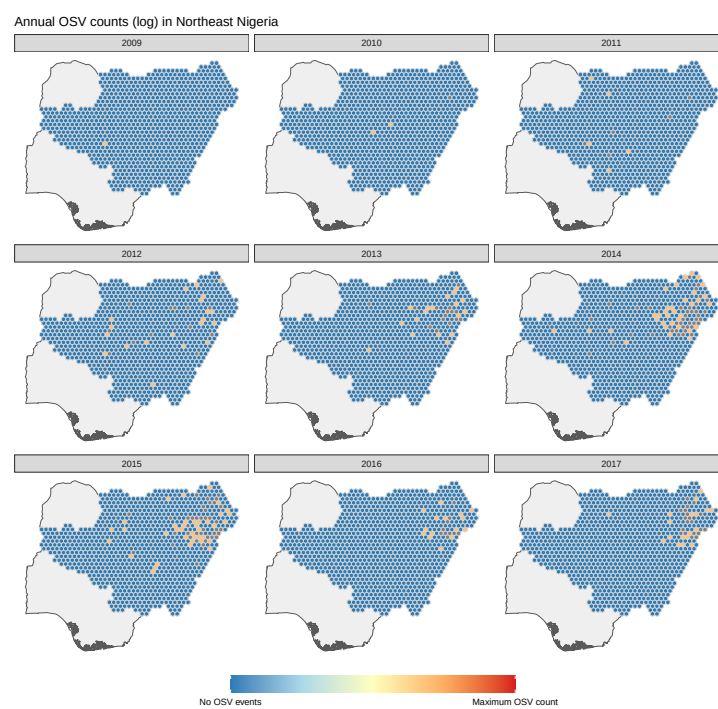


FIGURE A.2: Map of one-sided violence events for each year.

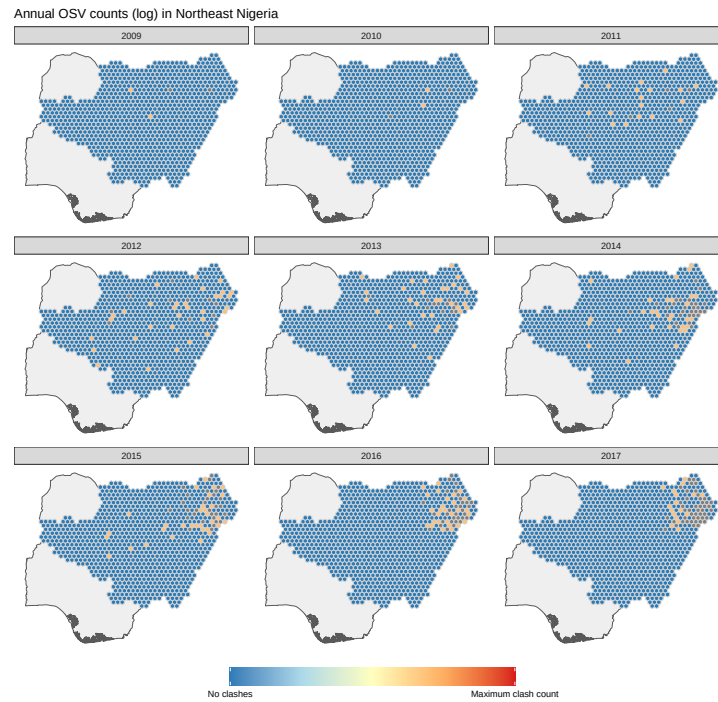


FIGURE A.3: Map of clashes for each year.

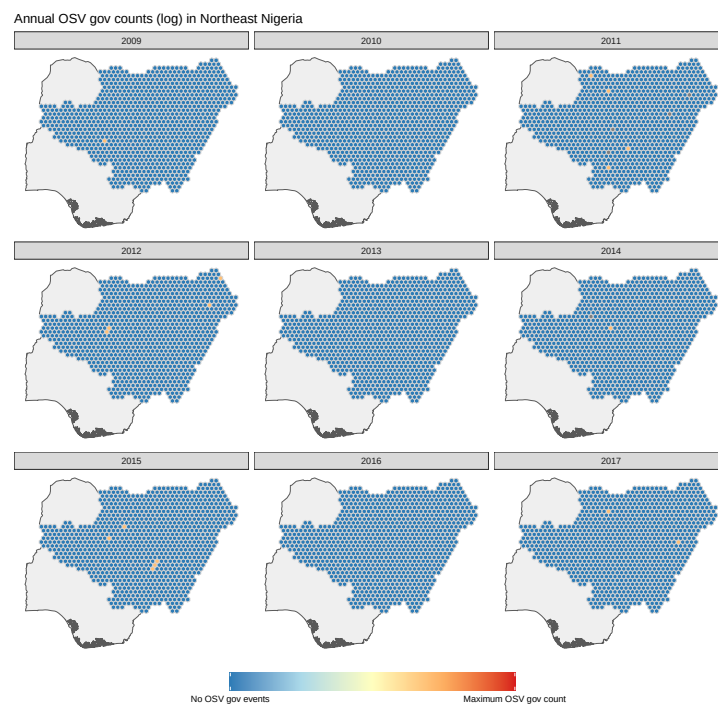


FIGURE A.4: Map of government one-sided violence events
for each year.

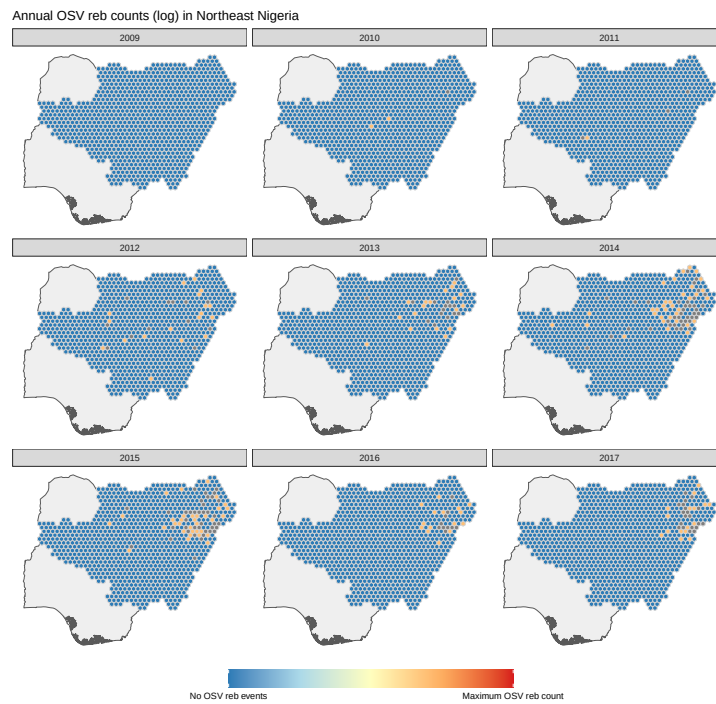


FIGURE A.5: Map of rebel one-sided violence events for each year.

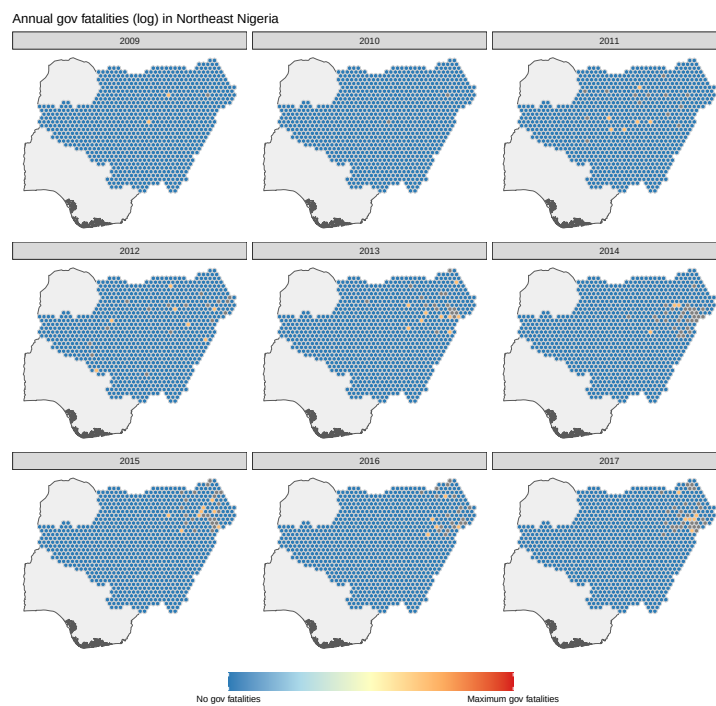


FIGURE A.6: Map of government fatalities for each year.

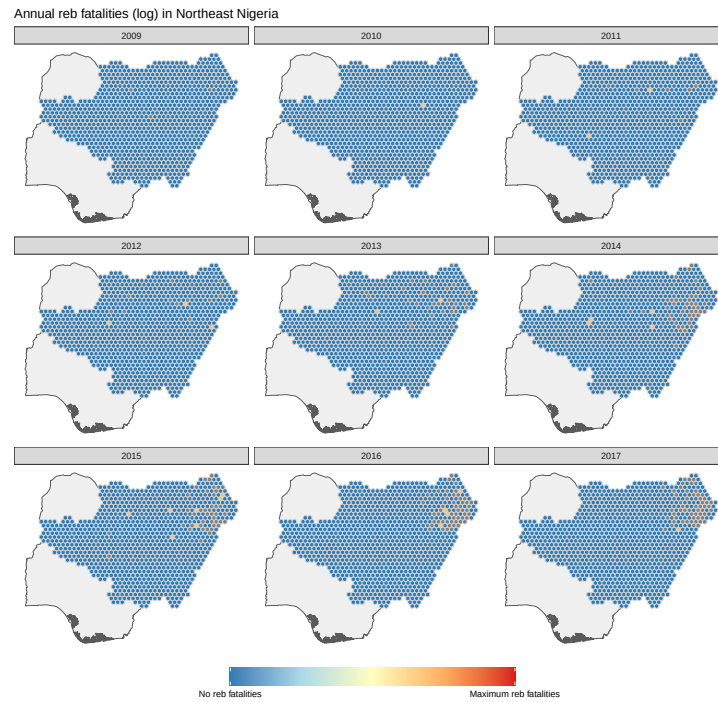


FIGURE A.7: Map of rebel fatalities for each year.

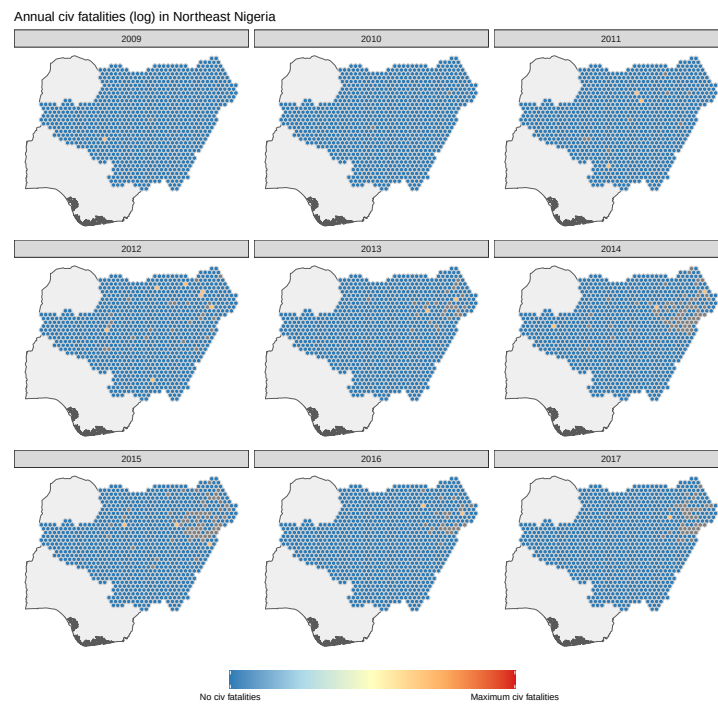


FIGURE A.8: Map of civilian fatalities for each year.

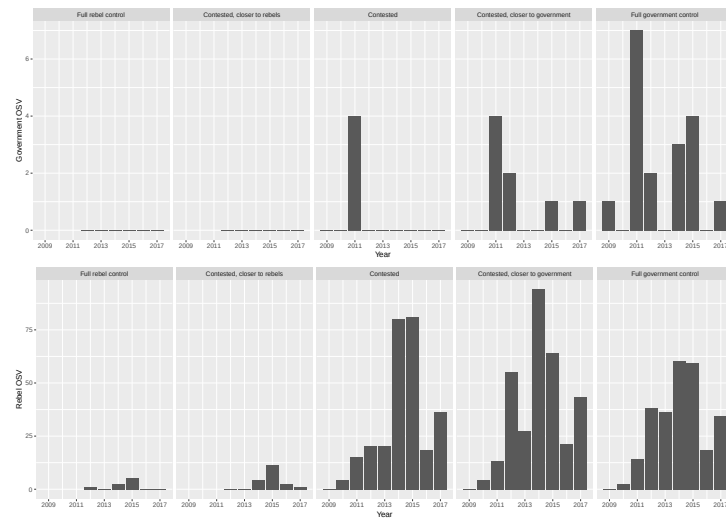


FIGURE A.9: Histograms of one-sided (OSV) violence by actor and level of territorial control for Nigeria (2009-2017).

A.2.2 Independent variables

Summary statistics month level

TABLE A.5: Summary statistics for independent variables on
month level (log)

Statistic	N	Mean	St. Dev.	Min	Max
Territorial advance $_{t-1 \rightarrow t}$	101,844	0.100	0.301	0	1
Distance to capital	101,844	5.802	0.613	3.438	7.095
Distance to int border	101,844	4.625	1.016	0.077	5.969
Nightlights	101,844	0.064	0.009	0.047	0.170
Petroleum	101,844	0.009	0.088	0.000	1.000
Mountains	101,844	0.117	0.206	0.000	0.993
Forest	101,844	0.035	0.113	0.000	0.763
Gemstone	101,844	0.112	0.250	0.000	1.000
Excluded ethnic groups	101,844	0.103	0.281	0.000	1.000
Population	101,844	12.364	0.799	9.189	14.894

TABLE A.6: Summary statistics for independent variables on
month level

Statistic	N	Mean	St. Dev.	Min	Max
Territorial advance $_{t-1 \rightarrow t}$	101,844	0.100	0.301	0	1
Distance to capital	101,844	386.532	198.299	30.114	1,204.831
Distance to int border	101,844	147.112	102.176	0.080	389.936
Nightlights	101,844	0.064	0.009	0.047	0.170
Petroleum	101,844	0.009	0.088	0.000	1.000
Mountains	101,844	0.117	0.206	0.000	0.993
Forest	101,844	0.035	0.113	0.000	0.763
Gemstone	101,844	0.112	0.250	0.000	1.000
Excluded ethnic groups	101,844	0.103	0.281	0.000	1.000
Population	101,844	321,335.500	294,351.800	9,790.399	2,938,954.00

Correlation plot month level



FIGURE A.10: Correlation plot of independent variables on month level.

Summary statistics annual level

TABLE A.7: Summary statistics for independent variables on
annual level (log)

Statistic	N	Mean	St. Dev.	Min	Max
Territorial advances $_{t-1 \rightarrow t}$	8,487	1.205	3.036	0	12
Distance to capital	8,487	5.802	0.613	3.438	7.095
Distance to int border	8,487	4.625	1.016	0.077	5.969
Nightlights	8,487	0.064	0.009	0.047	0.170
Petroleum	8,487	0.009	0.088	0.000	1.000
Mountains	8,487	0.117	0.206	0.000	0.993
Forest	8,487	0.035	0.113	0.000	0.763
Gemstone	8,487	0.112	0.250	0.000	1.000
Excluded ethnic groups	8,487	0.103	0.281	0.000	1.000
Population	8,487	12.364	0.799	9.189	14.894

TABLE A.8: Summary statistics for independent variables on
month level

Statistic	N	Mean	St. Dev.	Min	Max
Territorial advances $_{t-1 \rightarrow t}$	8,487	1.205	3.036	0	12
Distance to capital	8,487	386.532	198.310	30.114	1,204.831
Distance to int border	8,487	147.112	102.182	0.080	389.936
Nightlights	8,487	0.064	0.009	0.047	0.170
Petroleum	8,487	0.009	0.088	0.000	1.000
Mountains	8,487	0.117	0.206	0.000	0.993
Forest	8,487	0.035	0.113	0.000	0.763
Gemstone	8,487	0.112	0.250	0.000	1.000
Excluded ethnic groups	8,487	0.103	0.281	0.000	1.000
Population	8,487	321,335.500	294,367.700	9,790.399	2,938,954.000

Correlation plot annual level



FIGURE A.11: Correlation plot of independent variables on annual level.

A.3 Linear regression models

A.3.1 Observations on the year level: 2009 - 2017

TABLE A.9: Ordinary least squares regression results

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.961*** (0.003)						
OSV (lag)		0.976*** (0.003)					
SBV (lag)			0.986*** (0.002)				
OSV rebels (lag)				0.978*** (0.003)			
Gov fatalities (lag)					0.958*** (0.003)		
Reb fatalities (lag)						0.962*** (0.003)	
Civ casualties (lag)							0.952*** (0.004)
Territorial advance _{t-1} → _t	0.003*** (0.001)	0.0004 (0.0002)	0.001* (0.0002)	0.0003 (0.0002)	0.001*** (0.0004)	0.003*** (0.001)	0.002*** (0.001)
National capital distance	0.013* (0.006)	0.003 (0.001)	0.003 (0.001)	0.003 (0.001)	0.004 (0.003)	0.004 (0.004)	0.007 (0.005)
Border distance	0.002 (0.003)	0.001 (0.001)	0.0001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.0004 (0.002)	0.001 (0.003)
Nightlights	0.359 (0.260)	0.054 (0.069)	0.083 (0.067)	0.031 (0.067)	0.118 (0.115)	0.039 (0.184)	0.367 (0.221)
Petroleum	-0.002 (0.024)	-0.001 (0.006)	0.0003 (0.006)	-0.001 (0.006)	0.0001 (0.011)	0.001 (0.017)	-0.001 (0.020)
Mountains	0.004 (0.013)	0.005 (0.004)	0.001 (0.003)	0.004 (0.003)	-0.0004 (0.006)	0.005 (0.009)	0.013 (0.011)
Forest	-0.016 (0.024)	-0.006 (0.007)	-0.005 (0.006)	-0.006 (0.006)	-0.003 (0.011)	-0.013 (0.017)	-0.021 (0.021)
Gemstone	-0.004 (0.009)	-0.002 (0.002)	-0.0004 (0.002)	-0.001 (0.002)	-0.002 (0.004)	-0.003 (0.006)	-0.003 (0.008)
Excluded	0.002 (0.008)	0.0001 (0.001)	0.001 (0.002)	-0.0000 (0.002)	0.001 (0.003)	0.001 (0.006)	0.001 (0.007)
Population	-0.0004 (0.003)	0.001 (0.001)	-0.0004 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.0003 (0.002)	0.0004 (0.002)
Constant	-0.101 (0.061)	-0.028 (0.016)	-0.016 (0.016)	-0.025 (0.016)	-0.026 (0.027)	-0.018 (0.043)	-0.073 (0.052)
N	8487	8487	8487	8487	8487	8487	8487
R-squared	0.935	0.954	0.963	0.955	0.915	0.935	0.916
Adj. R-squared	0.935	0.954	0.963	0.955	0.914	0.935	0.916
Residual Std. Error (df = 8475)	0.191	0.051	0.049	0.049	0.085	0.135	0.162
F Statistic (df = 11; 8475)	11080.420***	15841.820***	20317.310***	16505.060***	8248.956***	11024.900***	8427.216***

*** p < .001; ** p < .01; * p < .05

A.3.2 Observations on the month level: 2009

TABLE A.10: Ordinary least squares regression results (2009)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	−0.035*** (0.009)						
OSV (lag)		−0.016 (0.009)					
SBV (lag)			0.183*** (0.009)				
OSV rebels (lag)							
Gov fatalities (lag)					−0.021* (0.009)		
Reb fatalities (lag)						−0.026** (0.009)	
Civ casualties (lag)							−0.013 (0.009)
Territorial advance _{t−1} → _t	0.143*** (0.008)	−0.001 (0.001)	0.030*** (0.002)	0.000 (0.000)	0.039*** (0.003)	0.098*** (0.006)	0.013*** (0.001)
National capital distance	0.003 (0.002)	0.0004* (0.0002)	0.001* (0.001)	0.000 (0.000)	0.001 (0.001)	0.003 (0.002)	0.0004 (0.0004)
Border distance	0.001 (0.001)	0.0001 (0.0001)	0.0004 (0.0003)	0.000 (0.000)	0.0004 (0.0004)	0.001 (0.001)	0.0001 (0.0002)
Nightlights	0.365*** (0.112)	0.128*** (0.010)	0.091** (0.032)	0.000 (0.000)	0.089* (0.040)	0.287*** (0.092)	0.144*** (0.022)
Petroleum	0.001 (0.008)	0.0005 (0.001)	−0.0002 (0.002)	0.000 (0.000)	0.0001 (0.003)	0.001 (0.007)	0.001 (0.002)
Mountains	0.003 (0.004)	0.0004 (0.0004)	0.0001 (0.001)	0.000 (0.000)	0.0004 (0.002)	0.003 (0.004)	0.002 (0.001)
Forest	0.002 (0.008)	−0.0005 (0.001)	0.001 (0.002)	0.000 (0.000)	0.001 (0.003)	−0.001 (0.007)	−0.002 (0.002)
Gemstone	0.003 (0.003)	0.0001 (0.0003)	0.0002 (0.001)	0.000 (0.000)	0.0003 (0.001)	0.003 (0.002)	0.002** (0.001)
Excluded	0.002 (0.003)	0.0004 (0.0002)	0.0005 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001 (0.002)	0.0004 (0.001)
Population	0.0001 (0.001)	−0.0003*** (0.0001)	0.0003 (0.0003)	0.000 (0.000)	0.0002 (0.0004)	0.0003 (0.001)	−0.0005* (0.0002)
Constant	−0.046* (0.020)	−0.005** (0.002)	−0.016** (0.006)	0.000 (0.000)	−0.015* (0.007)	−0.039* (0.016)	−0.005 (0.004)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.035	0.016	0.064		0.021	0.026	0.013
Adj. R-squared	0.034	0.015	0.063		0.020	0.025	0.012
Residual Std. Error	0.074	0.006	0.021	0.000	0.026	0.060	0.014
F Statistic	37.104***	16.776***	70.722***		21.721***	27.150***	13.287***

***p < .001, **p < .01, *p < .05

A.3.3 Observations on the month level: 2010

TABLE A.1.1: Ordinary least squares regression results (2010)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.415*** (0.017)						
OSV (lag)		0.913*** (0.009)					
SBV (lag)			0.626*** (0.010)				
OSV rebels (lag)				0.913*** (0.009)			
Gov fatalities (lag)					0.185*** (0.011)		
Reb fatalities (lag)						-0.011 (0.009)	
Civ casualties (lag)							0.413*** (0.027)
Territorial advance _{t-1} → _t	0.105*** (0.006)	0.026*** (0.002)	0.034*** (0.002)	0.026*** (0.002)	0.038*** (0.003)	0.008*** (0.001)	0.087*** (0.005)
National capital distance	0.003 (0.001)	0.001 (0.0004)	0.001* (0.001)	0.001 (0.0004)	0.002* (0.001)	0.00001 (0.0002)	0.001 (0.001)
Border distance	0.001 (0.001)	0.0002 (0.0002)	0.0003 (0.0003)	0.0002 (0.0002)	0.0003 (0.0004)	0.0001 (0.0001)	0.0005 (0.001)
Nightlights	0.399*** (0.099)	0.086*** (0.028)	0.111** (0.041)	0.086*** (0.028)	0.141** (0.047)	-0.009 (0.012)	0.309*** (0.089)
Petroleum	-0.0004 (0.006)	-0.0002 (0.002)	-0.0002 (0.002)	-0.0002 (0.002)	0.00005 (0.003)	0.00002 (0.001)	-0.001 (0.005)
Mountains	0.006 (0.003)	0.001 (0.001)	-0.0002 (0.001)	0.001 (0.001)	0.001 (0.002)	-0.0002 (0.0004)	0.005 (0.003)
Forest	-0.005 (0.006)	-0.0003 (0.002)	0.001 (0.003)	-0.0003 (0.002)	-0.0002 (0.003)	0.0003 (0.001)	-0.004 (0.005)
Genstone	-0.001 (0.002)	-0.0004 (0.001)	0.0003 (0.001)	-0.0004 (0.001)	0.002 (0.001)	-0.0001 (0.0003)	-0.002 (0.002)
Excluded	0.001 (0.002)	0.0003 (0.001)	0.001 (0.001)	0.0003 (0.001)	0.0005 (0.001)	0.00003 (0.0002)	0.001 (0.002)
Population	0.001 (0.001)	0.0002 (0.0002)	0.0003 (0.0003)	0.0002 (0.0002)	0.0003 (0.0004)	-0.0001 (0.0001)	0.001 (0.001)
Constant	-0.058*** (0.016)	-0.014** (0.004)	-0.021** (0.006)	-0.014** (0.004)	-0.025*** (0.007)	0.001 (0.002)	-0.042** (0.014)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.101	0.519	0.313	0.519	0.053	0.011	0.054
Adj. R-squared	0.100	0.519	0.312	0.519	0.052	0.010	0.053
Residual Std. Error	0.054	0.015	0.022	0.015	0.025	0.006	0.048
F Statistic	115.428***	1109.497***	468.272**	1109.497***	57.727***	11.715***	59.080***

*** p < .001; ** p < .01; * p < .05

A.3.4 Observations on the month level: 2011

TABLE A.12: Ordinary least squares regression results (2011)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.380*** (0.009)						
OSV (lag)		0.695*** (0.007)					
SBV (lag)			0.610*** (0.008)				
OSV rebels (lag)				0.756*** (0.006)			
Gov fatalities (lag)					0.352*** (0.010)		
Reb fatalities (lag)						0.205*** (0.010)	
Civ casualties (lag)							0.317*** (0.009)
Territorial advance _{t-1} → _t	0.076*** (0.005)	0.008*** (0.002)	0.026*** (0.002)	0.004** (0.001)	0.046*** (0.003)	0.025*** (0.002)	0.030*** (0.004)
National capital distance	0.009** (0.003)	0.003** (0.001)	0.003* (0.001)	0.002** (0.001)	0.003 (0.002)	0.003* (0.001)	0.005** (0.002)
Border distance	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.0004)	0.0005 (0.001)	0.001 (0.001)	0.001 (0.001)
Nightlights	1.006*** (0.184)	0.382*** (0.062)	0.061 (0.072)	0.307*** (0.048)	0.021 (0.110)	0.070 (0.080)	0.826*** (0.125)
Petroleum	0.0002 (0.013)	0.0001 (0.004)	-0.001 (0.005)	0.001 (0.003)	-0.001 (0.008)	-0.001 (0.005)	0.003 (0.009)
Mountains	-0.004 (0.007)	0.00002 (0.002)	-0.002 (0.003)	-0.0003 (0.002)	-0.003 (0.004)	-0.002 (0.003)	0.0003 (0.005)
Forest	0.005 (0.013)	0.001 (0.004)	0.004 (0.005)	0.001 (0.003)	0.005 (0.008)	0.004 (0.006)	-0.003 (0.009)
Genstone	-0.001 (0.005)	-0.001 (0.002)	-0.001 (0.002)	-0.0003 (0.001)	-0.002 (0.003)	-0.003 (0.002)	-0.001 (0.003)
Excluded	0.006 (0.004)	0.002 (0.001)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.006* (0.003)
Population	-0.001 (0.002)	-0.00001 (0.001)	0.001 (0.001)	-0.0003 (0.0004)	0.001 (0.001)	0.001 (0.001)	-0.002* (0.001)
Constant	-0.114*** (0.033)	-0.047*** (0.011)	-0.033** (0.013)	-0.033*** (0.009)	-0.034 (0.020)	-0.038** (0.014)	-0.060** (0.022)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.176	0.505	0.395	0.605	0.138	0.054	0.128
Adj. R-squared	0.175	0.504	0.394	0.604	0.138	0.053	0.127
Residual Std. Error	0.114	0.038	0.045	0.030	0.069	0.050	0.078
F Statistic	218.757***	1047.171***	669.658***	1571.897***	165.189***	58.154***	151.130***

*** p < .001; ** p < .01; * p < .05

A.3.5 Observations on the month level: 2012

TABLE A.13: Ordinary least squares regression results (2012)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.457*** (0.008)						
OSV (lag)		0.521*** (0.008)					
SBV (lag)			0.628*** (0.007)				
OSV rebels (lag)				0.524*** (0.008)			
Gov fatalities (lag)					0.321*** (0.008)		
Reb fatalities (lag)						0.656*** (0.007)	
Civ casualties (lag)							0.306*** (0.009)
Territorial advance _{t-1} → t	0.064*** (0.006)	0.017*** (0.002)	0.021*** (0.002)	0.017*** (0.002)	0.021*** (0.002)	0.014*** (0.003)	0.051*** (0.005)
National capital distance	0.011* (0.005)	0.005** (0.002)	0.003 (0.002)	0.005** (0.002)	0.002 (0.002)	0.005* (0.002)	0.012** (0.004)
Border distance	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.0001 (0.001)	0.002 (0.001)	0.003 (0.002)
Nightlights	0.273 (0.295)	0.235* (0.106)	0.049 (0.115)	0.197 (0.104)	-0.011 (0.120)	0.079 (0.141)	0.622* (0.250)
Petroleum	-0.007 (0.020)	-0.003 (0.007)	-0.003 (0.008)	-0.003 (0.007)	-0.003 (0.008)	-0.003 (0.009)	-0.009 (0.017)
Mountains	-0.011 (0.011)	-0.001 (0.004)	-0.006 (0.004)	-0.002 (0.004)	-0.007 (0.004)	-0.006 (0.005)	-0.005 (0.009)
Forest	0.023 (0.020)	0.007 (0.007)	0.010 (0.008)	0.008 (0.007)	0.009 (0.008)	0.013 (0.010)	0.021 (0.017)
Gemstone	-0.003 (0.007)	-0.002 (0.003)	-0.002 (0.003)	-0.001 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.0003 (0.006)
Excluded	0.003 (0.007)	0.001 (0.002)	0.001 (0.003)	0.001 (0.002)	0.001 (0.002)	0.001 (0.003)	0.001 (0.006)
Population	0.005* (0.002)	0.002 (0.001)	0.002* (0.001)	0.002* (0.001)	0.002 (0.001)	0.002 (0.001)	0.006** (0.002)
Constant	-0.154* (0.054)	-0.078*** (0.020)	-0.055** (0.021)	-0.075*** (0.019)	-0.032 (0.022)	-0.067** (0.026)	-0.201*** (0.046)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.250	0.288	0.413	0.290	0.138	0.420	0.124
Adj. R-squared	0.250	0.287	0.413	0.289	0.137	0.419	0.123
Residual Std. Error	0.181	0.065	0.071	0.064	0.074	0.087	0.153
F Statistic	343.244***	415.085***	723.270***	419.361***	164.954***	742.764***	144.818***

***p < .001; **p < .01; *p < .05

A.3.6 Observations on the month level: 2013

TABLE A.14: Ordinary least squares regression results (2013)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.200*** (0.009)						
OSV (lag)		0.304*** (0.009)					
SBV (lag)			0.340*** (0.009)				
OSV rebels (lag)				0.307*** (0.009)			
Gov fatalities (lag)					0.074*** (0.010)		
Reb fatalities (lag)						0.220*** (0.010)	
Civ casualties (lag)							0.065*** (0.009)
Territorial advance $t-1 \rightarrow t$	0.110*** (0.007)	0.017*** (0.002)	0.025*** (0.002)	0.017*** (0.002)	0.030*** (0.003)	0.062*** (0.005)	0.049*** (0.005)
National capital distance	0.026*** (0.007)	0.005*** (0.002)	0.006** (0.002)	0.005** (0.002)	0.007*** (0.003)	0.014** (0.005)	0.014*** (0.004)
Border distance	0.005 (0.004)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002 (0.003)	0.004 (0.002)
Nightlights	0.663 (0.383)	0.136 (0.093)	0.199 (0.103)	0.141 (0.093)	0.223 (0.154)	0.402 (0.279)	0.308 (0.239)
Petroleum	-0.005 (0.027)	-0.002 (0.007)	-0.003 (0.007)	-0.002 (0.007)	-0.001 (0.011)	-0.006 (0.020)	-0.0004 (0.017)
Mountains	-0.011 (0.015)	0.004 (0.004)	-0.001 (0.004)	0.004 (0.004)	-0.003 (0.006)	-0.010 (0.011)	-0.002 (0.009)
Forest	0.011 (0.028)	-0.001 (0.007)	0.005 (0.007)	-0.001 (0.007)	0.003 (0.011)	0.016 (0.020)	0.002 (0.017)
Genstone	-0.006 (0.010)	-0.002 (0.002)	-0.0003 (0.003)	-0.002 (0.002)	-0.003 (0.004)	-0.002 (0.007)	-0.002 (0.006)
Excluded	0.009 (0.009)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.003 (0.004)	0.004 (0.007)	0.005 (0.006)
Population	0.005 (0.003)	0.002** (0.001)	0.003** (0.001)	0.002** (0.001)	0.001 (0.001)	0.006* (0.002)	0.001 (0.002)
Constant	-0.276*** (0.072)	-0.073*** (0.018)	-0.085*** (0.019)	-0.073*** (0.018)	-0.076** (0.029)	-0.189*** (0.053)	-0.129** (0.045)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.079	0.119	0.159	0.120	0.021	0.069	0.022
Adj. R-squared	0.078	0.119	0.158	0.119	0.020	0.068	0.021
Residual Std. Error	0.248	0.060	0.066	0.060	0.100	0.181	0.155
F Statistic	87.849***	139.282***	193.795***	140.596***	21.678***	75.779***	23.464***

*** p < .001, ** p < .01, * p < .05

A.3.7 Observations on the month level: 2014

TABLE A.15: Ordinary least squares regression results (2014)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.236*** (0.009)						
OSV (lag)		0.250*** (0.009)					
SBV (lag)			0.088*** (0.009)				
OSV rebels (lag)				0.255*** (0.009)			
Gov fatalities (lag)					0.117*** (0.009)		
Reb fatalities (lag)						0.086*** (0.010)	
Civ casualties (lag)							0.243*** (0.009)
Territorial advance $_{t-1} \rightarrow t$	0.232*** (0.011)	0.053*** (0.003)	0.036*** (0.002)	0.052*** (0.003)	0.043*** (0.004)	0.093*** (0.007)	0.165*** (0.009)
National capital distance	0.021 (0.011)	0.006* (0.003)	0.003 (0.002)	0.006* (0.003)	0.002 (0.004)	0.011 (0.007)	0.015 (0.009)
Border distance	-0.002 (0.006)	-0.0004 (0.001)	0.0003 (0.001)	-0.0003 (0.001)	-0.002 (0.002)	0.0003 (0.004)	-0.002 (0.005)
Nightlights	0.473 (0.608)	0.130 (0.158)	-0.077 (0.116)	0.142 (0.157)	-0.255 (0.213)	-0.287 (0.378)	0.804 (0.502)
Petroleum	-0.003 (0.042)	-0.0001 (0.011)	-0.0001 (0.008)	0.0002 (0.011)	0.003 (0.015)	0.0005 (0.026)	-0.005 (0.035)
Mountains	0.086*** (0.023)	0.019** (0.006)	0.013** (0.004)	0.019** (0.006)	0.030*** (0.008)	0.030* (0.015)	0.064*** (0.019)
Forest	-0.107* (0.043)	-0.023* (0.011)	-0.016 (0.008)	-0.023* (0.011)	-0.042** (0.015)	-0.042 (0.027)	-0.074* (0.036)
Gemstone	-0.011 (0.016)	0.003 (0.004)	-0.003 (0.003)	0.002 (0.004)	-0.002 (0.005)	-0.007 (0.010)	-0.004 (0.013)
Excluded	-0.001 (0.014)	-0.0005 (0.004)	0.001 (0.003)	-0.0002 (0.004)	-0.001 (0.005)	0.001 (0.009)	-0.001 (0.012)
Population	0.014** (0.005)	0.003* (0.001)	0.002 (0.001)	0.003* (0.001)	0.001 (0.002)	0.004 (0.003)	0.012** (0.004)
Constant	-0.316** (0.117)	-0.078* (0.031)	-0.038 (0.022)	-0.079* (0.030)	-0.006 (0.041)	-0.099 (0.073)	-0.286** (0.097)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.130	0.125	0.050	0.127	0.034	0.035	0.116
Adj. R-squared	0.129	0.124	0.050	0.126	0.033	0.034	0.115
Residual Std. Error	0.389	0.101	0.074	0.100	0.136	0.241	0.320
F Statistic	153.823***	147.228***	54.619***	149.629***	36.312***	36.921***	134.900***

***p < .001, **p < .01, *p < .05

A.3.8 Observations on the month level: 2015

TABLE A.16: Ordinary least squares regression results (2015)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.239*** (0.009)						
OSV (lag)		0.274*** (0.009)					
SBV (lag)			0.203*** (0.009)				
OSV rebels (lag)				0.279*** (0.009)			
Gov fatalities (lag)					0.163*** (0.009)		
Reb fatalities (lag)						0.179*** (0.009)	
Civ casualties (lag)							0.213*** (0.009)
Territorial advance $_{t-1} \rightarrow t$	0.193*** (0.011)	0.038*** (0.003)	0.032*** (0.002)	0.037*** (0.003)	0.022*** (0.003)	0.075*** (0.007)	0.126*** (0.009)
National capital distance	0.044*** (0.011)	0.011*** (0.003)	0.005* (0.002)	0.011*** (0.003)	0.005 (0.003)	0.014* (0.007)	0.034*** (0.009)
Border distance	0.005 (0.006)	0.003* (0.001)	-0.0002 (0.001)	0.003* (0.001)	-0.001 (0.001)	-0.003 (0.003)	0.008 (0.005)
Nightlights	1.046 (0.622)	0.177 (0.153)	0.139 (0.126)	0.192 (0.151)	0.173 (0.150)	0.369 (0.368)	0.724 (0.498)
Petroleum	-0.003 (0.043)	-0.004 (0.011)	-0.0002 (0.009)	-0.003 (0.010)	0.001 (0.010)	-0.0004 (0.026)	-0.009 (0.035)
Mountains	-0.006 (0.024)	0.001 (0.006)	-0.001 (0.005)	0.001 (0.006)	-0.005 (0.006)	-0.010 (0.014)	-0.001 (0.019)
Forest	-0.020 (0.044)	0.003 (0.011)	-0.004 (0.009)	0.003 (0.011)	-0.002 (0.011)	-0.007 (0.026)	0.003 (0.035)
Gemstone	-0.001 (0.016)	-0.0001 (0.004)	-0.002 (0.003)	0.0004 (0.004)	-0.002 (0.004)	-0.0002 (0.009)	0.002 (0.013)
Excluded	0.011 (0.014)	0.002 (0.004)	0.002 (0.003)	0.002 (0.004)	0.002 (0.003)	0.005 (0.009)	0.006 (0.012)
Population	0.005 (0.005)	0.003* (0.001)	0.001 (0.001)	0.003* (0.001)	-0.0005 (0.001)	0.003 (0.003)	0.008 (0.004)
Constant	-0.396*** (0.120)	-0.124*** (0.030)	-0.047 (0.024)	-0.124*** (0.029)	-0.030 (0.029)	-0.129 (0.071)	-0.371*** (0.096)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.127	0.122	0.081	0.126	0.046	0.062	0.092
Adj. R-squared	0.127	0.122	0.080	0.125	0.045	0.061	0.091
Residual Std. Error	0.395	0.097	0.080	0.096	0.096	0.234	0.317
F Statistic	150.042***	143.450***	90.759***	148.549***	49.019***	67.881***	104.141***

***p < .001, **p < .01, *p < .05

A.3.9 Observations on the month level: 2016

TABLE A.17: Ordinary least squares regression results (2016)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.225*** (0.009)						
OSV (lag)		0.240*** (0.008)					
SBV (lag)			0.211*** (0.009)				
OSV rebels (lag)				0.243*** (0.008)			
Gov fatalities (lag)					0.011 (0.009)		
Reb fatalities (lag)						0.224*** (0.009)	
Civ casualties (lag)							0.225*** (0.008)
Territorial advance _{t-1} → t	0.211*** (0.009)	0.021*** (0.002)	0.069*** (0.003)	0.021*** (0.002)	0.032*** (0.003)	0.151*** (0.008)	0.058*** (0.005)
National capital distance	-0.003 (0.008)	0.002 (0.001)	-0.001 (0.002)	0.002 (0.001)	-0.001 (0.002)	-0.007 (0.006)	0.005 (0.004)
Border distance	-0.015*** (0.004)	0.001 (0.001)	-0.005*** (0.001)	0.001 (0.001)	-0.004*** (0.001)	-0.016*** (0.003)	0.001 (0.002)
Nightlights	-0.202 (0.421)	0.021 (0.078)	-0.125 (0.139)	0.021 (0.078)	0.046 (0.121)	-0.279 (0.359)	0.055 (0.219)
Petroleum	0.001 (0.030)	-0.002 (0.005)	-0.0001 (0.010)	-0.002 (0.005)	0.003 (0.009)	0.004 (0.025)	-0.004 (0.015)
Mountains	0.015 (0.016)	0.001 (0.003)	0.005 (0.005)	0.001 (0.003)	-0.002 (0.005)	0.013 (0.014)	0.005 (0.009)
Forest	-0.048 (0.030)	0.004 (0.006)	-0.017 (0.010)	0.004 (0.006)	-0.010 (0.009)	-0.056* (0.026)	0.007 (0.016)
Gemstone	0.011 (0.011)	0.003 (0.002)	0.002 (0.004)	0.003 (0.002)	0.004 (0.003)	0.002 (0.009)	0.007 (0.006)
Excluded	-0.005 (0.010)	-0.00003 (0.002)	-0.002 (0.003)	-0.0001 (0.002)	0.00000 (0.003)	-0.005 (0.008)	-0.0002 (0.005)
Population	0.008* (0.004)	0.002** (0.001)	0.002* (0.001)	0.002** (0.001)	-0.001 (0.001)	0.003 (0.003)	0.005** (0.002)
Constant	0.006 (0.079)	-0.044** (0.015)	0.011 (0.026)	-0.044** (0.015)	0.036 (0.023)	0.099 (0.068)	-0.108* (0.041)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.144	0.097	0.133	0.099	0.021	0.119	0.087
Adj. R-squared	0.144	0.097	0.132	0.098	0.020	0.118	0.086
Residual Std. Error	0.272	0.050	0.090	0.050	0.078	0.232	0.142
F Statistic	173.489***	110.979***	157.445***	112.386***	22.172***	138.965***	97.707***

*** p < .001; ** p < .01; * p < .05

A.3.10 Observations on the month level: 2017

TABLE A.18: Ordinary least squares regression results (2017)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.289*** (0.009)						
OSV (lag)		0.415*** (0.009)					
SBV (lag)			0.253*** (0.009)				
OSV rebels (lag)				0.422*** (0.009)			
Gov fatalities (lag)					0.037*** (0.010)		
Reb fatalities (lag)						0.217*** (0.009)	
Civ casualties (lag)							0.331*** (0.009)
Territorial advance _{t-1} → t	0.229*** (0.009)	0.027*** (0.002)	0.083*** (0.003)	0.026*** (0.002)	0.057*** (0.004)	0.142*** (0.007)	0.078*** (0.006)
National capital distance	0.007 (0.007)	0.005* (0.002)	-0.001 (0.003)	0.005* (0.002)	0.002 (0.003)	-0.002 (0.006)	0.009* (0.005)
Border distance	-0.001 (0.004)	0.002 (0.001)	-0.003* (0.001)	0.002 (0.001)	0.002 (0.002)	-0.006* (0.003)	0.003 (0.002)
Nightlights	0.199 (0.411)	0.156 (0.104)	-0.060 (0.153)	0.146 (0.103)	0.010 (0.163)	-0.032 (0.315)	0.314 (0.256)
Petroleum	-0.015 (0.029)	-0.005 (0.007)	-0.005 (0.011)	-0.005 (0.007)	-0.002 (0.012)	-0.005 (0.022)	-0.011 (0.018)
Mountains	0.016 (0.016)	0.003 (0.004)	0.003 (0.006)	0.003 (0.004)	0.003 (0.006)	0.009 (0.012)	0.006 (0.010)
Forest	0.003 (0.030)	0.007 (0.008)	-0.0001 (0.011)	0.007 (0.007)	0.002 (0.012)	-0.016 (0.023)	0.018 (0.019)
Gemstone	-0.009 (0.011)	-0.0004 (0.003)	-0.005 (0.004)	-0.0003 (0.003)	-0.003 (0.004)	-0.011 (0.008)	0.001 (0.007)
Excluded	-0.002 (0.010)	0.0002 (0.002)	-0.002 (0.004)	0.003 (0.002)	0.001 (0.004)	-0.002 (0.007)	0.0002 (0.006)
Population	0.015*** (0.004)	0.004*** (0.001)	0.006*** (0.001)	0.004*** (0.001)	0.001 (0.001)	0.007* (0.003)	0.010*** (0.002)
Constant	-0.238** (0.078)	-0.101*** (0.020)	-0.046 (0.029)	-0.097*** (0.020)	-0.039 (0.031)	-0.037 (0.059)	-0.221*** (0.048)
N	11316	11316	11316	11316	11316	11316	11316
R-squared	0.191	0.204	0.162	0.209	0.032	0.114	0.150
Adj. R-squared	0.190	0.203	0.161	0.209	0.031	0.113	0.149
Residual Std. Error	0.267	0.068	0.099	0.067	0.106	0.205	0.166
F Statistic	242.297***	263.511***	199.029***	272.219***	33.917***	131.913***	181.751***

***p < .001; **p < .01; *p < .05

A.4 Spatial lag regression models

A.4.1 Observations on the year level: 2009 - 2017

Regression table

TABLE A.19: Spatial lag regression results

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.959*** (0.004)						
OSV (lag)		0.973*** (0.003)					
SBV (lag)			0.984*** (0.003)				
OSV rebels (lag)				0.975*** (0.003)			
Gov fatalities (lag)					0.958*** (0.003)		
Reb fatalities (lag)						0.960*** (0.003)	
Civ casualties (lag)							0.948*** (0.004)
Territorial advance, $-1 \rightarrow t$	0.001 (0.001)	-0.0001 (0.0002)	0.0001 (0.0002)	-0.0003 (0.0002)	0.001*** (0.0004)	0.002*** (0.001)	0.0002 (0.001)
National capital distance	0.012* (0.006)	0.002 (0.002)	0.002 (0.001)	0.002 (0.001)	0.004 (0.003)	0.003 (0.004)	0.006 (0.005)
Border distance	0.003 (0.003)	0.003 (0.001)	0.0003 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.00001 (0.002)	0.001 (0.003)
Nightlights	0.342 (0.259)	0.050 (0.069)	0.083 (0.067)	0.029 (0.067)	0.118 (0.115)	0.047 (0.184)	0.348 (0.220)
Petroleum	-0.002 (0.024)	-0.001 (0.006)	0.0003 (0.006)	-0.001 (0.006)	0.0001 (0.011)	0.001 (0.017)	-0.001 (0.020)
Mountains	0.003 (0.013)	0.004 (0.004)	0.001 (0.003)	0.003 (0.003)	-0.0003 (0.006)	0.005 (0.009)	0.010 (0.011)
Forest	-0.010 (0.024)	-0.005 (0.007)	-0.004 (0.006)	-0.005 (0.006)	-0.003 (0.011)	-0.010 (0.017)	-0.016 (0.021)
Gemstone	-0.003 (0.009)	-0.002 (0.002)	-0.0002 (0.002)	-0.001 (0.002)	-0.002 (0.004)	-0.003 (0.006)	-0.002 (0.007)
Excluded	0.001 (0.008)	0.00002 (0.002)	0.0005 (0.002)	-0.00003 (0.002)	0.001 (0.003)	0.001 (0.006)	0.001 (0.007)
Population	0.0001 (0.001)	0.001 (0.001)	-0.0004 (0.001)	0.0004 (0.001)	-0.001 (0.001)	-0.0001 (0.002)	0.0003 (0.002)
ρ	0.03*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)	-0.00 (0.00)	0.02*** (0.00)	0.03*** (0.00)
Constant	-0.099 (0.061)	-0.025 (0.016)	-0.015 (0.016)	-0.021 (0.016)	-0.026 (0.027)	-0.020 (0.043)	-0.064 (0.052)
N	8487	8487	8487	8487	8487	8487	8487
Log Likelihood	2046.136	13242.510	13502.590	13534.910	8931.829	4974.948	3428.395
Wald Test (df = 1)	32.513***	29.039***	19.407***	34.469***	0.063	15.511***	48.730***
LR Test (df = 1)	33.012***	29.290***	19.789***	34.742***	0.065	15.733***	49.392***
AIC	-4064.273	-26457.030	-26977.180	-27041.820	-17835.660	-9921.895	-6828.791

***p < .001, **p < .01, *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.97	0.00	0.02	0.00	0.99	0.00
Territorial advance $_{t-1 \rightarrow t}$	-0.00	0.67	-0.00	0.64	-0.00	0.67
National capital distance	0.00	0.14	0.00	0.16	0.00	0.14
Border distance	0.00	0.47	0.00	0.48	0.00	0.47
Nightlights	0.05	0.46	0.00	0.48	0.05	0.46
Petroleum	-0.00	0.94	-0.00	0.94	-0.00	0.94
Mountains	0.00	0.25	0.00	0.26	0.00	0.25
Forest	-0.01	0.47	-0.00	0.48	-0.01	0.47
Gemstone	-0.00	0.57	-0.00	0.58	-0.00	0.57
Excluded	0.00	0.99	0.00	1.00	0.00	0.99
Population	0.00	0.53	0.00	0.54	0.00	0.53

TABLE A.20: Direct and indirect effects on the annual level (OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.98	0.00	0.01	0.00	1.00	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.00	0.78	0.00	0.85	0.00	0.78
National capital distance	0.00	0.11	0.00	0.14	0.00	0.11
Border distance	0.00	0.74	0.00	0.74	0.00	0.74
Nightlights	0.08	0.19	0.00	0.22	0.08	0.19
Petroleum	0.00	0.97	0.00	0.97	0.00	0.97
Mountains	0.00	0.82	0.00	0.82	0.00	0.82
Forest	-0.00	0.53	-0.00	0.55	-0.00	0.53
Gemstone	-0.00	0.87	-0.00	0.87	-0.00	0.87
Excluded	0.00	0.83	0.00	0.84	0.00	0.83
Population	-0.00	0.63	-0.00	0.64	-0.00	0.63

TABLE A.21: Direct and indirect effects on the annual level (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)	0.98	0.00	0.02	0.00	1.00	0.00
Territorial advance $_{t-1 \rightarrow t}$	-0.00	0.22	-0.00	0.24	-0.00	0.22
National capital distance	0.00	0.14	0.00	0.16	0.00	0.14
Border distance	0.00	0.55	0.00	0.56	0.00	0.55
Nightlights	0.03	0.63	0.00	0.64	0.03	0.63
Petroleum	-0.00	0.93	-0.00	0.93	-0.00	0.93
Mountains	0.00	0.30	0.00	0.31	0.00	0.30
Forest	-0.00	0.46	-0.00	0.47	-0.00	0.46
Gemstone	-0.00	0.54	-0.00	0.54	-0.00	0.54
Excluded	-0.00	0.97	-0.00	0.97	-0.00	0.97
Population	0.00	0.61	0.00	0.62	0.00	0.61

TABLE A.22: Direct and indirect effects on the annual level
(Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.96	0.00	-0.00	0.78	0.96	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.00	0.00	-0.00	0.74	0.00	0.00
National capital distance	0.00	0.13	-0.00	0.80	0.00	0.13
Border distance	0.00	0.54	-0.00	0.91	0.00	0.54
Nightlights	0.12	0.28	-0.00	0.82	0.12	0.28
Petroleum	0.00	1.00	-0.00	0.99	0.00	1.00
Mountains	-0.00	0.98	0.00	0.99	-0.00	0.98
Forest	-0.00	0.78	0.00	0.91	-0.00	0.78
Gemstone	-0.00	0.67	0.00	0.92	-0.00	0.67
Excluded	0.00	0.73	-0.00	0.93	0.00	0.73
Population	-0.00	0.61	0.00	0.89	-0.00	0.61

TABLE A.23: Direct and indirect effects on the annual level
(government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.96	0.00	0.02	0.00	0.98	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.00	0.00	0.00	0.00	0.00	0.00
National capital distance	0.00	0.42	0.00	0.44	0.00	0.42
Border distance	-0.00	0.97	-0.00	0.97	-0.00	0.97
Nightlights	0.05	0.76	0.00	0.77	0.05	0.76
Petroleum	0.00	0.99	0.00	0.98	0.00	0.98
Mountains	0.00	0.56	0.00	0.57	0.01	0.56
Forest	-0.01	0.54	-0.00	0.56	-0.01	0.54
Gemstone	-0.00	0.67	-0.00	0.68	-0.00	0.67
Excluded	0.00	0.91	0.00	0.93	0.00	0.91
Population	-0.00	0.98	-0.00	0.99	-0.00	0.98

TABLE A.24: Direct and indirect effects on the annual level
(rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.95	0.00	0.03	0.00	0.98	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.00	0.86	0.00	0.90	0.00	0.86
National capital distance	0.01	0.22	0.00	0.23	0.01	0.22
Border distance	0.00	0.72	0.00	0.72	0.00	0.72
Nightlights	0.35	0.10	0.01	0.11	0.36	0.10
Petroleum	-0.00	0.99	-0.00	0.99	-0.00	0.99
Mountains	0.01	0.36	0.00	0.37	0.01	0.36
Forest	-0.02	0.44	-0.00	0.45	-0.02	0.44
Gemstone	-0.00	0.78	-0.00	0.79	-0.00	0.78
Excluded	0.00	0.94	0.00	0.94	0.00	0.94
Population	0.00	0.95	0.00	0.94	0.00	0.95

TABLE A.25: Direct and indirect effects on the annual level
(civilian fatalities)

A.4.2 Observations on the month level: 2009

Regression table

TABLE A.26: Spatial lag regression results (2009)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
fatalitieslog_l1	-0.035*** (0.009)						
osvcountlog_l1		-0.016 (0.009)					
clashcountlog_l1			0.183*** (0.009)				
govdeathslog_l1					-0.021* (0.009)		
rebdeathslog_l1						-0.026** (0.009)	
civdeathslog_l1							-0.013 (0.009)
control_adv	0.144*** (0.008)	-0.001 (0.001)	0.030*** (0.002)	0.000	0.039*** (0.003)	0.099*** (0.006)	0.013*** (0.001)
capdistlog	0.003 (0.002)	0.0004* (0.0002)	0.001* (0.001)	0.000	0.001 (0.001)	0.003 (0.002)	0.0004 (0.0004)
bdists3log	0.001 (0.001)	0.0001 (0.0001)	0.0004 (0.0003)	0.000	0.0004 (0.0004)	0.001 (0.001)	0.0001 (0.0002)
nightsmean	0.369*** (0.112)	0.128*** (0.010)	0.092** (0.032)	0.000	0.089* (0.040)	0.289** (0.092)	0.144*** (0.022)
npetro	0.001 (0.008)	0.0005 (0.001)	-0.0002 (0.002)	0.000	0.0001 (0.003)	0.001 (0.007)	0.001 (0.002)
mountains_mean	0.003 (0.004)	0.0004 (0.0004)	0.0001 (0.001)	0.000	0.0004 (0.002)	0.003 (0.004)	0.002 (0.001)
forest	0.002 (0.008)	-0.0005 (0.001)	0.001 (0.002)	0.000	0.001 (0.003)	-0.001 (0.007)	-0.002 (0.002)
gem	0.003 (0.003)	0.0001 (0.0003)	0.0002 (0.001)	0.000	0.0003 (0.001)	0.003 (0.002)	0.002** (0.001)
excluded	0.002 (0.003)	0.0004 (0.0002)	0.0005 (0.001)	0.000	0.001 (0.001)	0.001 (0.002)	0.0004 (0.001)
poplog	0.0001 (0.001)	-0.0003*** (0.0003)	0.0003 (0.0003)	0.000	0.0002 (0.0004)	0.0003 (0.001)	-0.0005* (0.0002)
Constant	-0.047* (0.020)	-0.005** (0.002)	-0.017** (0.006)	0.000	-0.016* (0.007)	-0.039* (0.016)	-0.005 (0.004)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	13486.790	40995.030	27764.860		25162.390	15756.270	31869.990
Wald Test (df = 1)	3.273	0.870	1.928		1.116	1.700	0.485
LR Test (df = 1)	3.762	1.076	2.300		1.351	1.897	0.454
AIC	-26945.580	-81962.050	-55501.730		-50296.780	-31484.540	-63711.970

***p < .001, **p < .01, *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	-0.04	0.00	0.00	0.10	-0.03	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.14	0.00	-0.00	0.07	0.14	0.00
National capital distance	0.00	0.08	-0.00	0.25	0.00	0.08
Border distance	0.00	0.20	-0.00	0.34	0.00	0.20
Nightlights	0.37	0.00	-0.01	0.13	0.36	0.00
Petroleum	0.00	0.95	-0.00	0.94	0.00	0.95
Mountains	0.00	0.51	-0.00	0.58	0.00	0.51
Forest	0.00	0.80	-0.00	0.82	0.00	0.80
Gemstone	0.00	0.39	-0.00	0.47	0.00	0.39
Excluded	0.00	0.53	-0.00	0.61	0.00	0.53
Population	0.00	0.86	-0.00	0.88	0.00	0.86

TABLE A.27: Direct and indirect effects on the month level
2009 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	-0.02	0.08	0.00	0.45	-0.02	0.08
Territorial advance $_{t-1 \rightarrow t}$	-0.00	0.16	0.00	0.49	-0.00	0.16
National capital distance	0.00	0.02	-0.00	0.40	0.00	0.02
Border distance	0.00	0.46	-0.00	0.68	0.00	0.46
Nightlights	0.13	0.00	-0.00	0.33	0.13	0.00
Petroleum	0.00	0.50	-0.00	0.68	0.00	0.50
Mountains	0.00	0.35	-0.00	0.60	0.00	0.35
Forest	-0.00	0.50	0.00	0.67	-0.00	0.50
Gemstone	0.00	0.71	-0.00	0.78	0.00	0.71
Excluded	0.00	0.07	-0.00	0.44	0.00	0.07
Population	-0.00	0.00	0.00	0.35	-0.00	0.00

TABLE A.28: Direct and indirect effects on the month level
2009 (OSV)

rebfat missing, for some reason only NAs NaNs

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.18	0.00	-0.00	0.17	0.18	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.18	0.03	0.00
National capital distance	0.00	0.02	-0.00	0.28	0.00	0.02
Border distance	0.00	0.17	-0.00	0.39	0.00	0.17
Nightlights	0.09	0.00	-0.00	0.25	0.09	0.00
Petroleum	-0.00	0.91	0.00	0.94	-0.00	0.91
Mountains	0.00	0.89	-0.00	0.91	0.00	0.89
Forest	0.00	0.54	-0.00	0.64	0.00	0.54
Gemstone	0.00	0.88	-0.00	0.91	0.00	0.88
Excluded	0.00	0.51	-0.00	0.64	0.00	0.51
Population	0.00	0.33	-0.00	0.48	0.00	0.33

TABLE A.29: Direct and indirect effects on the month level
2009 (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	-0.02	0.03	0.00	0.37	-0.02	0.03
Territorial advance $_{t-1 \rightarrow t}$	0.04	0.00	-0.00	0.30	0.04	0.00
National capital distance	0.00	0.07	-0.00	0.42	0.00	0.07
Border distance	0.00	0.24	-0.00	0.50	0.00	0.24
Nightlights	0.09	0.02	-0.00	0.39	0.09	0.02
Petroleum	0.00	0.97	-0.00	0.99	0.00	0.97
Mountains	0.00	0.79	-0.00	0.87	0.00	0.79
Forest	0.00	0.71	-0.00	0.79	0.00	0.71
Gemstone	0.00	0.79	-0.00	0.85	0.00	0.79
Excluded	0.00	0.53	-0.00	0.69	0.00	0.53
Population	0.00	0.69	-0.00	0.77	0.00	0.69

TABLE A.30: Direct and indirect effects on the month level
2009 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	-0.03	0.00	0.00	0.25	-0.03	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.10	0.00	-0.00	0.19	0.10	0.00
National capital distance	0.00	0.06	-0.00	0.32	0.00	0.06
Border distance	0.00	0.33	-0.00	0.50	0.00	0.33
Nightlights	0.29	0.00	-0.00	0.24	0.28	0.00
Petroleum	0.00	0.89	-0.00	0.93	0.00	0.89
Mountains	0.00	0.38	-0.00	0.52	0.00	0.38
Forest	-0.00	0.92	0.00	0.93	-0.00	0.92
Gemstone	0.00	0.12	-0.00	0.37	0.00	0.12
Excluded	0.00	0.52	-0.00	0.62	0.00	0.52
Population	0.00	0.71	-0.00	0.78	0.00	0.71

TABLE A.31: Direct and indirect effects on the month level
2009 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	-0.01	0.16	0.00	0.62	-0.01	0.16
Territorial advance $_{t-1 \rightarrow t}$	0.01	0.00	-0.00	0.49	0.01	0.00
National capital distance	0.00	0.21	-0.00	0.63	0.00	0.21
Border distance	0.00	0.53	-0.00	0.77	0.00	0.53
Nightlights	0.14	0.00	-0.00	0.50	0.14	0.00
Petroleum	0.00	0.55	-0.00	0.78	0.00	0.55
Mountains	0.00	0.06	-0.00	0.57	0.00	0.06
Forest	-0.00	0.29	0.00	0.65	-0.00	0.29
Gemstone	0.00	0.00	-0.00	0.53	0.00	0.00
Excluded	0.00	0.44	-0.00	0.70	0.00	0.44
Population	-0.00	0.02	0.00	0.54	-0.00	0.02

TABLE A.32: Direct and indirect effects on the month level
2009 (civilian fatalities)

A.4.3 Observations on the month level: 2010

Regression table

TABLE A.33: Spatial lag regression results (2010)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.413*** (0.017)						
OSV (lag)		0.912*** (0.009)					
SBV (lag)			0.625*** (0.010)				
OSV rebels (lag)				0.912*** (0.009)			
Gov fatalities (lag)					0.185*** (0.011)		
Reb fatalities (lag)						-0.011 (0.009)	
Civ casualties (lag)							0.412*** (0.027)
Territorial advance _{<i>t</i>-1} → <i>t</i>	0.107*** (0.006)	0.027*** (0.002)	0.034*** (0.002)	0.027*** (0.002)	0.038*** (0.003)	0.008*** (0.001)	0.088*** (0.005)
National capital distance	0.003 (0.001)	0.001 (0.0004)	0.001* (0.001)	0.001 (0.0004)	0.002* (0.001)	0.00001 (0.0002)	0.001 (0.001)
Border distance	0.001 (0.001)	0.0002 (0.0002)	0.0003 (0.0003)	0.0002 (0.0002)	0.0004 (0.0004)	0.0001 (0.0001)	0.0005 (0.001)
Nightlights	0.403*** (0.099)	0.088** (0.028)	0.113** (0.041)	0.088** (0.028)	0.142*** (0.047)	-0.009 (0.012)	0.311*** (0.089)
Petroleum	-0.0005 (0.006)	-0.0002 (0.002)	-0.0002 (0.002)	-0.0002 (0.002)	0.00004 (0.003)	0.00002 (0.001)	-0.001 (0.005)
Mountains	0.006 (0.003)	0.001 (0.001)	-0.0002 (0.001)	0.001 (0.001)	0.001 (0.002)	-0.0002 (0.0004)	0.005 (0.003)
Forest	-0.005 (0.006)	-0.0003 (0.002)	0.001 (0.002)	-0.0003 (0.002)	-0.0002 (0.003)	0.0003 (0.001)	-0.004 (0.005)
Gemstone	-0.001 (0.002)	-0.0004 (0.001)	0.0003 (0.001)	-0.0004 (0.001)	0.002 (0.001)	-0.0001 (0.0003)	-0.002 (0.002)
Excluded	0.001 (0.002)	0.0003 (0.001)	0.001 (0.001)	0.0003 (0.001)	0.0005 (0.001)	0.00003 (0.0002)	0.001 (0.002)
Population	0.001 (0.001)	0.0003 (0.0002)	0.0003 (0.0003)	0.0003 (0.0002)	0.0003 (0.0004)	-0.0001 (0.0001)	0.001 (0.001)
ρ	-0.03* (0.01)	-0.02** (0.01)	-0.02* (0.01)	-0.02** (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.02 (0.01)
Constant	-0.059*** (0.016)	-0.014** (0.004)	-0.022*** (0.006)	-0.014** (0.004)	-0.025*** (0.007)	0.001 (0.002)	-0.042** (0.014)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	17071.940	31227.530	27034.430	31227.530	25632.280	40967.090	18370.890
Wald Test (df = 1)	5.872*	6.899**	3.875*	6.899**	2.210	0.199	3.042
LR Test (df = 1)	6.954**	7.796**	4.422*	7.796**	2.453	0.172	3.735
AIC	-34115.890	-62427.060	-54040.860	-62427.060	-51236.560	-81906.190	-36713.780

***p < .001; **p < .01; *p < .05

Direct and indirect effects: Fatalities

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.41	0.00	-0.01	0.01	0.40	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.11	0.00	-0.00	0.01	0.10	0.00
National capital distance	0.00	0.06	-0.00	0.15	0.00	0.06
Border distance	0.00	0.28	-0.00	0.34	0.00	0.28
Nightlights	0.40	0.00	-0.01	0.03	0.39	0.00
Petroleum	-0.00	0.93	0.00	0.94	-0.00	0.93
Mountains	0.01	0.06	-0.00	0.15	0.01	0.06
Forest	-0.00	0.39	0.00	0.45	-0.00	0.39
Gemstone	-0.00	0.74	0.00	0.76	-0.00	0.74
Excluded	0.00	0.62	-0.00	0.65	0.00	0.62
Population	0.00	0.27	-0.00	0.34	0.00	0.27

TABLE A.34: Direct and indirect effects on the month level
2010 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.91	0.00	-0.02	0.01	0.89	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.01	0.03	0.00
National capital distance	0.00	0.07	-0.00	0.16	0.00	0.07
Border distance	0.00	0.44	-0.00	0.47	0.00	0.44
Nightlights	0.09	0.00	-0.00	0.06	0.09	0.00
Petroleum	-0.00	0.93	0.00	0.92	-0.00	0.93
Mountains	0.00	0.50	-0.00	0.54	0.00	0.50
Forest	-0.00	0.86	0.00	0.87	-0.00	0.86
Gemstone	-0.00	0.48	0.00	0.52	-0.00	0.48
Excluded	0.00	0.56	-0.00	0.59	0.00	0.56
Population	0.00	0.23	-0.00	0.30	0.00	0.23

TABLE A.35: Direct and indirect effects on the month level
2010 (OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.62	0.00	-0.01	0.05	0.61	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.06	0.03	0.00
National capital distance	0.00	0.01	-0.00	0.16	0.00	0.01
Border distance	0.00	0.28	-0.00	0.38	0.00	0.28
Nightlights	0.11	0.00	-0.00	0.14	0.11	0.00
Petroleum	-0.00	0.97	0.00	0.97	-0.00	0.97
Mountains	-0.00	0.85	0.00	0.88	-0.00	0.85
Forest	0.00	0.79	-0.00	0.82	0.00	0.79
Gemstone	0.00	0.77	-0.00	0.81	0.00	0.77
Excluded	0.00	0.51	-0.00	0.56	0.00	0.51
Population	0.00	0.38	-0.00	0.46	0.00	0.38

TABLE A.36: Direct and indirect effects on the month level
2010 (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)	0.91	0.00	-0.02	0.01	0.89	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.01	0.03	0.00
National capital distance	0.00	0.07	-0.00	0.16	0.00	0.07
Border distance	0.00	0.44	-0.00	0.47	0.00	0.44
Nightlights	0.09	0.00	-0.00	0.06	0.09	0.00
Petroleum	-0.00	0.93	0.00	0.92	-0.00	0.93
Mountains	0.00	0.50	-0.00	0.54	0.00	0.50
Forest	-0.00	0.86	0.00	0.87	-0.00	0.86
Gemstone	-0.00	0.48	0.00	0.52	-0.00	0.48
Excluded	0.00	0.56	-0.00	0.59	0.00	0.56
Population	0.00	0.23	-0.00	0.30	0.00	0.23

TABLE A.37: Direct and indirect effects on the month level
2010 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.19	0.00	-0.00	0.15	0.18	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.04	0.00	-0.00	0.15	0.04	0.00
National capital distance	0.00	0.01	-0.00	0.23	0.00	0.01
Border distance	0.00	0.29	-0.00	0.45	0.00	0.29
Nightlights	0.14	0.00	-0.00	0.22	0.14	0.00
Petroleum	0.00	0.96	-0.00	0.97	0.00	0.96
Mountains	0.00	0.55	-0.00	0.64	0.00	0.55
Forest	-0.00	0.93	0.00	0.94	-0.00	0.93
Gemstone	0.00	0.06	-0.00	0.29	0.00	0.06
Excluded	0.00	0.61	-0.00	0.70	0.00	0.61
Population	0.00	0.39	-0.00	0.52	0.00	0.39

TABLE A.38: Direct and indirect effects on the month level
2010 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	-0.01	0.22	0.00	0.76	-0.01	0.22
Territorial advance $_{t-1 \rightarrow t}$	0.01	0.00	-0.00	0.65	0.01	0.00
National capital distance	0.00	0.95	-0.00	0.95	0.00	0.95
Border distance	0.00	0.56	-0.00	0.84	0.00	0.56
Nightlights	-0.01	0.48	0.00	0.80	-0.01	0.48
Petroleum	0.00	0.96	-0.00	0.99	0.00	0.96
Mountains	-0.00	0.67	0.00	0.87	-0.00	0.67
Forest	0.00	0.70	-0.00	0.88	0.00	0.70
Gemstone	-0.00	0.66	0.00	0.88	-0.00	0.66
Excluded	0.00	0.92	-0.00	0.94	0.00	0.93
Population	-0.00	0.48	0.00	0.81	-0.00	0.48

TABLE A.39: Direct and indirect effects on the month level
2010 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.41	0.00	-0.01	0.07	0.40	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.09	0.00	-0.00	0.07	0.09	0.00
National capital distance	0.00	0.20	-0.00	0.34	0.00	0.20
Border distance	0.00	0.46	-0.00	0.54	0.00	0.46
Nightlights	0.31	0.00	-0.01	0.11	0.31	0.00
Petroleum	-0.00	0.89	0.00	0.90	-0.00	0.89
Mountains	0.00	0.09	-0.00	0.25	0.00	0.09
Forest	-0.00	0.42	0.00	0.52	-0.00	0.42
Gemstone	-0.00	0.20	0.00	0.34	-0.00	0.20
Excluded	0.00	0.68	-0.00	0.72	0.00	0.68
Population	0.00	0.31	-0.00	0.43	0.00	0.31

TABLE A.40: Direct and indirect effects on the month level
2010 (civilian fatalities)

A.4.4 Observations on the month level: 2011

Regression table

TABLE A.41: Spatial lag regression results (2011)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.379*** (0.009)						
OSV (lag)		0.695*** (0.007)					
SBV (lag)			0.609*** (0.008)				
OSV rebels (lag)				0.756*** (0.006)			
Gov fatalities (lag)					0.351*** (0.010)		
Reb fatalities (lag)						0.205*** (0.010)	
Civ casualties (lag)							0.317*** (0.009)
Territorial advance $t_t - 1 \rightarrow t$	0.077*** (0.005)	0.008*** (0.002)	0.027*** (0.002)	0.004** (0.001)	0.047*** (0.003)	0.025*** (0.002)	0.030*** (0.004)
National capital distance	0.009** (0.003)	0.003*** (0.001)	0.003* (0.001)	0.003** (0.001)	0.003 (0.002)	0.003* (0.001)	0.005** (0.002)
Border distance	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.0004)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Nightlights	1.030*** (0.185)	0.392*** (0.062)	0.065 (0.072)	0.317*** (0.048)	0.025 (0.110)	0.072 (0.080)	0.836*** (0.125)
Petroleum	0.002 (0.012)	0.0001 (0.004)	-0.001 (0.005)	0.001 (0.003)	-0.001 (0.007)	-0.001 (0.005)	0.003 (0.008)
Mountains	-0.004 (0.007)	-0.00000 (0.002)	-0.002 (0.003)	-0.0003 (0.002)	-0.003 (0.004)	-0.002 (0.003)	0.0003 (0.005)
Forest	0.005 (0.013)	0.001 (0.004)	0.004 (0.005)	0.001 (0.003)	0.005 (0.008)	0.004 (0.006)	-0.003 (0.009)
Gemstone	-0.002 (0.005)	-0.001 (0.002)	-0.001 (0.002)	-0.0003 (0.001)	-0.003 (0.003)	-0.003 (0.002)	-0.001 (0.003)
Excluded	0.007 (0.004)	0.002 (0.001)	0.001 (0.002)	0.002 (0.001)	0.001 (0.002)	0.001 (0.002)	0.006* (0.003)
Population	-0.001 (0.002)	0.00002 (0.001)	0.001 (0.001)	-0.0003 (0.0004)	0.001 (0.001)	0.001 (0.001)	-0.002* (0.001)
ρ	-0.02* (0.01)	-0.02* (0.01)	-0.02* (0.01)	-0.02** (0.01)	-0.02* (0.01)	-0.01 (0.01)	-0.02 (0.01)
Constant	-0.118*** (0.033)	-0.049*** (0.011)	-0.037** (0.013)	-0.034*** (0.009)	-0.036 (0.020)	-0.038** (0.014)	-0.061** (0.022)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	8500.678	20840.480	19050.970	23700.650	14285.080	17886.570	12868.130
Wald Test (df = 1)	4.617*	5.493*	5.814*	7.235**	4.883*	1.217	2.451
LR Test (df = 1)	5.205*	6.088*	6.556*	7.973**	5.473*	1.403	2.872
AIC	-16973.350	-41652.970	-38073.940	-47373.300	-28542.150	-35745.140	-25708.260

*** p < .001; ** p < .01; * p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.38	0.00	-0.01	0.03	0.37	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.08	0.00	-0.00	0.03	0.08	0.00
National capital distance	0.01	0.00	-0.00	0.09	0.01	0.00
Border distance	0.00	0.29	-0.00	0.39	0.00	0.29
Nightlights	1.03	0.00	-0.02	0.05	1.01	0.00
Petroleum	0.00	0.90	-0.00	0.90	0.00	0.90
Mountains	-0.00	0.59	0.00	0.63	-0.00	0.59
Forest	0.01	0.68	-0.00	0.70	0.01	0.68
Gemstone	-0.00	0.69	0.00	0.72	-0.00	0.69
Excluded	0.01	0.09	-0.00	0.22	0.01	0.09
Population	-0.00	0.58	0.00	0.63	-0.00	0.58

TABLE A.42: Direct and indirect effects on the month level
2011 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.69	0.00	-0.01	0.02	0.68	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.01	0.00	-0.00	0.04	0.01	0.00
National capital distance	0.00	0.00	-0.00	0.07	0.00	0.00
Border distance	0.00	0.18	-0.00	0.29	0.00	0.18
Nightlights	0.39	0.00	-0.01	0.03	0.38	0.00
Petroleum	0.00	0.99	-0.00	1.00	0.00	0.99
Mountains	-0.00	0.98	0.00	0.99	-0.00	0.98
Forest	0.00	0.78	-0.00	0.79	0.00	0.78
Gemstone	-0.00	0.54	0.00	0.58	-0.00	0.54
Excluded	0.00	0.09	-0.00	0.20	0.00	0.09
Population	0.00	0.95	-0.00	0.95	0.00	0.95

TABLE A.43: Direct and indirect effects on the month level
2011 (OSV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)		0.61	0.00	-0.01	0.01	0.60	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.03	0.00	-0.00	0.02	0.03	0.00
National capital distance		0.00	0.02	-0.00	0.11	0.00	0.02
Border distance		0.00	0.26	-0.00	0.35	0.00	0.26
Nightlights		0.06	0.34	-0.00	0.41	0.06	0.34
Petroleum		-0.00	0.79	0.00	0.82	-0.00	0.79
Mountains		-0.00	0.54	0.00	0.59	-0.00	0.54
Forest		0.00	0.41	-0.00	0.46	0.00	0.41
Gemstone		-0.00	0.45	0.00	0.50	-0.00	0.45
Excluded		0.00	0.61	-0.00	0.65	0.00	0.61
Population		0.00	0.09	-0.00	0.20	0.00	0.09

TABLE A.44: Direct and indirect effects on the month level
2011 (SBV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)		0.76	0.00	-0.02	0.01	0.74	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.00	0.00	-0.00	0.06	0.00	0.00
National capital distance		0.00	0.00	-0.00	0.06	0.00	0.00
Border distance		0.00	0.23	-0.00	0.32	0.00	0.23
Nightlights		0.32	0.00	-0.01	0.02	0.31	0.00
Petroleum		0.00	0.89	-0.00	0.89	0.00	0.89
Mountains		-0.00	0.86	0.00	0.87	-0.00	0.86
Forest		0.00	0.79	-0.00	0.81	0.00	0.79
Gemstone		-0.00	0.75	0.00	0.75	-0.00	0.75
Excluded		0.00	0.15	-0.00	0.24	0.00	0.15
Population		-0.00	0.51	0.00	0.55	-0.00	0.51

TABLE A.45: Direct and indirect effects on the month level
2011 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.35	0.00	-0.01	0.02	0.34	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.05	0.00	-0.00	0.03	0.05	0.00
National capital distance	0.00	0.09	-0.00	0.21	0.00	0.09
Border distance	0.00	0.57	-0.00	0.60	0.00	0.57
Nightlights	0.03	0.78	-0.00	0.79	0.02	0.78
Petroleum	-0.00	0.87	0.00	0.87	-0.00	0.87
Mountains	-0.00	0.43	0.00	0.49	-0.00	0.43
Forest	0.01	0.50	-0.00	0.56	0.01	0.50
Gemstone	-0.00	0.33	0.00	0.42	-0.00	0.33
Excluded	0.00	0.75	-0.00	0.76	0.00	0.75
Population	0.00	0.22	-0.00	0.33	0.00	0.22

TABLE A.46: Direct and indirect effects on the month level
2011 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.21	0.00	-0.00	0.26	0.20	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.26	0.03	0.00
National capital distance	0.00	0.02	-0.00	0.35	0.00	0.02
Border distance	0.00	0.38	-0.00	0.56	0.00	0.38
Nightlights	0.07	0.34	-0.00	0.54	0.07	0.34
Petroleum	-0.00	0.82	0.00	0.89	-0.00	0.82
Mountains	-0.00	0.47	0.00	0.63	-0.00	0.47
Forest	0.00	0.48	-0.00	0.63	0.00	0.48
Gemstone	-0.00	0.14	0.00	0.44	-0.00	0.14
Excluded	0.00	0.56	-0.00	0.69	0.00	0.56
Population	0.00	0.14	-0.00	0.44	0.00	0.14

TABLE A.47: Direct and indirect effects on the month level
2011 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.32	0.00	-0.01	0.11	0.31	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.12	0.03	0.00
National capital distance	0.01	0.01	-0.00	0.20	0.01	0.01
Border distance	0.00	0.39	-0.00	0.50	0.00	0.39
Nightlights	0.84	0.00	-0.01	0.13	0.82	0.00
Petroleum	0.00	0.69	-0.00	0.72	0.00	0.69
Mountains	0.00	0.96	-0.00	0.95	0.00	0.96
Forest	-0.00	0.75	0.00	0.79	-0.00	0.75
Gemstone	-0.00	0.67	0.00	0.72	-0.00	0.67
Excluded	0.01	0.03	-0.00	0.23	0.01	0.03
Population	-0.00	0.03	0.00	0.23	-0.00	0.03

TABLE A.48: Direct and indirect effects on the month level
2011 (civilian fatalities)

A.4.5 Observations on the month level: 2012

Regression table

TABLE A.49: Spatial lag regression results (2012)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.457*** (0.008)						
OSV (lag)		0.521*** (0.008)					
SBV (lag)			0.627*** (0.007)				
OSV rebels (lag)				0.524*** (0.008)			
Gov fatalities (lag)					0.322*** (0.008)		
Reb fatalities (lag)						0.656*** (0.007)	
Civ casualties (lag)							0.306*** (0.009)
Territorial advance _{t-1} → _t	0.065*** (0.006)	0.018*** (0.002)	0.022*** (0.002)	0.018*** (0.002)	0.020*** (0.002)	0.014*** (0.003)	0.051*** (0.005)
National capital distance	0.011* (0.005)	0.005** (0.002)	0.004* (0.002)	0.005** (0.002)	0.002 (0.002)	0.005* (0.002)	0.012** (0.004)
Border distance	0.003 (0.003)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.0001 (0.001)	0.002 (0.001)	0.003 (0.002)
Nightlights	0.285 (0.295)	0.241* (0.106)	0.058 (0.115)	0.202 (0.104)	-0.013 (0.120)	0.082 (0.141)	0.625* (0.250)
Petroleum	-0.007 (0.020)	-0.003 (0.007)	-0.003 (0.008)	-0.003 (0.007)	-0.002 (0.008)	-0.003 (0.009)	-0.009 (0.017)
Mountains	-0.011 (0.011)	-0.001 (0.004)	-0.006 (0.004)	-0.002 (0.004)	-0.007 (0.004)	-0.006 (0.005)	-0.005 (0.009)
Forest	0.023 (0.020)	0.008 (0.007)	0.011 (0.008)	0.008 (0.007)	0.009 (0.008)	0.013 (0.010)	0.021 (0.017)
Gemstone	-0.003 (0.007)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.003 (0.003)	-0.003 (0.003)	-0.0003 (0.006)
Excluded	0.003 (0.007)	0.001 (0.002)	0.001 (0.003)	0.001 (0.002)	0.001 (0.003)	0.001 (0.003)	0.001 (0.006)
Population	0.005* (0.002)	0.002* (0.001)	0.003** (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.006** (0.002)
ρ	-0.01 (0.01)	-0.01 (0.01)	-0.03** (0.01)	-0.01 (0.01)	0.02 (0.01)	-0.01 (0.01)	-0.00 (0.01)
Constant	-0.157** (0.055)	-0.080*** (0.021)	-0.060** (0.021)	-0.076*** (0.019)	-0.030 (0.022)	-0.069** (0.026)	-0.201*** (0.046)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	3299.711	1484.930	13911.990	15106.320	13425.800	11628.090	5199.443
Wald Test (df = 1)	0.938	1.188	6.635**	1.124	2.330	1.287	0.038
LR Test (df = 1)	1.003	1.320	7.144**	1.252	2.466	1.434	0.040
AIC	-6571.422	-29741.870	-27795.980	-30184.630	-26823.600	-23228.190	-10370.890

***p < .001, **p < .01, *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.46	0.00	-0.00	0.32	0.45	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.06	0.00	-0.00	0.32	0.06	0.00
National capital distance	0.01	0.02	-0.00	0.40	0.01	0.02
Border distance	0.00	0.26	-0.00	0.53	0.00	0.26
Nightlights	0.29	0.35	-0.00	0.57	0.28	0.35
Petroleum	-0.01	0.73	0.00	0.82	-0.01	0.73
Mountains	-0.01	0.30	0.00	0.55	-0.01	0.30
Forest	0.02	0.25	-0.00	0.53	0.02	0.25
Gemstone	-0.00	0.69	0.00	0.78	-0.00	0.69
Excluded	0.00	0.67	-0.00	0.78	0.00	0.67
Population	0.00	0.05	-0.00	0.40	0.00	0.05

TABLE A.50: Direct and indirect effects on the month level
2012 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.52	0.00	-0.01	0.27	0.51	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	-0.00	0.27	0.02	0.00
National capital distance	0.01	0.00	-0.00	0.32	0.01	0.00
Border distance	0.00	0.11	-0.00	0.40	0.00	0.11
Nightlights	0.24	0.02	-0.00	0.35	0.24	0.02
Petroleum	-0.00	0.61	0.00	0.75	-0.00	0.61
Mountains	-0.00	0.70	0.00	0.79	-0.00	0.70
Forest	0.01	0.29	-0.00	0.52	0.01	0.29
Gemstone	-0.00	0.47	0.00	0.62	-0.00	0.47
Excluded	0.00	0.66	-0.00	0.75	0.00	0.66
Population	0.00	0.01	-0.00	0.35	0.00	0.01

TABLE A.51: Direct and indirect effects on the month level
2012 (OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.63	0.00	-0.02	0.01	0.61	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	-0.00	0.01	0.02	0.00
National capital distance	0.00	0.04	-0.00	0.14	0.00	0.04
Border distance	0.00	0.41	-0.00	0.45	0.00	0.41
Nightlights	0.06	0.58	-0.00	0.60	0.06	0.58
Petroleum	-0.00	0.64	0.00	0.66	-0.00	0.64
Mountains	-0.01	0.17	0.00	0.24	-0.01	0.17
Forest	0.01	0.17	-0.00	0.25	0.01	0.17
Gemstone	-0.00	0.34	0.00	0.40	-0.00	0.34
Excluded	0.00	0.78	-0.00	0.79	0.00	0.78
Population	0.00	0.01	-0.00	0.09	0.00	0.01

TABLE A.52: Direct and indirect effects on the month level
2012 (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)	0.52	0.00	-0.01	0.28	0.52	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	-0.00	0.28	0.02	0.00
National capital distance	0.00	0.00	-0.00	0.34	0.00	0.00
Border distance	0.00	0.12	-0.00	0.41	0.00	0.12
Nightlights	0.20	0.04	-0.00	0.38	0.20	0.04
Petroleum	-0.00	0.62	0.00	0.76	-0.00	0.62
Mountains	-0.00	0.65	0.00	0.77	-0.00	0.65
Forest	0.01	0.26	-0.00	0.51	0.01	0.26
Gemstone	-0.00	0.51	0.00	0.65	-0.00	0.51
Excluded	0.00	0.65	-0.00	0.75	0.00	0.65
Population	0.00	0.01	-0.00	0.36	0.00	0.01

TABLE A.53: Direct and indirect effects on the month level
2012 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.32	0.00	0.01	0.13	0.33	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.14	0.02	0.00
National capital distance	0.00	0.35	0.00	0.48	0.00	0.35
Border distance	-0.00	0.94	-0.00	0.93	-0.00	0.94
Nightlights	-0.01	0.95	-0.00	0.93	-0.01	0.95
Petroleum	-0.00	0.77	-0.00	0.82	-0.00	0.77
Mountains	-0.01	0.12	-0.00	0.33	-0.01	0.12
Forest	0.01	0.25	0.00	0.43	0.01	0.25
Gemstone	-0.00	0.33	-0.00	0.49	-0.00	0.33
Excluded	0.00	0.69	0.00	0.74	0.00	0.69
Population	0.00	0.08	0.00	0.30	0.00	0.08

TABLE A.54: Direct and indirect effects on the month level
2012 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.66	0.00	-0.01	0.24	0.65	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.01	0.00	-0.00	0.26	0.01	0.00
National capital distance	0.01	0.02	-0.00	0.32	0.01	0.02
Border distance	0.00	0.11	-0.00	0.40	0.00	0.11
Nightlights	0.08	0.53	-0.00	0.67	0.08	0.53
Petroleum	-0.00	0.74	0.00	0.79	-0.00	0.74
Mountains	-0.01	0.23	0.00	0.47	-0.01	0.23
Forest	0.01	0.17	-0.00	0.43	0.01	0.17
Gemstone	-0.00	0.35	0.00	0.52	-0.00	0.35
Excluded	0.00	0.65	-0.00	0.75	0.00	0.65
Population	0.00	0.11	-0.00	0.39	0.00	0.11

TABLE A.55: Direct and indirect effects on the month level
2012 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.31	0.00	-0.00	0.83	0.31	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.05	0.00	-0.00	0.83	0.05	0.00
National capital distance	0.01	0.00	-0.00	0.82	0.01	0.00
Border distance	0.00	0.16	-0.00	0.83	0.00	0.16
Nightlights	0.62	0.01	-0.00	0.82	0.62	0.01
Petroleum	-0.01	0.62	0.00	0.93	-0.01	0.62
Mountains	-0.00	0.61	0.00	0.93	-0.00	0.61
Forest	0.02	0.22	-0.00	0.86	0.02	0.22
Gemstone	-0.00	0.94	0.00	1.00	-0.00	0.94
Excluded	0.00	0.77	-0.00	0.95	0.00	0.77
Population	0.01	0.00	-0.00	0.83	0.01	0.00

TABLE A.56: Direct and indirect effects on the month level
2012 (civilian fatalities)

A.4.6 Observations on the month level: 2013

Regression table

TABLE A.57: Spatial lag regression results (2013)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.199*** (0.009)						
OSV (lag)		0.304*** (0.009)					
SBV (lag)			0.340*** (0.009)				
OSV rebels (lag)				0.307*** (0.009)			
Gov fatalities (lag)					0.075*** (0.010)		
Reb fatalities (lag)						0.220*** (0.010)	
Civ casualties (lag)							0.065*** (0.009)
Territorial advance, $t-1 \rightarrow t$	0.103*** (0.007)	0.017*** (0.002)	0.024*** (0.002)	0.017*** (0.002)	0.027*** (0.003)	0.061*** (0.005)	0.049*** (0.005)
National capital distance	0.023*** (0.007)	0.005** (0.002)	0.005** (0.002)	0.005** (0.002)	0.006* (0.003)	0.014** (0.005)	0.014*** (0.004)
Border distance	0.004 (0.004)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.003)	0.004 (0.002)
Nightlights	0.593 (0.381)	0.133 (0.093)	0.195 (0.103)	0.138 (0.093)	0.191 (0.152)	0.393 (0.279)	0.308 (0.239)
Petroleum	-0.004 (0.027)	-0.002 (0.007)	-0.003 (0.007)	-0.002 (0.007)	-0.001 (0.011)	-0.006 (0.020)	-0.0004 (0.017)
Mountains	-0.011 (0.015)	0.004 (0.004)	-0.001 (0.004)	0.004 (0.004)	-0.003 (0.006)	-0.010 (0.011)	-0.002 (0.009)
Forest	0.013 (0.027)	-0.001 (0.007)	0.005 (0.007)	-0.001 (0.007)	0.004 (0.011)	0.016 (0.020)	0.002 (0.017)
Gemstone	-0.005 (0.010)	-0.002 (0.002)	-0.0003 (0.003)	-0.002 (0.002)	-0.002 (0.004)	-0.002 (0.007)	-0.002 (0.006)
Excluded	0.008 (0.009)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.003 (0.004)	0.004 (0.006)	0.005 (0.006)
Population	0.005 (0.003)	0.002** (0.001)	0.003** (0.001)	0.002** (0.001)	0.001 (0.001)	0.006* (0.002)	0.001 (0.002)
ρ	0.08*** (0.01)	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)	0.15*** (0.01)	0.02 (0.01)	0.00 (0.01)
Constant	-0.254*** (0.072)	-0.071*** (0.018)	-0.083*** (0.019)	-0.071*** (0.018)	-0.067* (0.029)	-0.185*** (0.053)	-0.129** (0.045)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	-225.171	15767.560	14650.780	15773.900	10155.980	3318.443	5064.435
Wald Test (df = 1)	47.567***	2.921	1.400	2.887	187.693***	2.333	0.00002
LR Test (df = 1)	54.936***	3.487	1.537	3.445	194.916***	2.429	0.00002
AIC	478.341	-31507.110	-29273.570	-31519.800	-20283.970	-6608.887	-10100.870

***p < .001; **p < .01; *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.20	0.00	0.02	0.00	0.22	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.10	0.00	0.01	0.00	0.11	0.00
National capital distance	0.02	0.00	0.00	0.00	0.03	0.00
Border distance	0.00	0.21	0.00	0.22	0.00	0.21
Nightlights	0.59	0.11	0.05	0.12	0.64	0.11
Petroleum	-0.00	0.85	-0.00	0.85	-0.00	0.85
Mountains	-0.01	0.47	-0.00	0.48	-0.01	0.47
Forest	0.01	0.62	0.00	0.63	0.01	0.62
Gemstone	-0.01	0.56	-0.00	0.57	-0.01	0.56
Excluded	0.01	0.37	0.00	0.37	0.01	0.37
Population	0.01	0.12	0.00	0.13	0.01	0.12

TABLE A.58: Direct and indirect effects on the month level
2013 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.30	0.00	0.01	0.09	0.31	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.10	0.02	0.00
National capital distance	0.01	0.00	0.00	0.14	0.01	0.00
Border distance	0.00	0.16	0.00	0.33	0.00	0.16
Nightlights	0.13	0.13	0.00	0.31	0.14	0.13
Petroleum	-0.00	0.73	-0.00	0.75	-0.00	0.73
Mountains	0.00	0.34	0.00	0.46	0.00	0.34
Forest	-0.00	0.90	-0.00	0.92	-0.00	0.90
Gemstone	-0.00	0.46	-0.00	0.55	-0.00	0.46
Excluded	0.00	0.62	0.00	0.68	0.00	0.62
Population	0.00	0.01	0.00	0.17	0.00	0.01

TABLE A.59: Direct and indirect effects on the month level
2013 (OSV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)		0.34	0.00	0.00	0.25	0.34	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.02	0.00	0.00	0.25	0.02	0.00
National capital distance		0.01	0.00	0.00	0.30	0.01	0.00
Border distance		0.00	0.35	0.00	0.56	0.00	0.35
Nightlights		0.20	0.05	0.00	0.36	0.20	0.05
Petroleum		-0.00	0.71	-0.00	0.80	-0.00	0.71
Mountains		-0.00	0.68	-0.00	0.78	-0.00	0.68
Forest		0.01	0.45	0.00	0.61	0.01	0.45
Gemstone		-0.00	0.87	-0.00	0.90	-0.00	0.87
Excluded		0.00	0.57	0.00	0.68	0.00	0.57
Population		0.00	0.00	0.00	0.29	0.00	0.00

TABLE A.60: Direct and indirect effects on the month level
2013 (SBV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)		0.31	0.00	0.01	0.10	0.31	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.02	0.00	0.00	0.10	0.02	0.00
National capital distance		0.01	0.00	0.00	0.15	0.01	0.00
Border distance		0.00	0.16	0.00	0.33	0.00	0.16
Nightlights		0.14	0.12	0.00	0.29	0.14	0.12
Petroleum		-0.00	0.72	-0.00	0.75	-0.00	0.72
Mountains		0.00	0.33	0.00	0.45	0.00	0.33
Forest		-0.00	0.89	-0.00	0.91	-0.00	0.89
Gemstone		-0.00	0.45	-0.00	0.54	-0.00	0.45
Excluded		0.00	0.63	0.00	0.69	0.00	0.63
Population		0.00	0.01	0.00	0.18	0.00	0.01

TABLE A.61: Direct and indirect effects on the month level
2013 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.08	0.00	0.01	0.00	0.09	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	0.00	0.00	0.03	0.00
National capital distance	0.01	0.02	0.00	0.02	0.01	0.02
Border distance	0.00	0.38	0.00	0.39	0.00	0.38
Nightlights	0.19	0.19	0.03	0.19	0.22	0.19
Petroleum	-0.00	0.93	-0.00	0.94	-0.00	0.93
Mountains	-0.00	0.61	-0.00	0.61	-0.00	0.61
Forest	0.00	0.74	0.00	0.74	0.00	0.74
Gemstone	-0.00	0.50	-0.00	0.50	-0.00	0.50
Excluded	0.00	0.44	0.00	0.44	0.00	0.44
Population	0.00	0.44	0.00	0.44	0.00	0.44

TABLE A.62: Direct and indirect effects on the month level
2013 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.22	0.00	0.00	0.14	0.22	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.06	0.00	0.00	0.14	0.06	0.00
National capital distance	0.01	0.00	0.00	0.20	0.01	0.00
Border distance	0.00	0.39	0.00	0.54	0.00	0.39
Nightlights	0.39	0.14	0.01	0.34	0.40	0.14
Petroleum	-0.01	0.75	-0.00	0.80	-0.01	0.75
Mountains	-0.01	0.33	-0.00	0.47	-0.01	0.33
Forest	0.02	0.42	0.00	0.53	0.02	0.42
Gemstone	-0.00	0.74	-0.00	0.79	-0.00	0.74
Excluded	0.00	0.53	0.00	0.63	0.00	0.53
Population	0.01	0.02	0.00	0.24	0.01	0.02

TABLE A.63: Direct and indirect effects on the month level
2013 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.06	0.00	0.00	0.99	0.06	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.05	0.00	0.00	0.99	0.05	0.00
National capital distance	0.01	0.00	0.00	0.97	0.01	0.00
Border distance	0.00	0.10	0.00	0.98	0.00	0.10
Nightlights	0.31	0.18	0.00	0.96	0.31	0.18
Petroleum	-0.00	0.96	-0.00	0.98	-0.00	0.96
Mountains	-0.00	0.81	-0.00	0.99	-0.00	0.81
Forest	0.00	0.90	0.00	0.99	0.00	0.90
Gemstone	-0.00	0.78	-0.00	0.98	-0.00	0.78
Excluded	0.01	0.35	0.00	0.98	0.01	0.35
Population	0.00	0.67	0.00	0.98	0.00	0.67

TABLE A.64: Direct and indirect effects on the month level
2013 (civilian fatalities)

A.4.7 Observations on the month level: 2014

Regression table

TABLE A.65: Spatial lag regression results (2014)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.235*** (0.009)						
OSV (lag)		0.248*** (0.009)					
SBV (lag)			0.088*** (0.009)				
OSV rebels (lag)				0.252*** (0.009)			
Gov fatalities (lag)					0.117*** (0.009)		
Reb fatalities (lag)						0.086*** (0.010)	
Civ casualties (lag)							0.242*** (0.009)
Territorial advance _{t-1} → _t	0.214*** (0.012)	0.051*** (0.003)	0.034*** (0.002)	0.050*** (0.003)	0.040*** (0.004)	0.090*** (0.007)	0.157*** (0.009)
National capital distance	0.017 (0.011)	0.005 (0.003)	0.003 (0.002)	0.005 (0.003)	0.001 (0.004)	0.010 (0.007)	0.010 (0.009)
Border distance	-0.002 (0.006)	-0.0003 (0.001)	0.0002 (0.001)	-0.0002 (0.001)	-0.001 (0.002)	0.0003 (0.004)	-0.002 (0.005)
Nightlights	0.120 (0.606)	0.120 (0.158)	-0.076 (0.116)	0.132 (0.157)	-0.240 (0.212)	-0.282 (0.377)	0.749 (0.501)
Petroleum	-0.002 (0.011)	-0.00001 (0.0042)	-0.0001 (0.008)	0.0002 (0.011)	0.003 (0.015)	0.0004 (0.026)	-0.004 (0.035)
Mountains	0.075*** (0.023)	0.018** (0.006)	0.011* (0.004)	0.018** (0.006)	0.027*** (0.008)	0.027 (0.015)	0.060** (0.019)
Forest	-0.088* (0.043)	-0.021 (0.011)	-0.014 (0.008)	-0.021 (0.011)	-0.038* (0.015)	-0.038 (0.027)	-0.067 (0.036)
Gemstone	-0.009 (0.016)	0.003 (0.004)	-0.002 (0.003)	0.002 (0.004)	-0.001 (0.005)	-0.007 (0.010)	-0.004 (0.013)
Excluded	-0.001 (0.014)	-0.0004 (0.004)	0.001 (0.003)	-0.0001 (0.004)	-0.001 (0.005)	0.001 (0.009)	-0.001 (0.012)
Population	0.013* (0.001)	0.003* (0.001)	0.002 (0.001)	0.003* (0.001)	0.001 (0.002)	0.004 (0.003)	0.012** (0.004)
ρ	0.08*** (0.01)	0.05*** (0.01)	0.08*** (0.01)	0.05*** (0.01)	0.06*** (0.01)	0.04*** (0.01)	0.05*** (0.01)
Constant	-0.279* (0.117)	-0.073* (0.031)	-0.033 (0.022)	-0.073* (0.030)	-0.003 (0.041)	-0.093 (0.073)	-0.268** (0.097)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	-5324.396	9901.362	13401.680	9984.435	6554.776	44.481	-3162.798
Wald Test (df = 1)	56.632***	21.301***	49.765***	22.434***	28.734***	14.767***	20.090***
LR Test (df = 1)	62.952***	23.490***	55.034***	24.688***	34.518***	16.955***	22.003***
AIC	10676.790	-19774.720	-26775.370	-19940.870	-13081.550	-60.963	6353.596

***p < .001, **p < .01, *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.24	0.00	0.02	0.00	0.26	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.21	0.00	0.02	0.00	0.23	0.00
National capital distance	0.02	0.10	0.00	0.11	0.02	0.10
Border distance	-0.00	0.81	-0.00	0.81	-0.00	0.81
Nightlights	0.40	0.48	0.03	0.49	0.43	0.48
Petroleum	-0.00	0.93	-0.00	0.94	-0.00	0.93
Mountains	0.07	0.00	0.01	0.00	0.08	0.00
Forest	-0.09	0.04	-0.01	0.04	-0.10	0.04
Gemstone	-0.01	0.58	-0.00	0.59	-0.01	0.58
Excluded	-0.00	0.97	-0.00	0.97	-0.00	0.97
Population	0.01	0.02	0.00	0.02	0.01	0.01

TABLE A.66: Direct and indirect effects on the month level
2014 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.25	0.00	0.01	0.00	0.26	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.05	0.00	0.00	0.00	0.05	0.00
National capital distance	0.01	0.08	0.00	0.10	0.01	0.08
Border distance	-0.00	0.82	-0.00	0.82	-0.00	0.81
Nightlights	0.12	0.42	0.01	0.43	0.13	0.42
Petroleum	-0.00	0.98	-0.00	0.98	-0.00	0.98
Mountains	0.02	0.00	0.00	0.01	0.02	0.00
Forest	-0.02	0.07	-0.00	0.09	-0.02	0.07
Gemstone	0.00	0.47	0.00	0.49	0.00	0.47
Excluded	-0.00	0.97	-0.00	0.97	-0.00	0.97
Population	0.00	0.03	0.00	0.06	0.00	0.03

TABLE A.67: Direct and indirect effects on the month level
2014 (OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.09	0.00	0.01	0.00	0.10	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	0.00	0.00	0.04	0.00
National capital distance	0.00	0.16	0.00	0.17	0.00	0.16
Border distance	0.00	0.80	0.00	0.80	0.00	0.80
Nightlights	-0.08	0.53	-0.01	0.53	-0.08	0.53
Petroleum	-0.00	0.97	-0.00	0.97	-0.00	0.97
Mountains	0.01	0.01	0.00	0.02	0.01	0.01
Forest	-0.01	0.10	-0.00	0.11	-0.01	0.10
Gemstone	-0.00	0.43	-0.00	0.44	-0.00	0.43
Excluded	0.00	0.86	0.00	0.86	0.00	0.86
Population	0.00	0.12	0.00	0.13	0.00	0.12

TABLE A.68: Direct and indirect effects on the month level
2014 (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)	0.25	0.00	0.01	0.00	0.27	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.05	0.00	0.00	0.00	0.05	0.00
National capital distance	0.01	0.07	0.00	0.09	0.01	0.07
Border distance	-0.00	0.86	-0.00	0.86	-0.00	0.86
Nightlights	0.13	0.37	0.01	0.38	0.14	0.37
Petroleum	0.00	1.00	0.00	0.99	0.00	1.00
Mountains	0.02	0.00	0.00	0.01	0.02	0.00
Forest	-0.02	0.06	-0.00	0.08	-0.02	0.06
Gemstone	0.00	0.54	0.00	0.56	0.00	0.54
Excluded	-0.00	0.97	-0.00	0.97	-0.00	0.97
Population	0.00	0.05	0.00	0.07	0.00	0.05

TABLE A.69: Direct and indirect effects on the month level
2014 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.12	0.00	0.01	0.00	0.12	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.04	0.00	0.00	0.00	0.04	0.00
National capital distance	0.00	0.70	0.00	0.71	0.00	0.70
Border distance	-0.00	0.47	-0.00	0.48	-0.00	0.47
Nightlights	-0.24	0.27	-0.02	0.29	-0.26	0.27
Petroleum	0.00	0.84	0.00	0.84	0.00	0.84
Mountains	0.03	0.00	0.00	0.00	0.03	0.00
Forest	-0.04	0.01	-0.00	0.02	-0.04	0.01
Gemstone	-0.00	0.76	-0.00	0.76	-0.00	0.76
Excluded	-0.00	0.82	-0.00	0.83	-0.00	0.82
Population	0.00	0.51	0.00	0.52	0.00	0.51

TABLE A.70: Direct and indirect effects on the month level
2014 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.09	0.00	0.00	0.00	0.09	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.09	0.00	0.00	0.00	0.09	0.00
National capital distance	0.01	0.14	0.00	0.17	0.01	0.14
Border distance	0.00	0.90	0.00	0.92	0.00	0.90
Nightlights	-0.28	0.47	-0.01	0.49	-0.29	0.47
Petroleum	0.00	0.99	0.00	1.00	0.00	0.99
Mountains	0.03	0.06	0.00	0.10	0.03	0.06
Forest	-0.04	0.16	-0.00	0.19	-0.04	0.16
Gemstone	-0.01	0.46	-0.00	0.48	-0.01	0.46
Excluded	0.00	0.89	0.00	0.89	0.00	0.89
Population	0.00	0.20	0.00	0.24	0.00	0.20

TABLE A.71: Direct and indirect effects on the month level
2014 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.24	0.00	0.01	0.00	0.25	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.16	0.00	0.01	0.00	0.17	0.00
National capital distance	0.01	0.12	0.00	0.14	0.01	0.12
Border distance	-0.00	0.67	-0.00	0.66	-0.00	0.67
Nightlights	0.75	0.12	0.04	0.14	0.79	0.12
Petroleum	-0.00	0.91	-0.00	0.91	-0.00	0.91
Mountains	0.06	0.00	0.00	0.01	0.06	0.00
Forest	-0.07	0.06	-0.00	0.09	-0.07	0.06
Gemstone	-0.00	0.79	-0.00	0.80	-0.00	0.79
Excluded	-0.00	0.95	-0.00	0.95	-0.00	0.95
Population	0.01	0.01	0.00	0.02	0.01	0.01

TABLE A.72: Direct and indirect effects on the month level
2014 (civilian fatalities)

A.4.8 Observations on the month level: 2015

Regression table

TABLE A.73: Spatial lag regression results (2015)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.237*** (0.009)						
OSV (lag)		0.271*** (0.009)					
SBV (lag)			0.202*** (0.009)				
OSV rebels (lag)				0.276*** (0.009)			
Gov fatalities (lag)					0.162*** (0.009)		
Reb fatalities (lag)						0.178*** (0.009)	
Civ casualties (lag)							0.211*** (0.009)
Territorial advance $_{t-1} \rightarrow t$	0.180*** (0.011)	0.034*** (0.003)	0.030*** (0.002)	0.033*** (0.003)	0.021*** (0.003)	0.073*** (0.007)	0.119*** (0.009)
National capital distance	0.040*** (0.011)	0.009*** (0.003)	0.005* (0.002)	0.010*** (0.003)	0.005 (0.003)	0.013* (0.007)	0.032*** (0.009)
Border distance	0.004 (0.006)	0.003 (0.001)	-0.0002 (0.001)	0.003 (0.001)	-0.001 (0.001)	-0.003 (0.003)	0.007 (0.005)
Nightlights	0.966 (0.620)	0.165 (0.152)	0.132 (0.126)	0.179 (0.150)	0.167 (0.150)	0.355 (0.368)	0.697 (0.497)
Petroleum	-0.003 (0.043)	-0.003 (0.011)	-0.0002 (0.009)	-0.003 (0.010)	0.001 (0.010)	-0.0004 (0.026)	-0.008 (0.035)
Mountains	-0.006 (0.024)	0.001 (0.006)	-0.001 (0.005)	0.001 (0.006)	-0.005 (0.006)	-0.010 (0.014)	-0.001 (0.019)
Forest	-0.014 (0.044)	0.003 (0.011)	-0.004 (0.009)	0.003 (0.011)	-0.002 (0.011)	-0.006 (0.026)	0.004 (0.035)
Gemstone	0.0005 (0.016)	0.0001 (0.004)	-0.002 (0.003)	0.001 (0.004)	-0.002 (0.004)	0.00002 (0.009)	0.002 (0.013)
Excluded	0.010 (0.014)	0.001 (0.004)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.004 (0.009)	0.006 (0.012)
Population	0.005 (0.005)	0.003* (0.001)	0.001 (0.001)	0.003* (0.001)	-0.0004 (0.001)	0.003 (0.003)	0.008 (0.004)
ρ	0.06*** (0.01)	0.09*** (0.01)	0.04*** (0.01)	0.09*** (0.01)	0.03** (0.01)	0.03** (0.01)	0.05*** (0.01)
Constant	-0.369** (0.120)	-0.111*** (0.030)	-0.045 (0.024)	-0.112*** (0.029)	-0.029 (0.029)	-0.126 (0.071)	-0.354*** (0.096)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	-5533.096	10354.090	12488.320	10487.180	10503.970	382.916	-3032.859
Wald Test (df = 1)	33.623***	71.748***	14.621***	71.319***	7.787**	6.733**	19.451***
LR Test (df = 1)	36.502***	78.405***	15.591***	77.922***	9.029**	7.173**	21.950***
AIC	11094.190	-20680.190	-24948.650	-20946.370	-20979.950	-737.833	6093.718

***p < .001; **p < .01; *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.24	0.00	0.02	0.00	0.25	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.18	0.00	0.01	0.00	0.19	0.00
National capital distance	0.04	0.00	0.00	0.00	0.04	0.00
Border distance	0.00	0.44	0.00	0.45	0.00	0.44
Nightlights	0.97	0.10	0.06	0.12	1.03	0.10
Petroleum	-0.00	0.93	-0.00	0.93	-0.00	0.93
Mountains	-0.01	0.78	-0.00	0.78	-0.01	0.78
Forest	-0.01	0.75	-0.00	0.76	-0.02	0.75
Gemstone	0.00	0.95	0.00	0.94	0.00	0.95
Excluded	0.01	0.47	0.00	0.48	0.01	0.47
Population	0.00	0.36	0.00	0.37	0.01	0.36

TABLE A.74: Direct and indirect effects on the month level
2015 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.27	0.00	0.03	0.00	0.30	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	0.00	0.00	0.04	0.00
National capital distance	0.01	0.00	0.00	0.00	0.01	0.00
Border distance	0.00	0.05	0.00	0.06	0.00	0.05
Nightlights	0.17	0.25	0.02	0.26	0.18	0.25
Petroleum	-0.00	0.74	-0.00	0.74	-0.00	0.74
Mountains	0.00	0.90	0.00	0.90	0.00	0.90
Forest	0.00	0.75	0.00	0.75	0.00	0.75
Gemstone	0.00	0.99	0.00	0.99	0.00	0.99
Excluded	0.00	0.69	0.00	0.69	0.00	0.69
Population	0.00	0.04	0.00	0.05	0.00	0.04

TABLE A.75: Direct and indirect effects on the month level
2015 (OSV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)		0.20	0.00	0.01	0.00	0.21	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.03	0.00	0.00	0.00	0.03	0.00
National capital distance		0.01	0.03	0.00	0.06	0.01	0.03
Border distance		-0.00	0.88	-0.00	0.87	-0.00	0.88
Nightlights		0.13	0.27	0.01	0.30	0.14	0.27
Petroleum		-0.00	1.00	-0.00	0.99	-0.00	1.00
Mountains		-0.00	0.77	-0.00	0.77	-0.00	0.77
Forest		-0.00	0.68	-0.00	0.69	-0.00	0.68
Gemstone		-0.00	0.48	-0.00	0.51	-0.00	0.48
Excluded		0.00	0.59	0.00	0.60	0.00	0.59
Population		0.00	0.54	0.00	0.56	0.00	0.54

TABLE A.76: Direct and indirect effects on the month level
2015 (SBV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)		0.28	0.00	0.03	0.00	0.30	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.03	0.00	0.00	0.00	0.04	0.00
National capital distance		0.01	0.00	0.00	0.00	0.01	0.00
Border distance		0.00	0.06	0.00	0.07	0.00	0.06
Nightlights		0.18	0.21	0.02	0.22	0.20	0.21
Petroleum		-0.00	0.78	-0.00	0.78	-0.00	0.78
Mountains		0.00	0.88	0.00	0.88	0.00	0.88
Forest		0.00	0.76	0.00	0.76	0.00	0.76
Gemstone		0.00	0.91	0.00	0.91	0.00	0.91
Excluded		0.00	0.61	0.00	0.61	0.00	0.61
Population		0.00	0.04	0.00	0.05	0.00	0.04

TABLE A.77: Direct and indirect effects on the month level
2015 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.16	0.00	0.01	0.01	0.17	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.01	0.02	0.00
National capital distance	0.00	0.11	0.00	0.17	0.00	0.11
Border distance	-0.00	0.64	-0.00	0.65	-0.00	0.64
Nightlights	0.17	0.24	0.01	0.30	0.17	0.24
Petroleum	0.00	0.93	0.00	0.93	0.00	0.93
Mountains	-0.00	0.40	-0.00	0.45	-0.00	0.40
Forest	-0.00	0.83	-0.00	0.85	-0.00	0.83
Gemstone	-0.00	0.55	-0.00	0.59	-0.00	0.55
Excluded	0.00	0.51	0.00	0.54	0.00	0.51
Population	-0.00	0.76	-0.00	0.77	-0.00	0.76

TABLE A.78: Direct and indirect effects on the month level
2015 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.18	0.00	0.01	0.01	0.18	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.07	0.00	0.00	0.01	0.07	0.00
National capital distance	0.01	0.05	0.00	0.13	0.01	0.05
Border distance	-0.00	0.45	-0.00	0.49	-0.00	0.45
Nightlights	0.35	0.31	0.01	0.38	0.37	0.31
Petroleum	-0.00	0.97	-0.00	0.98	-0.00	0.97
Mountains	-0.01	0.46	-0.00	0.50	-0.01	0.46
Forest	-0.01	0.83	-0.00	0.85	-0.01	0.83
Gemstone	0.00	0.98	0.00	0.97	0.00	0.98
Excluded	0.00	0.62	0.00	0.65	0.00	0.62
Population	0.00	0.32	0.00	0.38	0.00	0.32

TABLE A.79: Direct and indirect effects on the month level
2015 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.21	0.00	0.01	0.00	0.22	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.12	0.00	0.01	0.00	0.13	0.00
National capital distance	0.03	0.00	0.00	0.01	0.03	0.00
Border distance	0.01	0.14	0.00	0.17	0.01	0.14
Nightlights	0.70	0.14	0.04	0.17	0.73	0.14
Petroleum	-0.01	0.79	-0.00	0.79	-0.01	0.79
Mountains	-0.00	0.94	-0.00	0.94	-0.00	0.94
Forest	0.00	0.90	0.00	0.89	0.00	0.90
Gemstone	0.00	0.82	0.00	0.83	0.00	0.82
Excluded	0.01	0.63	0.00	0.65	0.01	0.63
Population	0.01	0.07	0.00	0.11	0.01	0.07

TABLE A.80: Direct and indirect effects on the month level
2015 (civilian fatalities)

A.4.9 Observations on the month level: 2016

Regression table

TABLE A.81: Spatial lag regression results (2016)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.219*** (0.009)						
OSV (lag)		0.239*** (0.008)					
SBV (lag)			0.201*** (0.009)				
OSV rebels (lag)				0.242*** (0.008)			
Gov fatalities (lag)					0.011 (0.009)		
Reb fatalities (lag)						0.211*** (0.009)	
Civ casualties (lag)							0.225*** (0.008)
Territorial advance $e_{t-1} \rightarrow t$	0.190*** (0.010)	0.020*** (0.002)	0.061*** (0.003)	0.020*** (0.002)	0.032*** (0.003)	0.132*** (0.008)	0.058*** (0.005)
National capital distance	-0.003 (0.008)	0.002 (0.001)	-0.002 (0.002)	0.002 (0.001)	-0.001 (0.002)	-0.007 (0.006)	-0.005 (0.004)
Border distance	-0.014*** (0.004)	0.001 (0.001)	-0.004*** (0.001)	0.001 (0.001)	-0.004*** (0.001)	-0.014*** (0.003)	0.001 (0.002)
Nightlights	-0.191 (0.418)	0.021 (0.077)	-0.115 (0.138)	0.021 (0.077)	0.047 (0.121)	-0.264 (0.355)	0.055 (0.219)
Petroleum	0.001 (0.030)	-0.002 (0.005)	0.00003 (0.010)	-0.002 (0.005)	0.003 (0.009)	0.003 (0.025)	-0.004 (0.015)
Mountains	0.015 (0.016)	0.001 (0.003)	0.005 (0.005)	0.001 (0.003)	-0.002 (0.005)	0.014 (0.014)	0.005 (0.009)
Forest	-0.043 (0.030)	0.004 (0.006)	-0.015 (0.010)	0.004 (0.006)	-0.011 (0.009)	-0.049 (0.026)	0.007 (0.016)
Gemstone	0.011 (0.011)	0.003 (0.002)	0.002 (0.004)	0.003 (0.002)	0.004 (0.003)	0.002 (0.009)	0.007 (0.006)
Excluded	-0.004 (0.010)	-0.00003 (0.002)	-0.002 (0.003)	-0.0001 (0.002)	-0.00000 (0.003)	-0.004 (0.008)	-0.0002 (0.005)
Population	0.007 (0.004)	0.002** (0.001)	0.002 (0.001)	0.002** (0.001)	-0.001 (0.001)	0.003 (0.003)	0.005** (0.002)
ρ	0.10*** (0.01)	0.04*** (0.01)	0.12*** (0.01)	0.04*** (0.01)	-0.01 (0.01)	0.13*** (0.01)	0.01 (0.01)
Constant	0.007 (0.079)	-0.042** (0.015)	0.010 (0.026)	-0.041** (0.015)	0.037 (0.023)	0.087 (0.067)	-0.106* (0.041)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	-1292.612	17800.090	11283.700	17806.970	12768.660	542.814	6057.091
Wald Test (df = 1)	77.851***	15.243***	122.919***	15.034***	0.501	135.733***	1.278
LR Test (df = 1)	84.033***	15.733***	129.180***	15.518***	0.617	148.999***	1.313
AIC	2613.224	-35572.180	-22539.390	-35585.930	-25509.330	-1057.627	-12086.180

***p < .001; **p < .01; *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.22	0.00	0.02	0.00	0.24	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.19	0.00	0.02	0.00	0.21	0.00
National capital distance	-0.00	0.70	-0.00	0.70	-0.00	0.70
Border distance	-0.01	0.00	-0.00	0.00	-0.02	0.00
Nightlights	-0.19	0.67	-0.02	0.68	-0.21	0.67
Petroleum	0.00	1.00	0.00	1.00	0.00	1.00
Mountains	0.02	0.35	0.00	0.36	0.02	0.35
Forest	-0.04	0.16	-0.00	0.17	-0.05	0.16
Gemstone	0.01	0.33	0.00	0.34	0.01	0.33
Excluded	-0.00	0.67	-0.00	0.67	-0.00	0.67
Population	0.01	0.05	0.00	0.06	0.01	0.05

TABLE A.82: Direct and indirect effects on the month level
2016 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.24	0.00	0.01	0.00	0.25	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.00	0.02	0.00
National capital distance	0.00	0.17	0.00	0.20	0.00	0.17
Border distance	0.00	0.27	0.00	0.30	0.00	0.27
Nightlights	0.02	0.74	0.00	0.76	0.02	0.74
Petroleum	-0.00	0.74	-0.00	0.74	-0.00	0.74
Mountains	0.00	0.74	0.00	0.75	0.00	0.74
Forest	0.00	0.47	0.00	0.49	0.00	0.47
Gemstone	0.00	0.17	0.00	0.21	0.00	0.17
Excluded	-0.00	0.97	-0.00	0.97	-0.00	0.97
Population	0.00	0.00	0.00	0.02	0.00	0.00

TABLE A.83: Direct and indirect effects on the month level
2016 (OSV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)		0.20	0.00	0.03	0.00	0.23	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.06	0.00	0.01	0.00	0.07	0.00
National capital distance		-0.00	0.52	-0.00	0.52	-0.00	0.52
Border distance		-0.00	0.00	-0.00	0.00	-0.01	0.00
Nightlights		-0.12	0.42	-0.02	0.42	-0.13	0.42
Petroleum		0.00	0.99	0.00	0.99	0.00	0.99
Mountains		0.01	0.32	0.00	0.32	0.01	0.32
Forest		-0.01	0.13	-0.00	0.13	-0.02	0.13
Gemstone		0.00	0.48	0.00	0.49	0.00	0.48
Excluded		-0.00	0.59	-0.00	0.59	-0.00	0.59
Population		0.00	0.07	0.00	0.07	0.00	0.07

TABLE A.84: Direct and indirect effects on the month level
2016 (SBV)

	Coefficient	Direct		Indirect		Total	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)		0.24	0.00	0.01	0.00	0.25	0.00
Territorial advance $_{t-1 \rightarrow t}$		0.02	0.00	0.00	0.00	0.02	0.00
National capital distance		0.00	0.19	0.00	0.22	0.00	0.19
Border distance		0.00	0.27	0.00	0.30	0.00	0.27
Nightlights		0.02	0.74	0.00	0.76	0.02	0.74
Petroleum		-0.00	0.73	-0.00	0.73	-0.00	0.73
Mountains		0.00	0.74	0.00	0.75	0.00	0.74
Forest		0.00	0.46	0.00	0.49	0.00	0.46
Gemstone		0.00	0.18	0.00	0.22	0.00	0.18
Excluded		-0.00	0.95	-0.00	0.95	-0.00	0.95
Population		0.00	0.00	0.00	0.02	0.00	0.00

TABLE A.85: Direct and indirect effects on the month level
2016 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.01	0.23	-0.00	0.61	0.01	0.23
Territorial advance $_{t-1 \rightarrow t}$	0.03	0.00	-0.00	0.47	0.03	0.00
National capital distance	-0.00	0.70	0.00	0.84	-0.00	0.70
Border distance	-0.00	0.00	0.00	0.49	-0.00	0.00
Nightlights	0.05	0.66	-0.00	0.78	0.05	0.66
Petroleum	0.00	0.69	-0.00	0.84	0.00	0.69
Mountains	-0.00	0.64	0.00	0.82	-0.00	0.64
Forest	-0.01	0.23	0.00	0.60	-0.01	0.24
Gemstone	0.00	0.14	-0.00	0.58	0.00	0.14
Excluded	-0.00	0.97	0.00	0.98	-0.00	0.97
Population	-0.00	0.23	0.00	0.62	-0.00	0.23

TABLE A.86: Direct and indirect effects on the month level
2016 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.21	0.00	0.03	0.00	0.24	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.13	0.00	0.02	0.00	0.15	0.00
National capital distance	-0.01	0.26	-0.00	0.26	-0.01	0.26
Border distance	-0.01	0.00	-0.00	0.00	-0.02	0.00
Nightlights	-0.27	0.48	-0.04	0.48	-0.30	0.48
Petroleum	0.00	0.88	0.00	0.88	0.00	0.88
Mountains	0.01	0.31	0.00	0.32	0.02	0.31
Forest	-0.05	0.06	-0.01	0.06	-0.06	0.06
Gemstone	0.00	0.86	0.00	0.86	0.00	0.86
Excluded	-0.00	0.61	-0.00	0.61	-0.00	0.61
Population	0.00	0.36	0.00	0.36	0.00	0.36

TABLE A.87: Direct and indirect effects on the month level
2016 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.22	0.00	0.00	0.27	0.23	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.06	0.00	0.00	0.27	0.06	0.00
National capital distance	0.00	0.23	0.00	0.50	0.00	0.23
Border distance	0.00	0.52	0.00	0.68	0.00	0.52
Nightlights	0.06	0.76	0.00	0.85	0.06	0.76
Petroleum	-0.00	0.79	-0.00	0.83	-0.00	0.79
Mountains	0.00	0.57	0.00	0.70	0.00	0.57
Forest	0.01	0.63	0.00	0.73	0.01	0.63
Gemstone	0.01	0.19	0.00	0.48	0.01	0.19
Excluded	-0.00	0.93	-0.00	0.94	-0.00	0.93
Population	0.01	0.01	0.00	0.33	0.01	0.01

TABLE A.88: Direct and indirect effects on the month level
2016 (civilian fatalities)

A.4.10 Observations on the month level: 2017

Regression table

TABLE A.89: Spatial lag regression results (2017)

	Fatalities Model 1	OSV Model 2	SBV Model 3	OSV (rebels) Model 4	Gov fatalities Model 5	Reb fatalities Model 6	Civ fatalities Model 7
Fatalities (lag)	0.287*** (0.009)						
OSV (lag)		0.413*** (0.009)					
SBV (lag)			0.246*** (0.009)				
OSV rebels (lag)				0.421*** (0.009)			
Gov fatalities (lag)					0.038*** (0.010)		
Reb fatalities (lag)						0.215*** (0.009)	
Civ casualties (lag)							0.329*** (0.009)
Territorial advance _{t-1} → _t	0.204*** (0.010)	0.025*** (0.002)	0.073*** (0.004)	0.024*** (0.002)	0.055*** (0.004)	0.124*** (0.007)	0.072*** (0.006)
National capital distance	0.005 (0.007)	0.004* (0.002)	-0.001 (0.003)	0.004* (0.002)	0.002 (0.003)	-0.002 (0.006)	0.008 (0.005)
Border distance	-0.001 (0.004)	0.002 (0.001)	-0.002 (0.001)	0.002 (0.001)	0.002 (0.002)	-0.005 (0.003)	0.003 (0.002)
Nightlights	0.158 (0.409)	0.151 (0.104)	-0.063 (0.151)	0.142 (0.103)	0.006 (0.163)	-0.049 (0.313)	0.296 (0.255)
Petroleum	-0.013 (0.029)	-0.005 (0.007)	-0.005 (0.011)	-0.004 (0.007)	-0.002 (0.012)	-0.005 (0.022)	-0.010 (0.018)
Mountains	0.015 (0.016)	0.003 (0.004)	0.003 (0.006)	0.002 (0.004)	0.003 (0.006)	0.010 (0.012)	0.005 (0.010)
Forest	0.005 (0.030)	0.007 (0.008)	0.001 (0.011)	0.007 (0.007)	0.002 (0.012)	-0.013 (0.023)	0.019 (0.019)
Gemstone	-0.007 (0.011)	-0.0003 (0.003)	-0.005 (0.004)	-0.0002 (0.003)	-0.003 (0.004)	-0.010 (0.008)	0.001 (0.007)
Excluded	-0.001 (0.010)	0.0002 (0.002)	-0.002 (0.004)	0.0003 (0.002)	0.0005 (0.004)	-0.002 (0.007)	0.0002 (0.006)
Population	0.014*** (0.004)	0.004*** (0.001)	0.005*** (0.001)	0.004*** (0.001)	0.001 (0.001)	0.006* (0.003)	0.010*** (0.002)
ρ	0.10*** (0.01)	0.05*** (0.01)	0.12*** (0.01)	0.05*** (0.01)	0.03** (0.01)	0.12*** (0.01)	0.07*** (0.01)
Constant	-0.213** (0.077)	-0.095*** (0.020)	-0.041 (0.029)	-0.091*** (0.020)	-0.037 (0.031)	-0.035 (0.059)	-0.205*** (0.048)
N	11316	11316	11316	11316	11316	11316	11316
Log Likelihood	-1079.300	14398.750	10163.080	14519.830	9350.344	1937.813	4260.492
Wald Test (df = 1)	84.418***	18.406***	122.129***	19.685***	7.591**	119.827***	38.152***
LR Test (df = 1)	86.648***	19.781***	132.209***	21.218***	7.697**	123.230***	39.849***
AIC	2186.601	-28769.510	-20298.160	-29011.660	-18672.690	-3847.625	-8492.984

***p < .001, **p < .01, *p < .05

Direct and indirect effects

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Fatalities (lag)	0.29	0.00	0.03	0.00	0.32	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.20	0.00	0.02	0.00	0.23	0.00
National capital distance	0.01	0.47	0.00	0.47	0.01	0.47
Border distance	-0.00	0.85	-0.00	0.85	-0.00	0.85
Nightlights	0.16	0.66	0.02	0.67	0.17	0.66
Petroleum	-0.01	0.65	-0.00	0.66	-0.01	0.65
Mountains	0.02	0.34	0.00	0.34	0.02	0.34
Forest	0.01	0.85	0.00	0.85	0.01	0.85
Gemstone	-0.01	0.48	-0.00	0.48	-0.01	0.48
Excluded	-0.00	0.85	-0.00	0.85	-0.00	0.85
Population	0.01	0.00	0.00	0.00	0.02	0.00

TABLE A.90: Direct and indirect effects on the month level
2017 (fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV (lag)	0.41	0.00	0.02	0.00	0.43	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.00	0.03	0.00
National capital distance	0.00	0.02	0.00	0.04	0.00	0.02
Border distance	0.00	0.12	0.00	0.15	0.00	0.12
Nightlights	0.15	0.13	0.01	0.16	0.16	0.13
Petroleum	-0.00	0.52	-0.00	0.54	-0.00	0.53
Mountains	0.00	0.49	0.00	0.52	0.00	0.50
Forest	0.01	0.32	0.00	0.35	0.01	0.32
Gemstone	-0.00	0.94	-0.00	0.94	-0.00	0.94
Excluded	0.00	0.96	0.00	0.97	0.00	0.96
Population	0.00	0.00	0.00	0.00	0.00	0.00

TABLE A.91: Direct and indirect effects on the month level
2017 (OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
SBV (lag)	0.25	0.00	0.03	0.00	0.28	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.07	0.00	0.01	0.00	0.08	0.00
National capital distance	-0.00	0.64	-0.00	0.65	-0.00	0.64
Border distance	-0.00	0.12	-0.00	0.12	-0.00	0.12
Nightlights	-0.06	0.70	-0.01	0.71	-0.07	0.70
Petroleum	-0.00	0.63	-0.00	0.63	-0.01	0.63
Mountains	0.00	0.64	0.00	0.64	0.00	0.64
Forest	0.00	0.94	0.00	0.94	0.00	0.94
Gemstone	-0.00	0.22	-0.00	0.22	-0.01	0.22
Excluded	-0.00	0.65	-0.00	0.65	-0.00	0.65
Population	0.01	0.00	0.00	0.00	0.01	0.00

TABLE A.92: Direct and indirect effects on the month level
2017 (SBV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
OSV rebels (lag)	0.42	0.00	0.02	0.00	0.44	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.02	0.00	0.00	0.00	0.03	0.00
National capital distance	0.00	0.03	0.00	0.05	0.00	0.03
Border distance	0.00	0.10	0.00	0.13	0.00	0.10
Nightlights	0.14	0.15	0.01	0.18	0.15	0.15
Petroleum	-0.00	0.51	-0.00	0.51	-0.00	0.50
Mountains	0.00	0.54	0.00	0.55	0.00	0.54
Forest	0.01	0.33	0.00	0.36	0.01	0.33
Gemstone	-0.00	0.98	-0.00	0.99	-0.00	0.98
Excluded	0.00	0.96	0.00	0.96	0.00	0.96
Population	0.00	0.00	0.00	0.00	0.00	0.00

TABLE A.93: Direct and indirect effects on the month level
2017 (Rebel OSV)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Gov fatalities (lag)	0.04	0.00	0.00	0.03	0.04	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.06	0.00	0.00	0.01	0.06	0.00
National capital distance	0.00	0.52	0.00	0.56	0.00	0.52
Border distance	0.00	0.28	0.00	0.35	0.00	0.28
Nightlights	0.01	0.94	0.00	0.95	0.01	0.94
Petroleum	-0.00	0.86	-0.00	0.87	-0.00	0.86
Mountains	0.00	0.68	0.00	0.70	0.00	0.68
Forest	0.00	0.86	0.00	0.86	0.00	0.86
Gemstone	-0.00	0.52	-0.00	0.56	-0.00	0.52
Excluded	0.00	0.95	0.00	0.95	0.00	0.95
Population	0.00	0.35	0.00	0.41	0.00	0.35

TABLE A.94: Direct and indirect effects on the month level
2017 (government fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Reb fatalities (lag)	0.22	0.00	0.03	0.00	0.24	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.12	0.00	0.02	0.00	0.14	0.00
National capital distance	-0.00	0.67	-0.00	0.67	-0.00	0.67
Border distance	-0.00	0.09	-0.00	0.10	-0.01	0.09
Nightlights	-0.05	0.91	-0.01	0.91	-0.06	0.91
Petroleum	-0.00	0.84	-0.00	0.84	-0.01	0.84
Mountains	0.01	0.42	0.00	0.42	0.01	0.42
Forest	-0.01	0.57	-0.00	0.57	-0.01	0.57
Gemstone	-0.01	0.19	-0.00	0.20	-0.01	0.19
Excluded	-0.00	0.80	-0.00	0.80	-0.00	0.80
Population	0.01	0.03	0.00	0.04	0.01	0.03

TABLE A.95: Direct and indirect effects on the month level
2017 (rebel fatalities)

Coefficient	Direct		Indirect		Total	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Civ casualties (lag)	0.33	0.00	0.02	0.00	0.35	0.00
Territorial advance $_{t-1 \rightarrow t}$	0.07	0.00	0.01	0.00	0.08	0.00
National capital distance	0.01	0.07	0.00	0.08	0.01	0.07
Border distance	0.00	0.19	0.00	0.21	0.00	0.19
Nightlights	0.30	0.22	0.02	0.24	0.32	0.22
Petroleum	-0.01	0.57	-0.00	0.57	-0.01	0.57
Mountains	0.01	0.60	0.00	0.61	0.01	0.60
Forest	0.02	0.30	0.00	0.31	0.02	0.30
Gemstone	0.00	0.82	0.00	0.83	0.00	0.82
Excluded	0.00	0.99	0.00	0.99	0.00	0.99
Population	0.01	0.00	0.00	0.00	0.01	0.00

TABLE A.96: Direct and indirect effects on the month level
2017 (civilian fatalities)

Appendix B

Supplemental information for: Staying local: The effect of battlefield dynamics on the timing and location of terrorism in civil conflicts

B.1 Overview

This supplemental material provides additional information about the data and models. A correlation plot for the independent variables, plots showing the distributions of variable values for the training and test data, and maps with the geographical distribution of terrorism with minimum, intermediate, and maximum severity are in the first section. The second section shows model diagnostics for the random effects in the form of violin plots to illustrate variation in random intercepts. The third section provides regression tables for different model specifications for the four dependent variables. The fifth section provides marginal effects tables and plots for the full models for all dependent variables. Lastly, sixth section provides out-of-sample metrics, ROC curves, and confusion matrices for the full models.

B.2 Summary statistics

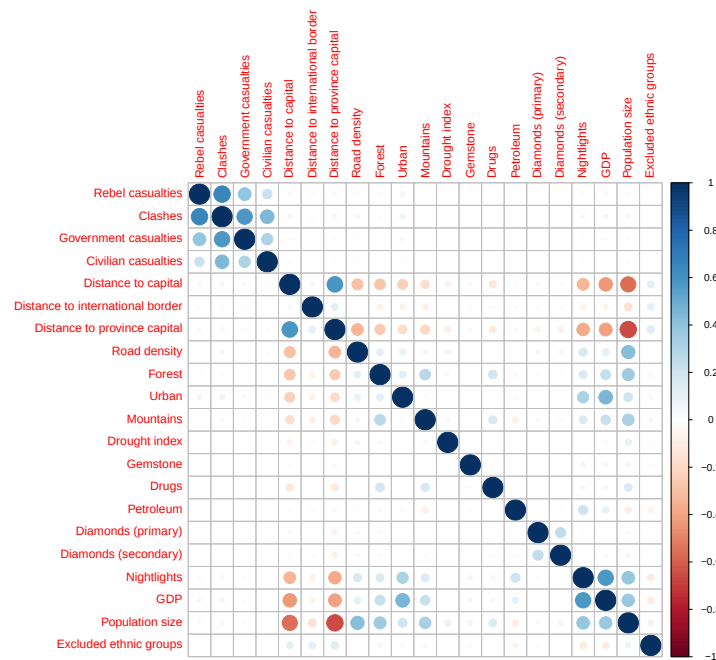


FIGURE B.1: Correlation plot with all independent variables used in the analyses.

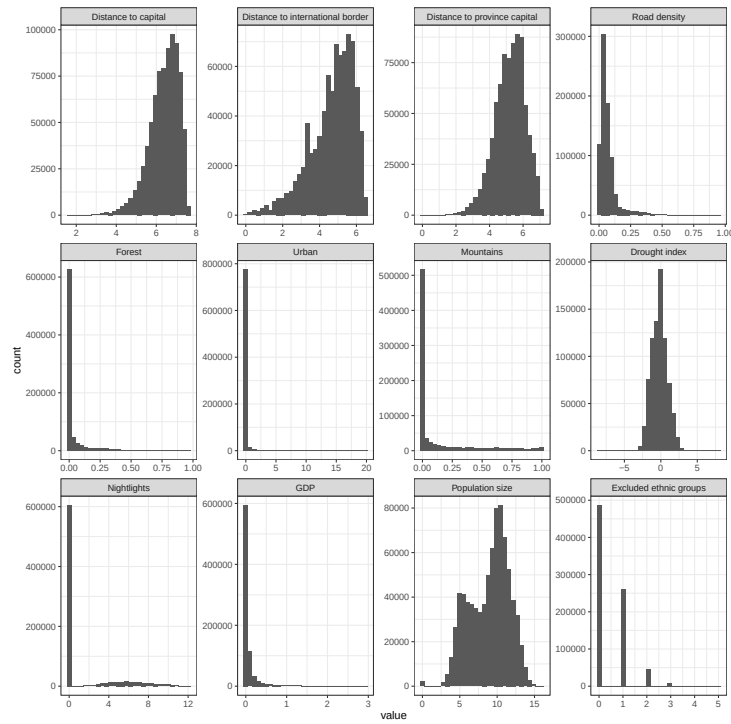


FIGURE B.2: Values for selected variables in the training data.

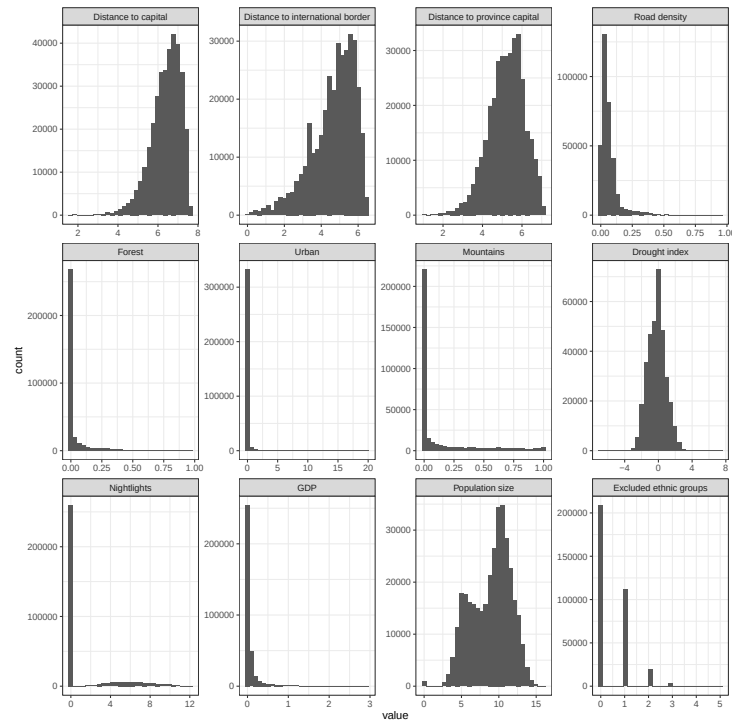


FIGURE B.3: Values for selected variables in the test data.

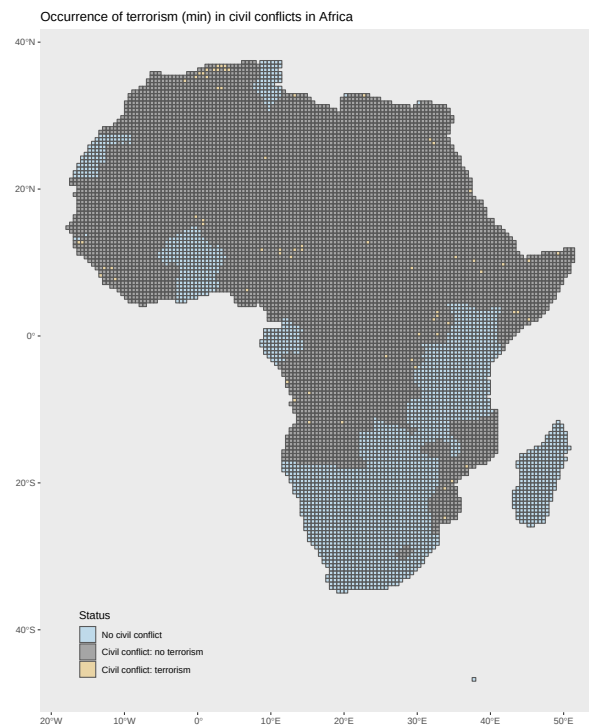


FIGURE B.4: Geographical distribution of active civil conflicts and terrorism (min) occurrences. Observations were collapsed on the grid cell.

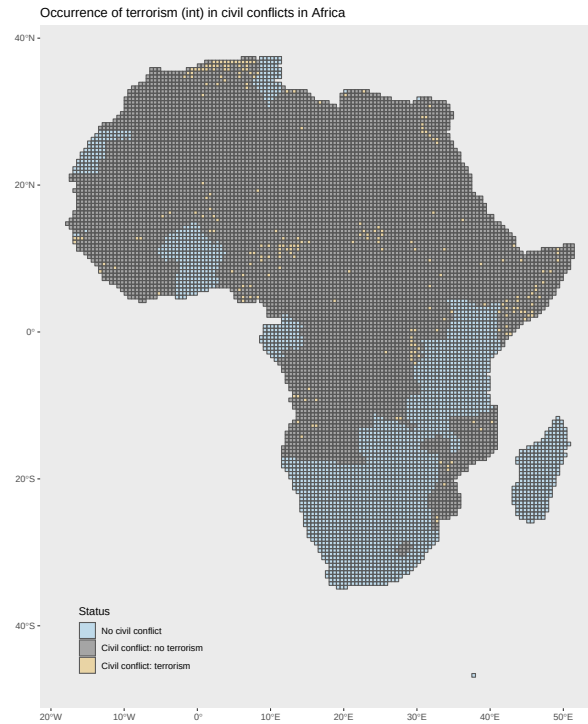


FIGURE B.5: Geographical distribution of active civil conflicts and terrorism (int) occurrences. Observations were collapsed on the grid cell.

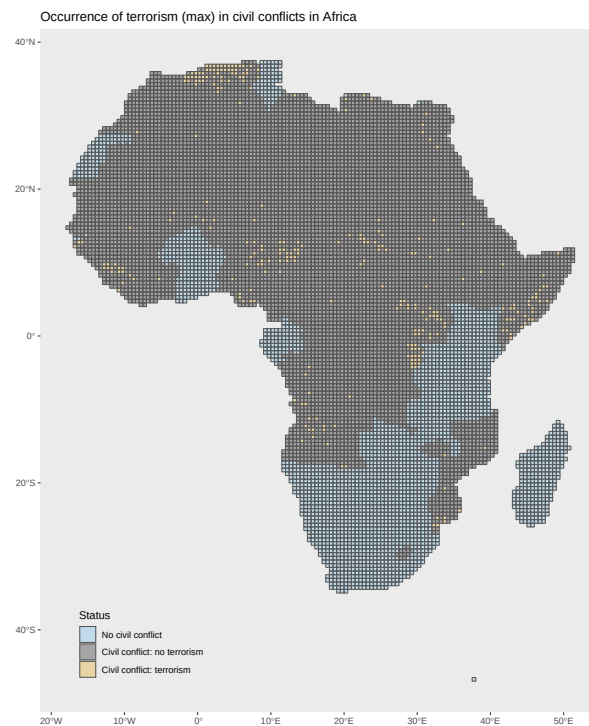


FIGURE B.6: Geographical distribution of active civil conflicts and terrorism (max) occurrences. Observations were collapsed on the grid cell.

B.3 Model diagnostics

The plots presented in this section indicate the importance or relevance of the random effects chosen. On the country level, the violin plots look as expected with some civil conflicts showing a higher prevalence of terrorism than others, except model 2 for terrorism with minimum severity. However, for all models the variance in grid cells is less well distributed, indicating that the vast majority of grid cells experience no terrorism and thus the violin plot is less well shaped.

B.3.1 Model 1

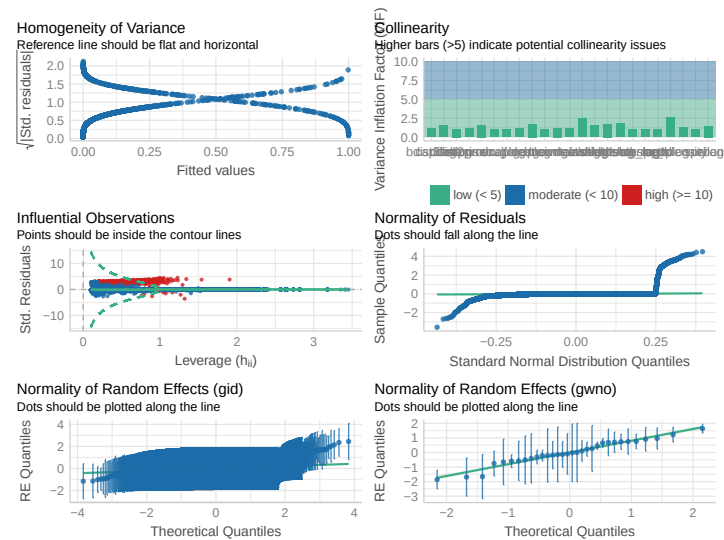


FIGURE B.7: Diagnostics for model 1.

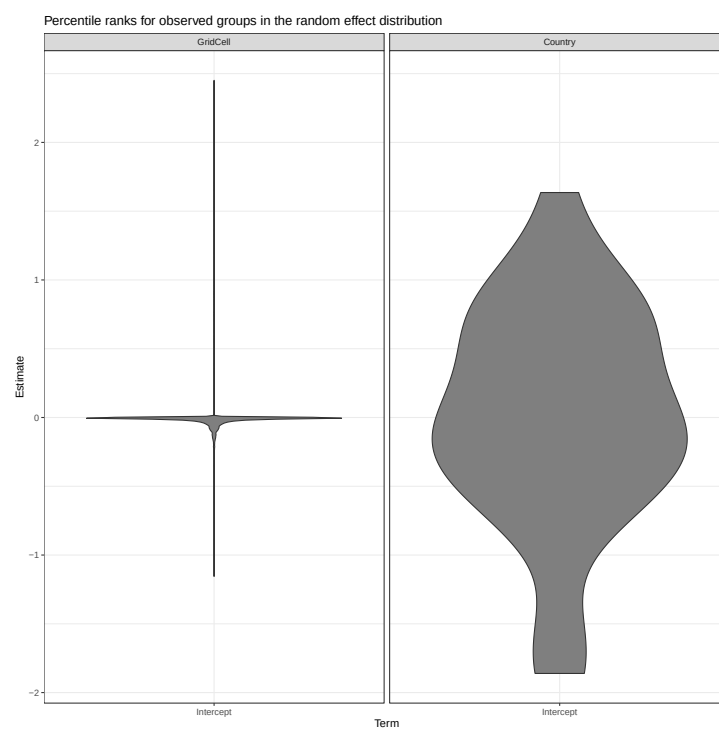


FIGURE B.8: Violin plots of random effects for model 1.

B.3.2 Model 2

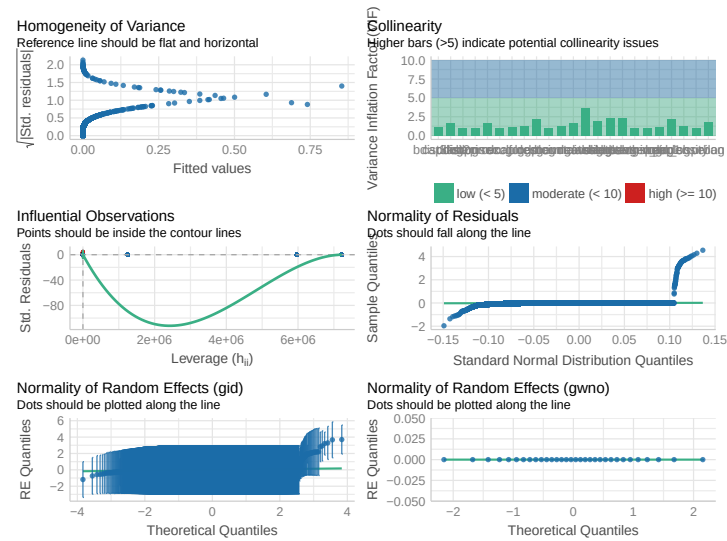


FIGURE B.9: Diagnostics for model 2.

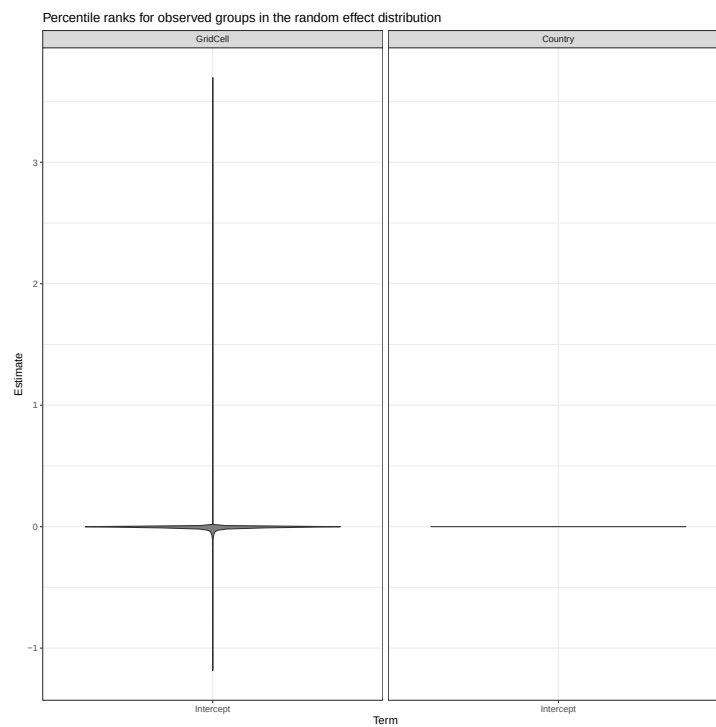


FIGURE B.10: Violin plots of random effects for model 2.

B.3.3 Model 3

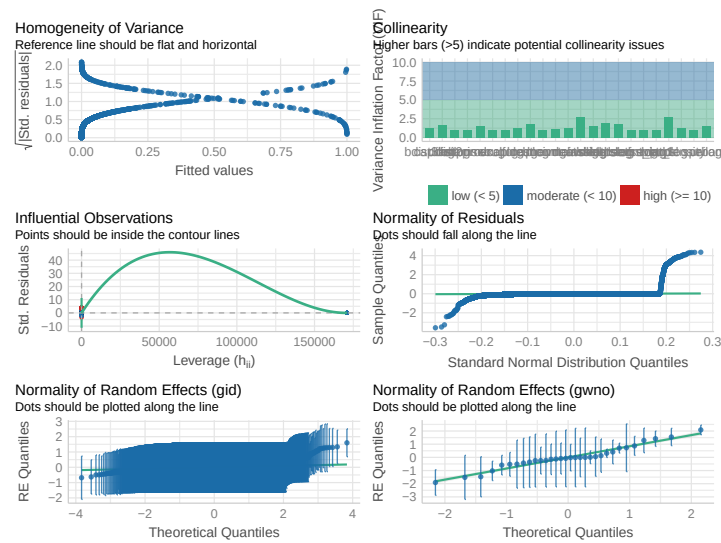


FIGURE B.11: Diagnostics for model 3.

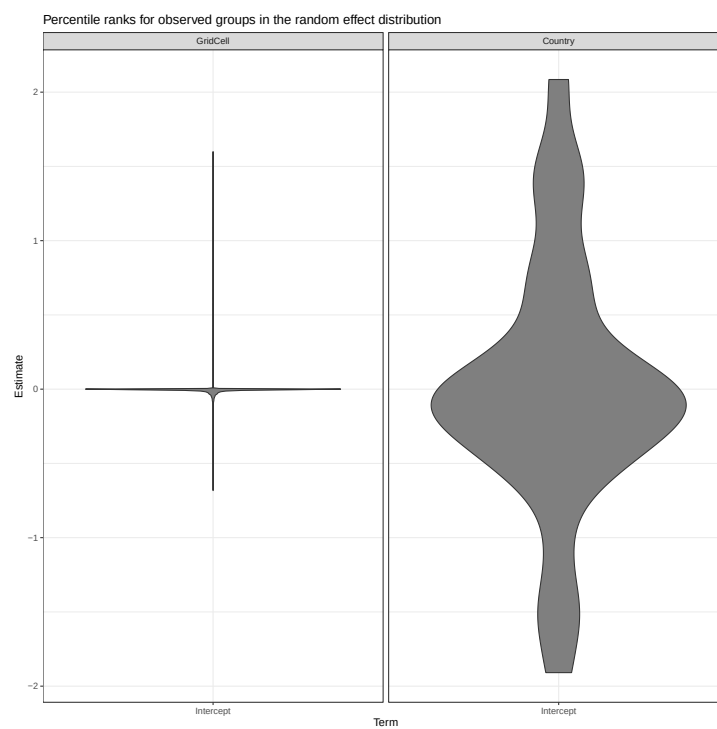


FIGURE B.12: Violin plots of random effects for model 3.

B.3.4 Model 4

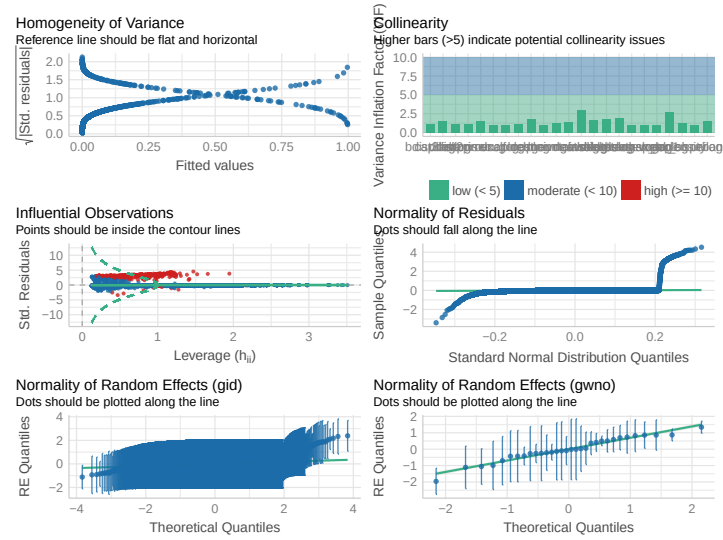


FIGURE B.13: Diagnostics for model 4.

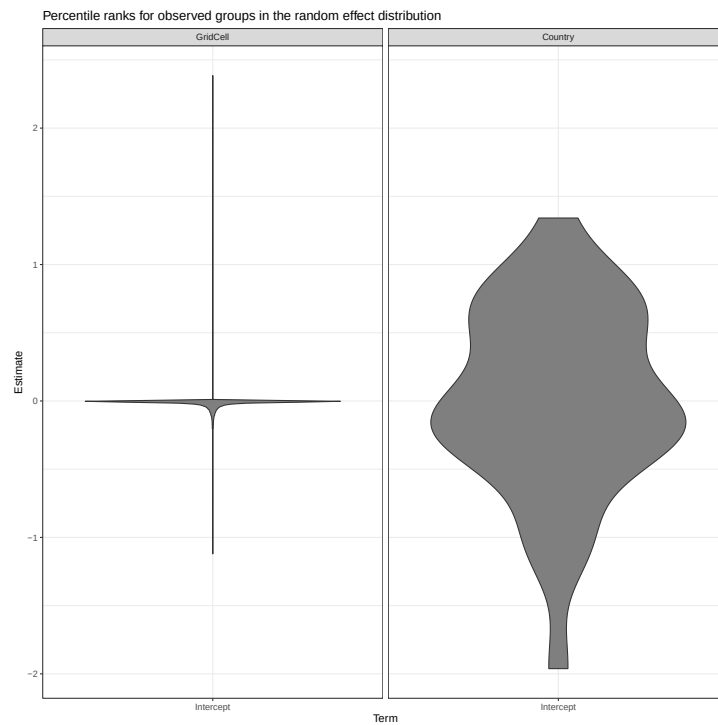


FIGURE B.14: Violin plots of random effects for model 4.

B.4 Full regression tables

This section provides regression tables for all four dependent variables. There are five models for each dependent variable, sequentially adding new covariates and stretching from a basic model which only includes the main independent variables and spatial and temporal lags to the full models presented in the main text.

B.4.1 Model 1

TABLE B.1: Generalized linear mixed effects regression re-
sults

	Terror				
	Model 1	Model 2	Model 3	Model 4	Model 5
Rebel casualties	−0.242* (0.106)	−0.225* (0.104)	−0.210* (0.103)	−0.212* (0.104)	−0.183 (0.103)
Clashes	4.144*** (0.219)	3.877*** (0.209)	3.833*** (0.208)	3.763*** (0.213)	3.676*** (0.209)
Government casualties	0.237* (0.120)	0.235* (0.116)	0.222 (0.114)	0.210 (0.115)	0.192 (0.113)
Civilian casualties				0.263 (0.159)	0.223 (0.160)
Terror temporal lag	2.481*** (0.147)	2.454*** (0.146)	2.420*** (0.146)	2.420*** (0.145)	2.431*** (0.144)
National capital distance		−0.205** (0.074)	−0.029 (0.083)	−0.024 (0.084)	0.221** (0.085)
Border distance		−0.287*** (0.046)	−0.269*** (0.049)	−0.272*** (0.049)	−0.131** (0.048)
Province capital distance		−1.044*** (0.069)	−0.896*** (0.072)	−0.894*** (0.073)	−0.338*** (0.080)
Road density			3.153*** (0.655)	3.156*** (0.660)	1.328* (0.636)
Forest			0.585 (0.426)	0.602 (0.427)	0.217 (0.426)
Urban			0.137*** (0.042)	0.138*** (0.042)	0.046 (0.039)
Mountains			0.990*** (0.235)	0.998*** (0.238)	0.341 (0.245)
Drought index			0.124** (0.044)	0.122** (0.044)	0.116** (0.044)
Gemstone				0.134 (0.454)	0.087 (0.421)
Drugs				−0.042 (0.310)	−0.170 (0.299)
Petroleum				0.025 (0.221)	0.125 (0.213)
Diamonds (prim)				−1.258 (1.167)	−1.327 (1.151)
Diamonds (sec)				0.411 (0.466)	0.297 (0.449)
Nightlights					0.148*** (0.025)
GDP					−0.097 (0.193)
Population					0.459*** (0.062)
Excluded					0.378*** (0.107)
Terror spatial lag	0.072 (0.138)	0.042 (0.136)	−0.005 (0.136)	−0.0002 (0.136)	0.025 (0.135)
Constant	−7.850*** (0.290)	−0.857 (0.480)	−3.152*** (0.593)	−3.205*** (0.603)	−12.805*** (1.098)
Number of countries	32	32	32	32	32
Number of grid cells	7955	7955	7955	7955	7955
sd(country)	1.391	1.085	0.974	0.999	1.028
sd(grid cell)	1.705	1.208	1.204	1.208	0.963
N	804414	804414	804414	804414	804414
Log Likelihood	−3820.848	−3596.104	−3561.872	−3559.094	−3462.879
AIC	7657.695	7214.207	7155.743	7162.188	6977.758
BIC	7750.478	7341.784	7341.309	7417.341	7279.303

***p < .001; **p < .01; *p < .05

B.4.2 Model 2

TABLE B.2: Generalized linear mixed effects regression results

	Terror (min)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Rebel casualties	0.385 (0.234)	0.259 (0.216)	0.268 (0.218)	0.251 (0.226)	0.278 (0.224)
Clashes	2.167*** (0.474)	2.051*** (0.430)	1.998*** (0.431)	2.132*** (0.475)	2.078*** (0.458)
Government casualties	0.379 (0.268)	0.299 (0.257)	0.315 (0.258)	0.350 (0.253)	0.326 (0.250)
Civilian casualties				-0.206 (0.318)	-0.245 (0.312)
Terror temporal lag	1.591* (0.632)	1.902** (0.626)	1.879** (0.629)	1.892** (0.635)	2.011** (0.630)
National capital distance		-0.139 (0.177)	0.032 (0.203)	0.063 (0.206)	0.217 (0.188)
Border distance		-0.387*** (0.117)	-0.356** (0.120)	-0.353** (0.121)	-0.282* (0.116)
Province capital distance		-1.121*** (0.174)	-1.080*** (0.180)	-1.094*** (0.182)	-0.651** (0.202)
Road density			1.463 (1.615)	1.556 (1.607)	0.873 (1.551)
Forest			-0.175 (1.153)	-0.081 (1.138)	-0.583 (1.162)
Urban			0.154 (0.081)	0.154 (0.081)	0.065 (0.083)
Mountains			-0.069 (0.614)	0.004 (0.607)	-0.548 (0.563)
Drought index			0.141 (0.141)	0.136 (0.141)	0.119 (0.142)
Gemstone				1.249 (1.105)	1.067 (1.064)
Drugs				-0.684 (1.085)	-0.719 (1.062)
Petroleum				0.571 (0.519)	0.587 (0.525)
Diamonds (prim)				-13.978 (2566.759)	-14.126 (2443.253)
Diamonds (sec)				-14.873 (1166.816)	-14.777 (1118.492)
Nightlights					0.150* (0.065)
GDP					-0.032 (0.451)
Population					0.410** (0.145)
Excluded					0.208 (0.279)
Terror spatial lag	-1.756* (0.828)	-1.401 (0.821)	-1.480 (0.824)	-1.503 (0.828)	-1.443 (0.827)
Constant	-10.267*** (0.332)	-2.523* (1.001)	-3.956** (1.376)	-4.116** (1.405)	-12.177*** (2.401)
Number of countries	32	32	32	32	32
Number of grid cells	7955	7955	7955	7955	7955
sd(country)	1.07	0.726	0.647	0.572	0
sd(grid cell)	2.728	1.591	1.618	1.615	1.492
N	804414	804414	804414	804414	804414
Log Likelihood	-517.914	-471.909	-468.864	-466.22	-453.261
AIC	1051.827	965.817	969.727	976.44	958.522
BIC	1144.61	1093.394	1155.293	1231.593	1260.067

***p < .001; **p < .01; *p < .05

B.4.3 Model 3

TABLE B.3: Generalized linear mixed effects regression re-
sults

	Terror (int)				
	Model 1	Model 2	Model 3	Model 4	Model 5
Rebel casualties	−0.581*** (0.148)	−0.569*** (0.145)	−0.564*** (0.144)	−0.571*** (0.145)	−0.531*** (0.145)
Clashes	4.427*** (0.273)	4.065*** (0.259)	4.046*** (0.258)	4.084*** (0.265)	3.998*** (0.259)
Government casualties	0.392** (0.143)	0.391** (0.138)	0.366** (0.136)	0.371** (0.136)	0.361** (0.132)
Civilian casualties				−0.132 (0.208)	−0.163 (0.202)
Terror temporal lag	2.802*** (0.242)	2.711*** (0.238)	2.658*** (0.237)	2.654*** (0.237)	2.655*** (0.235)
National capital distance		−0.114 (0.097)	0.076 (0.112)	0.036 (0.112)	0.286** (0.109)
Border distance		−0.315*** (0.060)	−0.282*** (0.064)	−0.303*** (0.064)	−0.162* (0.064)
Province capital distance		−1.081*** (0.090)	−0.973*** (0.094)	−0.986*** (0.094)	−0.427*** (0.105)
Road density			2.162* (0.867)	2.175* (0.854)	0.279 (0.845)
Forest			0.999 (0.547)	1.007 (0.551)	0.571 (0.559)
Urban			0.124** (0.047)	0.115* (0.047)	0.023 (0.043)
Mountains			0.707* (0.332)	0.636 (0.336)	−0.041 (0.347)
Drought index			0.040 (0.068)	0.039 (0.069)	0.032 (0.069)
Gemstone				0.146 (0.588)	0.178 (0.553)
Drugs				−0.601 (0.590)	−0.728 (0.569)
Petroleum				−1.135** (0.431)	−0.973* (0.411)
Diamonds (prim)				−12.841 (412.072)	−12.852 (413.373)
Diamonds (sec)				0.032 (0.837)	0.077 (0.809)
Nightlights					0.177*** (0.036)
GDP					0.005 (0.244)
Population					0.464*** (0.088)
Excluded					0.463** (0.150)
Terror spatial lag	−0.247 (0.261)	−0.303 (0.250)	−0.372 (0.252)	−0.397 (0.254)	−0.358 (0.251)
Constant	−8.661*** (0.265)	−1.976** (0.610)	−4.102*** (0.796)	−3.650*** (0.801)	−13.606*** (1.493)
Number of countries	32	32	32	32	32
Number of grid cells	7955	7955	7955	7955	7955
sd(country)	1.132	1.192	1.145	1.17	1.142
sd(grid cell)	1.64	1.133	1.133	1.088	0.81
N	804414	804414	804414	804414	804414
Log Likelihood	−1828.841	−1700.564	−1688.883	−1682.594	−1622.957
AIC	3673.682	3423.129	3409.766	3409.188	3297.914
BIC	3766.465	3550.705	3595.331	3664.341	3599.458

***p < .001; **p < .01; *p < .05

B.4.4 Model 4

TABLE B.4: Generalized linear mixed effects regression results

	Model 1	Model 2	Terror (max)		
			Model 3	Model 4	Model 5
Rebel casualties	0.125 (0.120)	0.137 (0.117)	0.139 (0.116)	0.148 (0.117)	0.184 (0.115)
Clashes	3.148*** (0.259)	2.793*** (0.245)	2.765*** (0.243)	2.723*** (0.255)	2.628*** (0.249)
Government casualties	0.097 (0.154)	0.123 (0.149)	0.126 (0.147)	0.112 (0.149)	0.094 (0.145)
Civilian casualties				0.139 (0.172)	0.085 (0.168)
Terror temporal lag	2.350*** (0.219)	2.304*** (0.216)	2.275*** (0.215)	2.264*** (0.214)	2.306*** (0.211)
National capital distance		−0.251** (0.086)	−0.069 (0.099)	−0.053 (0.100)	0.153 (0.101)
Border distance		−0.283*** (0.056)	−0.261*** (0.059)	−0.262*** (0.060)	−0.142* (0.059)
Province capital distance		−1.040*** (0.082)	−0.885*** (0.086)	−0.872*** (0.087)	−0.370*** (0.098)
Road density			3.380*** (0.749)	3.404*** (0.755)	1.939** (0.736)
Forest			0.365 (0.513)	0.391 (0.514)	0.070 (0.521)
Urban			0.128** (0.047)	0.133** (0.047)	0.062 (0.046)
Mountains			1.124*** (0.276)	1.183*** (0.279)	0.626* (0.291)
Drought index			0.140* (0.057)	0.139* (0.057)	0.132* (0.057)
Gemstone				0.335 (0.520)	0.284 (0.489)
Drugs				0.0003 (0.378)	−0.137 (0.366)
Petroleum				0.470 (0.259)	0.541* (0.253)
Diamonds (prim)				−0.967 (1.171)	−0.994 (1.153)
Diamonds (sec)				0.691 (0.496)	0.603 (0.483)
Nightlights					0.136*** (0.031)
GDP					−0.311 (0.242)
Population					0.435*** (0.077)
Excluded					0.242 (0.136)
Terror spatial lag	−0.351 (0.225)	−0.355 (0.220)	−0.394 (0.219)	−0.396 (0.219)	−0.346 (0.217)
Constant	−8.243*** (0.329)	−1.010 (0.544)	−3.433*** (0.697)	−3.654*** (0.709)	−12.393*** (1.330)
Number of countries	32	32	32	32	32
Number of grid cells	7955	7955	7955	7955	7955
sd(country)	1.553	1.047	0.931	0.937	0.95
sd(grid cell)	1.664	1.22	1.224	1.237	1.032
N	804414	804414	804414	804414	804414
Log Likelihood	−2483.282	−2319.939	−2293.11	−2289.99	−2240.251
AIC	4982.565	4661.877	4618.22	4623.98	4532.501
BIC	5075.348	4789.454	4803.786	4879.133	4834.046

***p < .001; **p < .01; *p < .05

B.5 Marginal effects

This section presents marginal effects for all full models and variables. It differentiates between continuous variables, for which the impact of a one standard deviation (sd) change is displayed, and binary variables, for which the difference between presence and absence are shown. In addition, for each full model the predicted probabilities for terrorism occurrence as a result of distance to province capital and number of clashes are displayed. Lastly, plots are also shown for selected countries to illustrate the random effects and the differences across countries.

B.5.1 Model 1

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.Hi
Border distance	sd	-0.16	0.06	-2.71	0.01	-0.27	-0.05
Nat cap dist	sd	0.16	0.06	2.61	0.01	0.04	0.28
Prov cap dist	sd	-0.30	0.07	-4.20	0.00	-0.45	-0.15
Excluded	sd	0.25	0.07	3.53	0.00	0.11	0.39
Forest	sd	0.02	0.05	0.51	0.61	-0.07	0.11
GDP	sd	-0.02	0.04	-0.50	0.62	-0.10	0.06
Civ casualties	sd	0.01	0.00	1.39	0.16	-0.00	0.02
Clashes	sd	0.13	0.01	17.59	0.00	0.12	0.14
Govt casualties	sd	0.01	0.01	1.69	0.09	-0.00	0.02
Nightlights	sd	0.42	0.07	5.99	0.00	0.28	0.56
Reb casualties	sd	-0.01	0.01	-1.77	0.08	-0.02	0.01
Population	sd	1.20	0.16	7.45	0.00	0.89	1.51
Road density	sd	0.09	0.04	2.09	0.04	0.01	0.17
Drought index	sd	0.12	0.05	2.62	0.01	0.03	0.21
Urban	sd	0.02	0.02	1.18	0.24	-0.02	0.06

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.Hi
Dia (prim)	Max - Min	-1.33	1.15	-1.15	0.25	-3.58	0.92
Dia (sec)	Max - Min	0.30	0.45	0.66	0.51	-0.58	1.18
Drugs	Max - Min	-0.17	0.30	-0.57	0.57	-0.76	0.42
Gemstone	Max - Min	0.09	0.42	0.21	0.84	-0.74	0.92
Mountains	Max - Min	0.34	0.24	1.39	0.16	-0.14	0.82
Terror tp lag	Max - Min	2.43	0.14	16.86	0.00	2.15	2.71
Terror sp lag	Max - Min	0.03	0.13	0.19	0.85	-0.24	0.30
Petroleum	Max - Min	0.13	0.21	0.59	0.56	-0.29	0.55

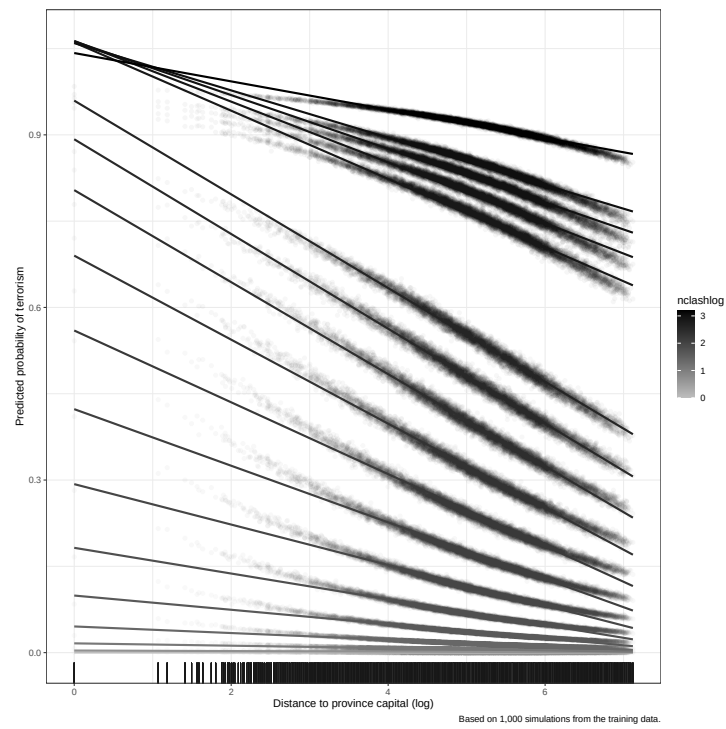


FIGURE B.15: Substantive effects of distance to province capital and number of battles for model 1.

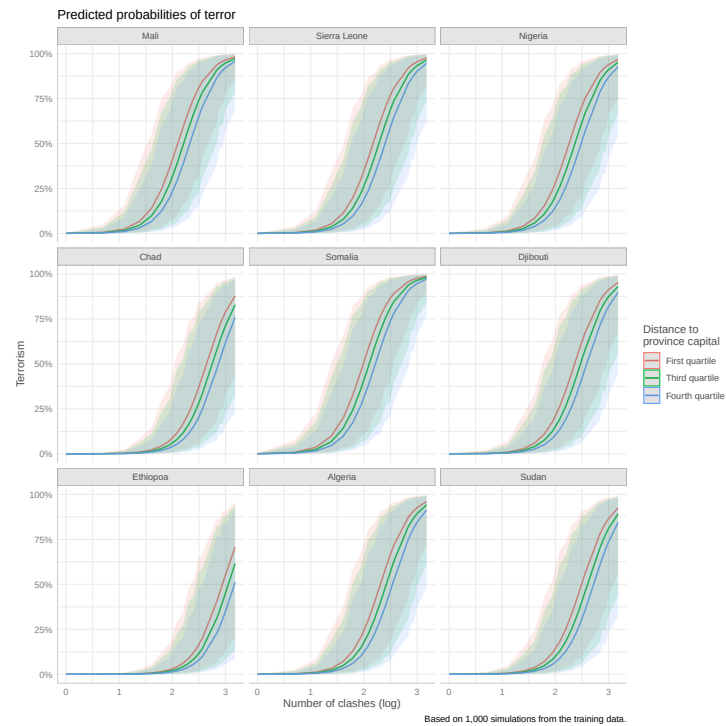


FIGURE B.16: Substantive effects of distance to province capital and number of battles for model 1 for different countries.

B.5.2 Model 2

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Border distance	sd	-0.34	0.14	-2.43	0.02	-0.61	-0.07
Nat cap dist	sd	0.16	0.14	1.15	0.25	-0.11	0.43
Prov cap dist	sd	-0.59	0.18	-3.23	0.00	-0.94	-0.24
Excluded	sd	0.14	0.19	0.75	0.45	-0.23	0.51
Forest	sd	-0.07	0.13	-0.50	0.62	-0.32	0.18
GDP	sd	-0.01	0.09	-0.07	0.94	-0.19	0.17
Civ casualties	sd	-0.01	0.01	-0.79	0.43	-0.02	0.00
Clashes	sd	0.07	0.02	4.54	0.00	0.04	0.10
Govt casualties	sd	0.02	0.01	1.30	0.19	-0.01	0.05
Nightlights	sd	0.43	0.19	2.30	0.02	0.06	0.79
Reb casualties	sd	0.02	0.01	1.24	0.21	-0.01	0.05
Population	sd	1.08	0.38	2.82	0.00	0.33	1.83
Road density	sd	0.06	0.11	0.56	0.57	-0.15	0.27
Drought index	sd	0.13	0.15	0.84	0.40	-0.17	0.43
Urban	sd	0.03	0.04	0.79	0.43	-0.05	0.11

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Dia (prim)	Max - Min	-14.13	2443.25	-0.01	1.00	-4802.81	4778.55
Dia (sec)	Max - Min	-14.78	1118.49	-0.01	0.99	-2206.98	2177.41
Drugs	Max - Min	-0.72	1.06	-0.68	0.50	-2.80	1.36
Gemstone	Max - Min	1.07	1.06	1.00	0.32	-1.02	3.16
Mountains	Max - Min	-0.55	0.56	-0.97	0.33	-1.65	0.55
Terr (min) tp lag	Max - Min	2.01	0.63	3.19	0.00	0.78	3.24
Terr (min) sp lag	Max - Min	-1.44	0.83	-1.74	0.08	-3.06	0.18
Petroleum	Max - Min	0.59	0.52	1.12	0.26	-0.44	1.62

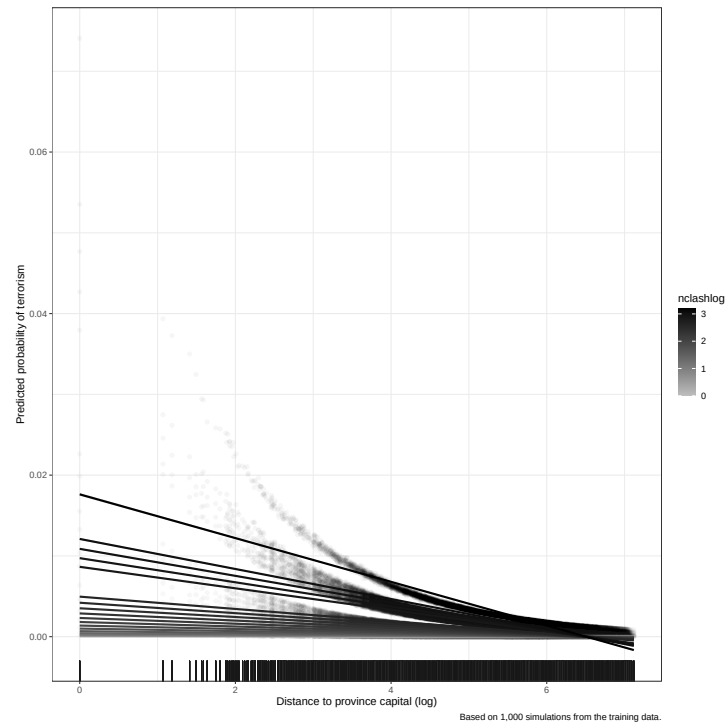


FIGURE B.17: Substantive effects of distance to province capital and number of battles for model 2.

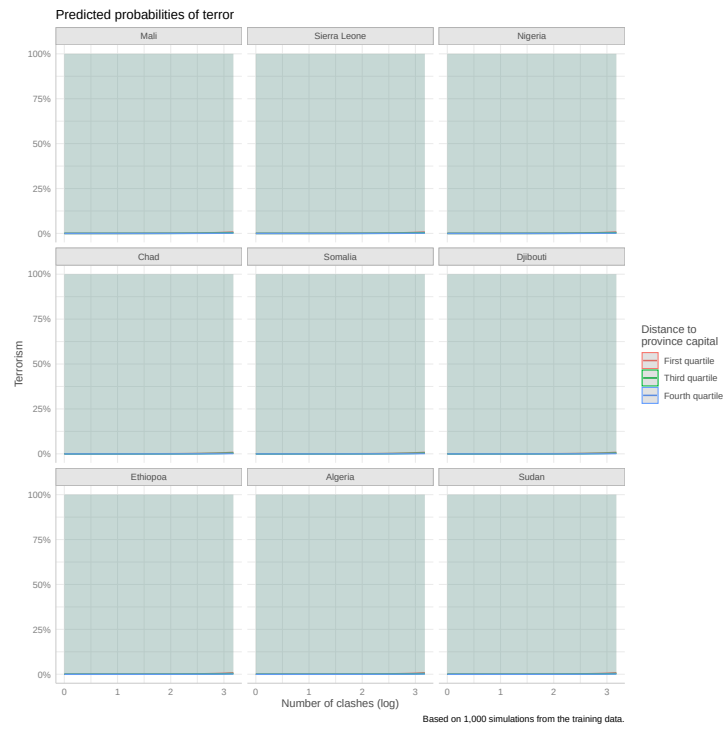


FIGURE B.18: Substantive effects of distance to province capital and number of battles for model 2 for different countries.

B.5.3 Model 3

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Border distance	sd	-0.19	0.08	-2.52	0.01	-0.34	-0.04
Nat cap dist	sd	0.21	0.08	2.61	0.01	0.05	0.37
Prov cap dist	sd	-0.38	0.09	-4.07	0.00	-0.57	-0.19
Excluded	sd	0.31	0.10	3.09	0.00	0.11	0.51
Forest	sd	0.06	0.06	1.02	0.31	-0.06	0.18
GDP	sd	0.00	0.05	0.02	0.98	-0.10	0.10
Civ casualties	sd	-0.00	0.01	-0.81	0.42	-0.02	0.02
Clashes	sd	0.14	0.01	15.41	0.00	0.12	0.16
Govt casualties	sd	0.02	0.01	2.73	0.01	0.01	0.03
Nightlights	sd	0.51	0.10	4.89	0.00	0.30	0.72
Reb casualties	sd	-0.03	0.01	-3.67	0.00	-0.05	-0.01
Population	sd	1.22	0.23	5.24	0.00	0.76	1.68
Road density	sd	0.02	0.06	0.33	0.74	-0.10	0.14
Drought index	sd	0.03	0.07	0.46	0.64	-0.11	0.17
Urban	sd	0.01	0.02	0.52	0.60	-0.03	0.05

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Dia (prim)	Max - Min	-12.85	413.37	-0.03	0.98	-823.05	797.35
Dia (sec)	Max - Min	0.08	0.81	0.10	0.92	-1.51	1.67
Drugs	Max - Min	-0.73	0.57	-1.28	0.20	-1.84	0.38
Gemstone	Max - Min	0.18	0.55	0.32	0.75	-0.91	1.27
Mountains	Max - Min	-0.04	0.35	-0.12	0.91	-0.72	0.64
Terr (int) tp lag	Max - Min	2.65	0.23	11.30	0.00	2.19	3.11
Terr (int) sp lag	Max - Min	-0.36	0.25	-1.43	0.15	-0.85	0.13
Petroleum	Max - Min	-0.97	0.41	-2.37	0.02	-1.78	-0.16

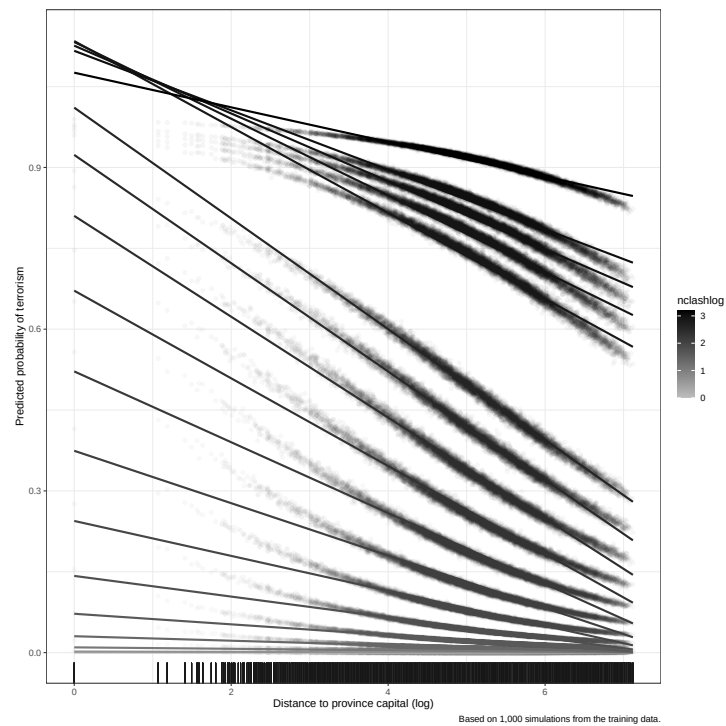


FIGURE B.19: Substantive effects of distance to province capital and number of battles for model 3.

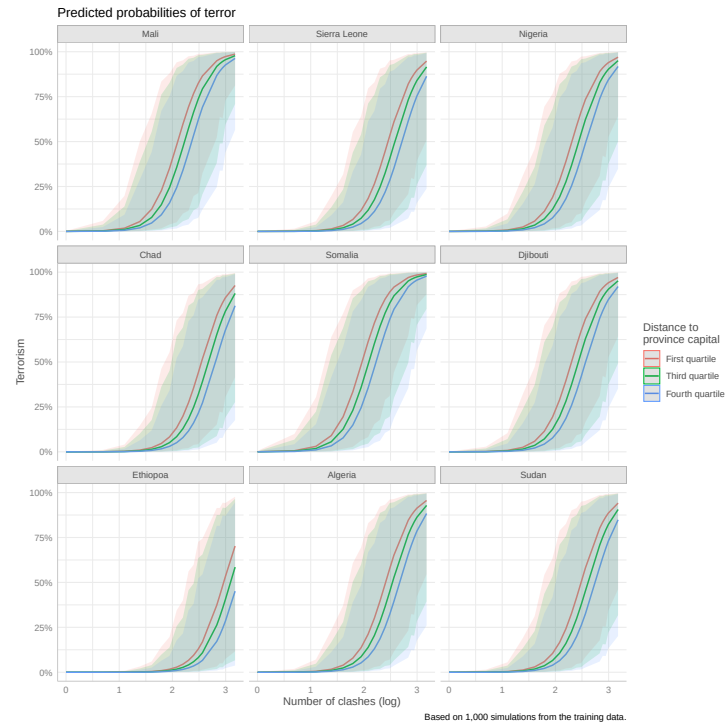


FIGURE B.20: Substantive effects of distance to province capital and number of battles for model 3 for different countries.

B.5.4 Model 4

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Border distance	sd	-0.17	0.07	-2.41	0.02	-0.31	-0.03
Nat cap dist	sd	0.11	0.07	1.51	0.13	-0.03	0.24
Prov cap dist	sd	-0.33	0.09	-3.78	0.00	-0.50	-0.17
Excluded	sd	0.16	0.09	1.78	0.07	-0.02	0.34
Forest	sd	0.01	0.06	0.13	0.89	-0.11	0.13
GDP	sd	-0.07	0.05	-1.28	0.20	-0.16	0.02
Civ casualties	sd	0.00	0.00	0.51	0.61	-0.01	0.01
Clashes	sd	0.09	0.01	10.56	0.00	0.08	0.10
Govt casualties	sd	0.00	0.01	0.65	0.52	-0.01	0.01
Nightlights	sd	0.39	0.09	4.39	0.00	0.21	0.57
Reb casualties	sd	0.01	0.01	1.59	0.11	-0.00	0.02
Population	sd	1.14	0.20	5.68	0.00	0.75	1.53
Road density	sd	0.14	0.05	2.63	0.01	0.03	0.25
Drought index	sd	0.14	0.06	2.31	0.02	0.02	0.26
Urban	sd	0.03	0.02	1.36	0.17	-0.01	0.07

Variable	Contrast	Estimate	Std.Error	Statistic	p-value	Conf.Low	Conf.High
Dia (prim)	Max - Min	-0.99	1.15	-0.86	0.39	-3.25	1.27
Dia (sec)	Max - Min	0.60	0.48	1.25	0.21	-0.34	1.54
Drugs	Max - Min	-0.14	0.37	-0.37	0.71	-0.85	0.57
Gemstone	Max - Min	0.28	0.49	0.58	0.56	-0.67	1.23
Mountains	Max - Min	0.63	0.29	2.15	0.03	0.06	1.20
Terr (max) tp lag	Max - Min	2.31	0.21	10.91	0.00	1.89	2.73
Terr (max) sp lag	Max - Min	-0.35	0.22	-1.60	0.11	-0.77	0.07
Petroleum	Max - Min	0.54	0.25	2.14	0.03	0.05	1.03

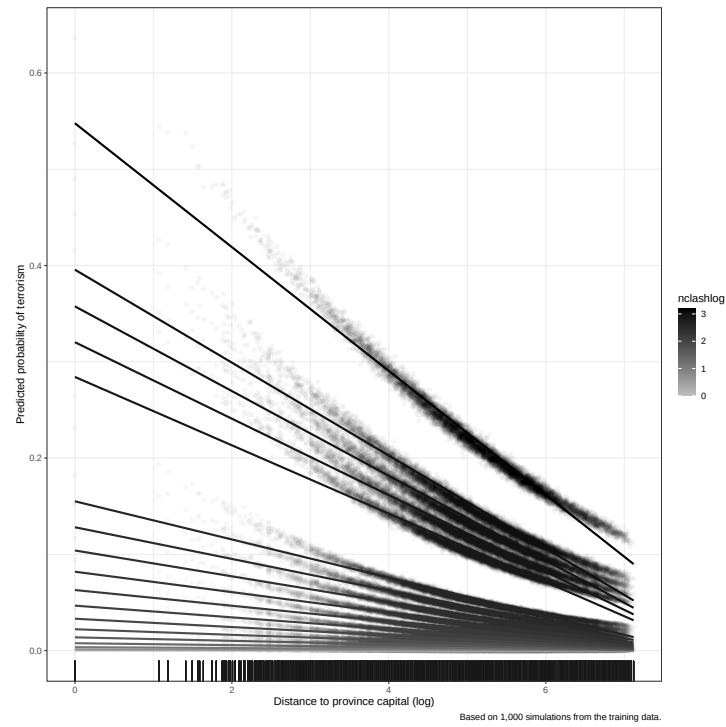


FIGURE B.21: Substantive effects of distance to province capital and number of battles for model 4.

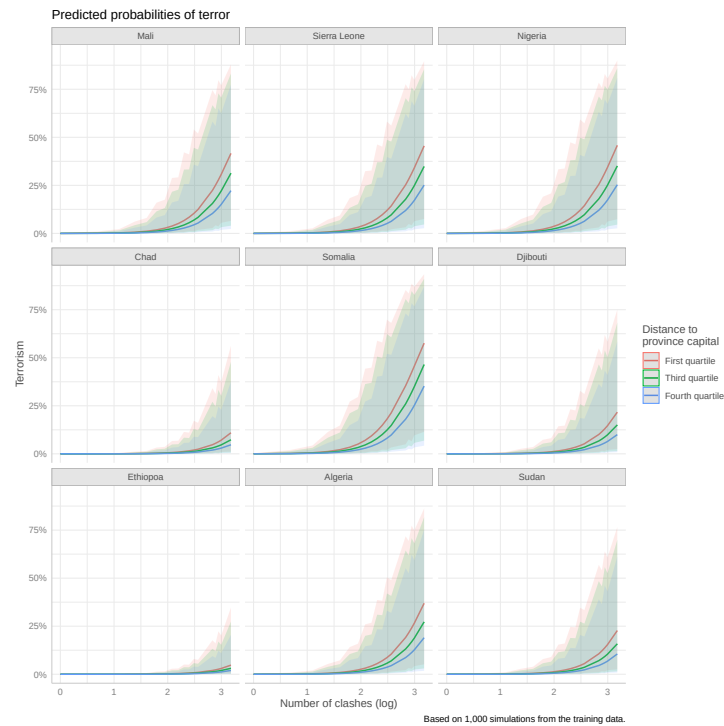


FIGURE B.22: Substantive effects of distance to province capital and number of battles for model 4 for different countries.

B.6 Out-of-sample metrics

This section contains additional out-of-sample performance metrics, ROC plots and confusion matrices. Below are additional metrics for the full models. As was already discussed in the paper, accuracy and specificity alone do not convey how well the model deals with unseen data. The balanced accuracy, sensitivity and detection rates and prevalences indicate that the model does well in predicting the absence of terrorism but is not at desirable levels regarding the prediction terrorism occurrences in civil conflicts. Likewise, the ROC curves on the following pages have very good metrics but these are a result of the absences of terrorism. The confusion matrices indicate this as well.

TABLE B.5

Statistic	Model 1	Model 2	Model 3	Model 4
Balanced Accuracy	0.553	0.509	0.543	0.528
Accuracy	0.999	0.999	0.999	0.999
F1	0.176	0.036	0.150	0.101
Sensitivity	0.107	0.018	0.086	0.055
Specificity	1.000	1.000	1.000	1.000
Pos Pred Value	0.500	1.000	0.609	0.600
Neg Pred Value	0.999	0.999	0.999	0.999
AUC	0.553	0.509	0.543	0.528
Lower CI	0.537	0.502	0.528	0.515
Upper CI	0.570	0.515	0.558	0.540
Kappa	0.176	0.036	0.150	0.101
MCC	0.231	0.135	0.228	0.182
Detection Rate	0.0001	0.00002	0.0001	0.0001
Detection Prevalence	0.0002	0.00002	0.0001	0.0001
Prevalence	0.001	0.001	0.001	0.001

B.6.1 Model 1

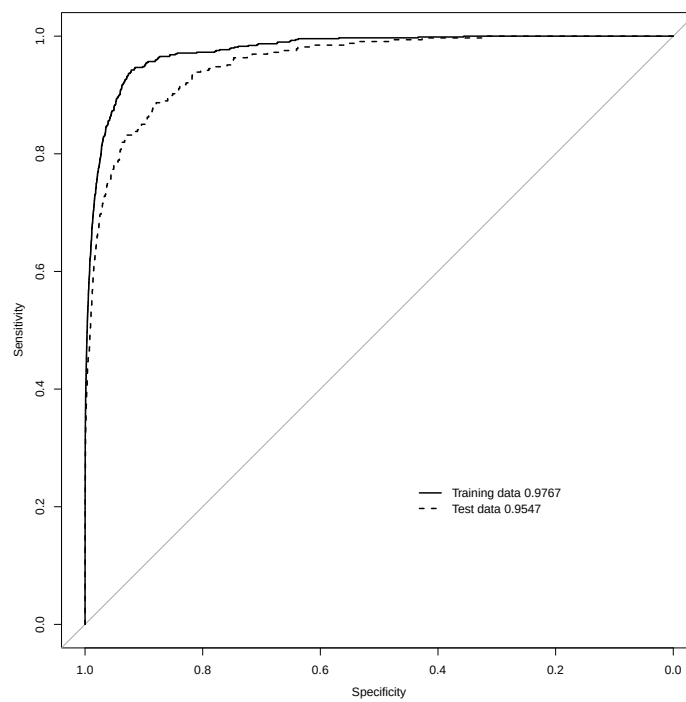


FIGURE B.23: ROC curve for model 1: Terror.

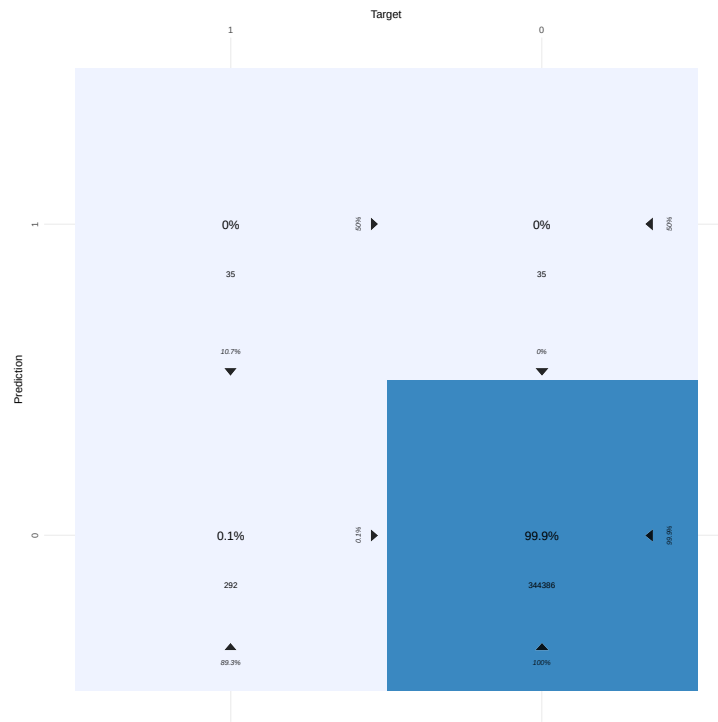


FIGURE B.24: Confusion matrix for model 1: Terror.

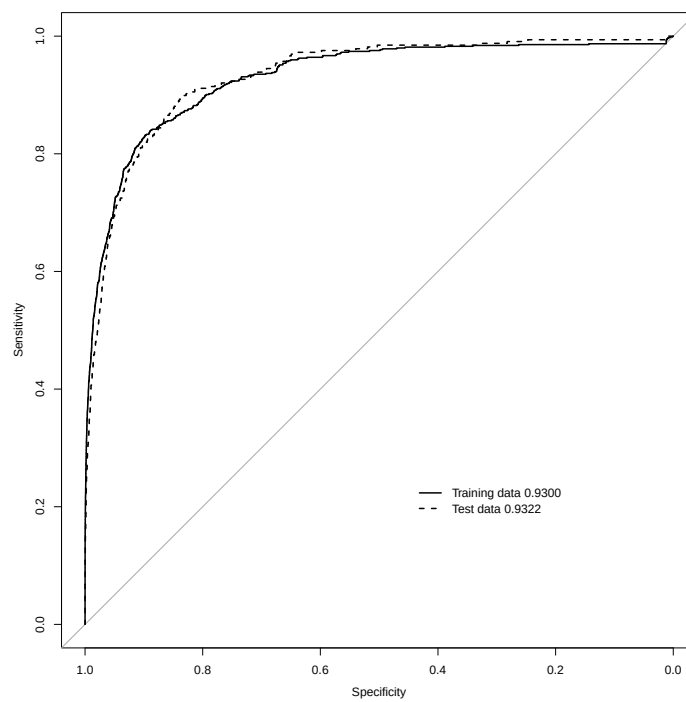
B.6.2 Model 2

FIGURE B.25: ROC curve for model 2: Terror (min).

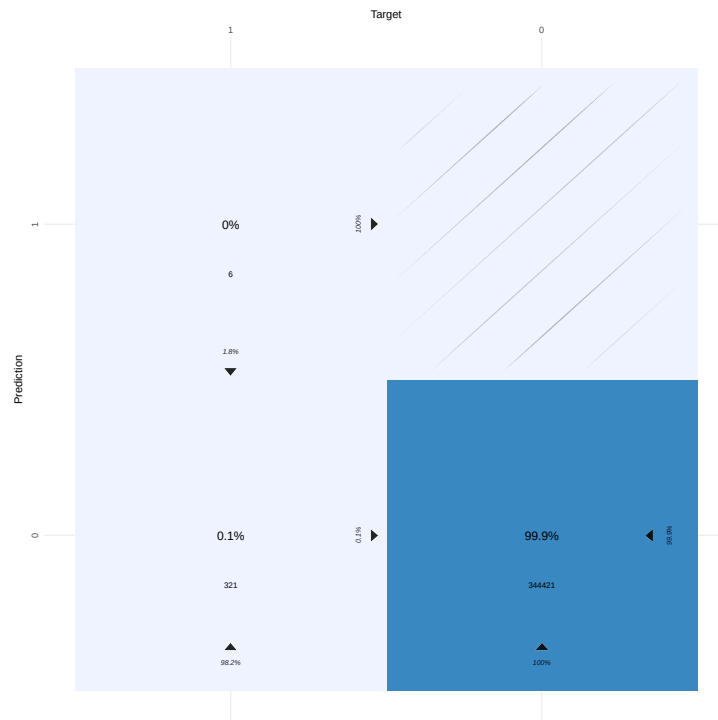


FIGURE B.26: Confusion matrix for model 2: Terror (min).

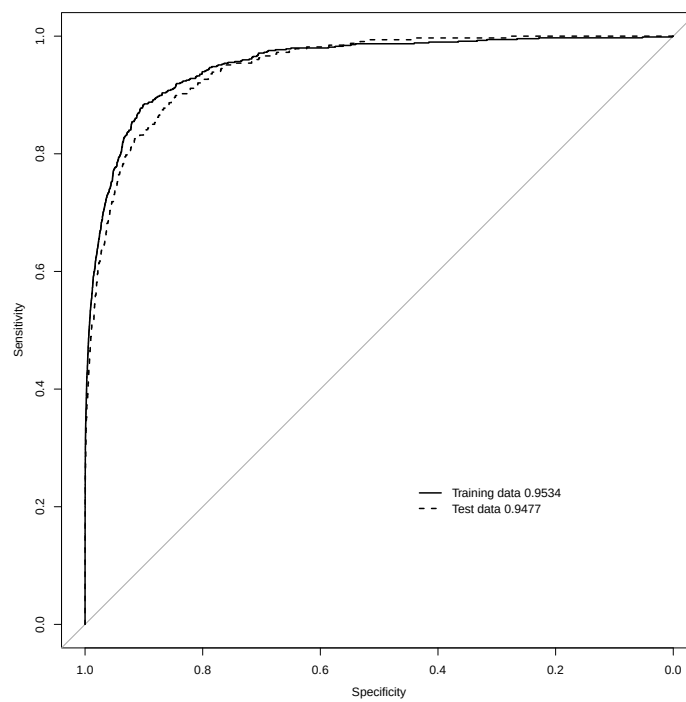
B.6.3 Model 3

FIGURE B.27: ROC curve for model 3: Terror (int).

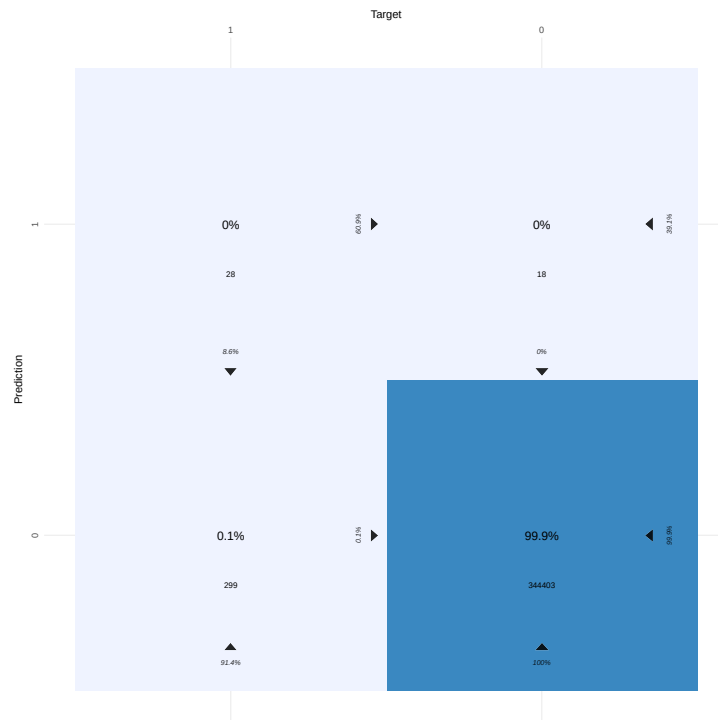


FIGURE B.28: Confusion matrix for model 3: Terror (int).

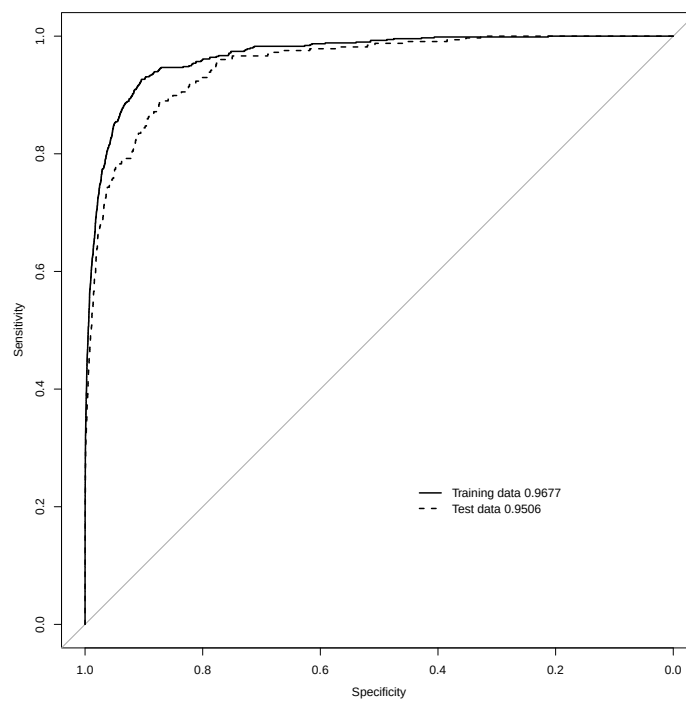
B.6.4 Model 4

FIGURE B.29: ROC curve for model 4: Terror (max).

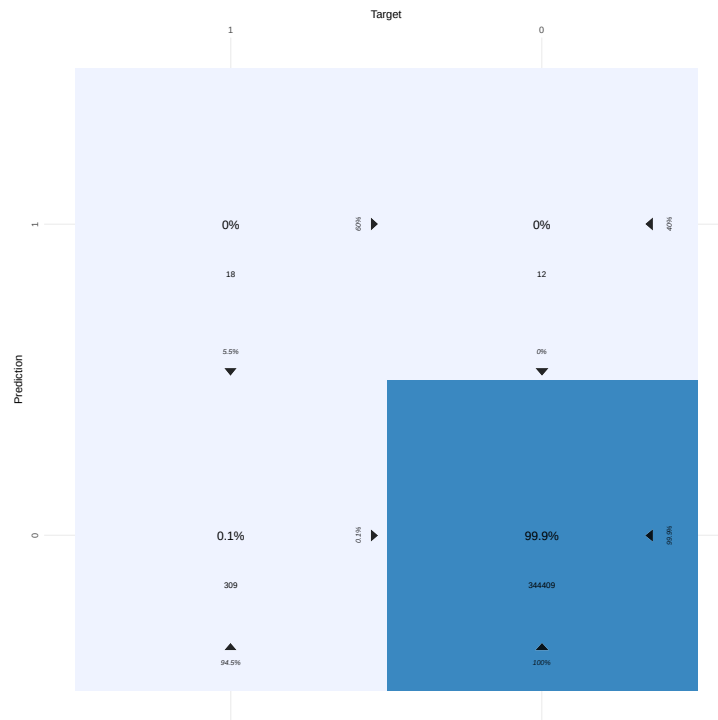


FIGURE B.30: Confusion matrix for model 4: Terror (max).

Appendix C

Supplemental information for: Margin of (t)error: Predicting terrorism in civil conflicts for theory building and improvement

C.1 Overview

This appendix provides additional descriptives about the dependent and independent variables. In addition, it provides tuning parameter search plots, confusion matrices, receiver-operator curve plots, and additional interaction and partial dependence plots.

C.1.1 Descriptive statistics

TABLE C.1: Summary statistics for all independent variables.

Statistic	Mean	St. Dev.	Min	Max
Ethnic claim (ACD2EPR)	0.037	1.008	−1.285	2.000
Ethnic recruitment (ACD2EPR)	0.024	0.992	−1.372	0.000
Ethnic support (ACD2EPR)	0.024	1.005	−0.808	1.000
Territorial conflict	0.035	1.003	−0.906	1.000
Democracy	0.057	1.001	−0.957	1.000
Ethnoreligious ideology	0.033	1.025	−0.490	2.000
External support for rebel group	0.042	1.001	−0.953	1.000
Fariss (mavg,2-5)	0.002	0.966	−3.733	2.000
Fariss (mavg,2-5) x Relative rebel losses (lag)	0.006	1.018	−1.184	2.000
GDP (log)	0.031	1.015	−2.603	2.000
Relative government losses (lag)	−0.019	0.943	−0.104	5.000
Out-group antagonism	0.001	1.000	−1.683	0.000
Out-group antagonism x Relative rebel losses (lag)	0.009	1.059	−0.232	2.000
Battle event without rebel losses (dummy, lag)	−0.002	0.999	−0.731	1.000
Rebel centralized leadership	−0.023	1.028	−2.870	0.000
Rebel group strength	0.009	0.991	−0.946	4.000
Government one-sided violence	0.004	1.161	−0.015	8.000
Government one-sided violence (log)	−0.012	0.965	−0.372	1.000
Rebel one-sided violence	0.004	1.138	−0.066	6.000
Rebel one-sided violence (log)	0.027	1.002	−0.561	6.000
Rebel group competition	−0.025	0.992	−0.501	3.000
Population (log)	0.039	0.995	−2.469	1.000
Repression (PTS)	0.016	0.942	−2.984	1.000
Repression (PTS mavg, 2-5)	0.019	0.972	−3.853	1.000
Repression (PTS mavg, 1-5)	0.020	0.964	−3.946	1.000
Repression (PTS mavg, 2-5) x Relative rebel losses (lag)	0.008	1.033	−0.251	2.000
Proportion of rebel losses (interpolated, lag)	0.0001	1.048	−26.194	3.000
Relative rebel losses	−0.008	0.920	−0.216	3.000
Relative rebel losses (lag)	0.010	1.039	−0.251	2.000
Religious ideology	−0.005	0.996	−0.427	2.000
Change of leader (lag)	−0.00004	1.002	−0.391	5.000
Rebel group territorial control	0.036	1.010	−0.738	1.000
Time since last terror attack	−0.074	0.867	−0.480	5.000
Time since last terror attack (squared)	−0.063	0.742	−0.248	7.000
Time since last terror attack (cubed)	−0.059	0.598	−0.168	7.000
Conflict intensification	−0.043	0.995	−0.903	1.000

Notice that binary variables appear here with negative values as minimum value and positive values unequal to 1 as maximum value. The scaling and standardizing of all predictors kept the binary nature of these variables but changed the values from 0 and 1 to a negative and a positive

value.

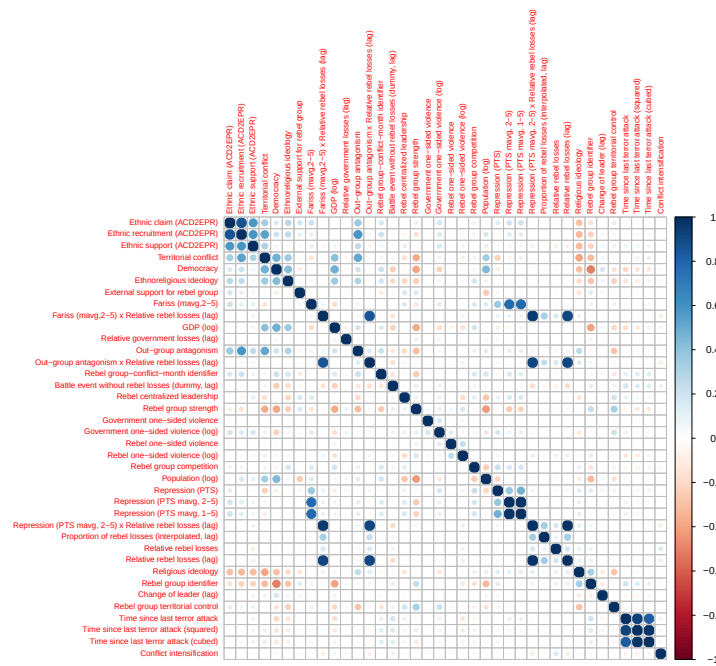


FIGURE C.1: Correlation plot with all independent variables used in the analyses.

Pairs of features with high positive correlations are the different ethnicity measures with each other (ACD2EPR variables and out-group antagonism), time since last attack (normal, squared, and cubed), repression (different PTS moving averages with Fariss moving average), the interaction terms including relative rebel losses (Fariss, PTS, out-group antagonism) with lagged relative rebel losses, PTS measures with different moving averages. Pairs of features with relatively high negative correlations are

[think about facetwrap stuff to visualize the features and their distributions more]

C.1.2 Terror hard - additional plots and tables

This section presents tuning parameter search plots, additional performance metrics and confusion matrix and ROC curve plots, additional interaction plots and partial dependence plots.

Tuning parameter search

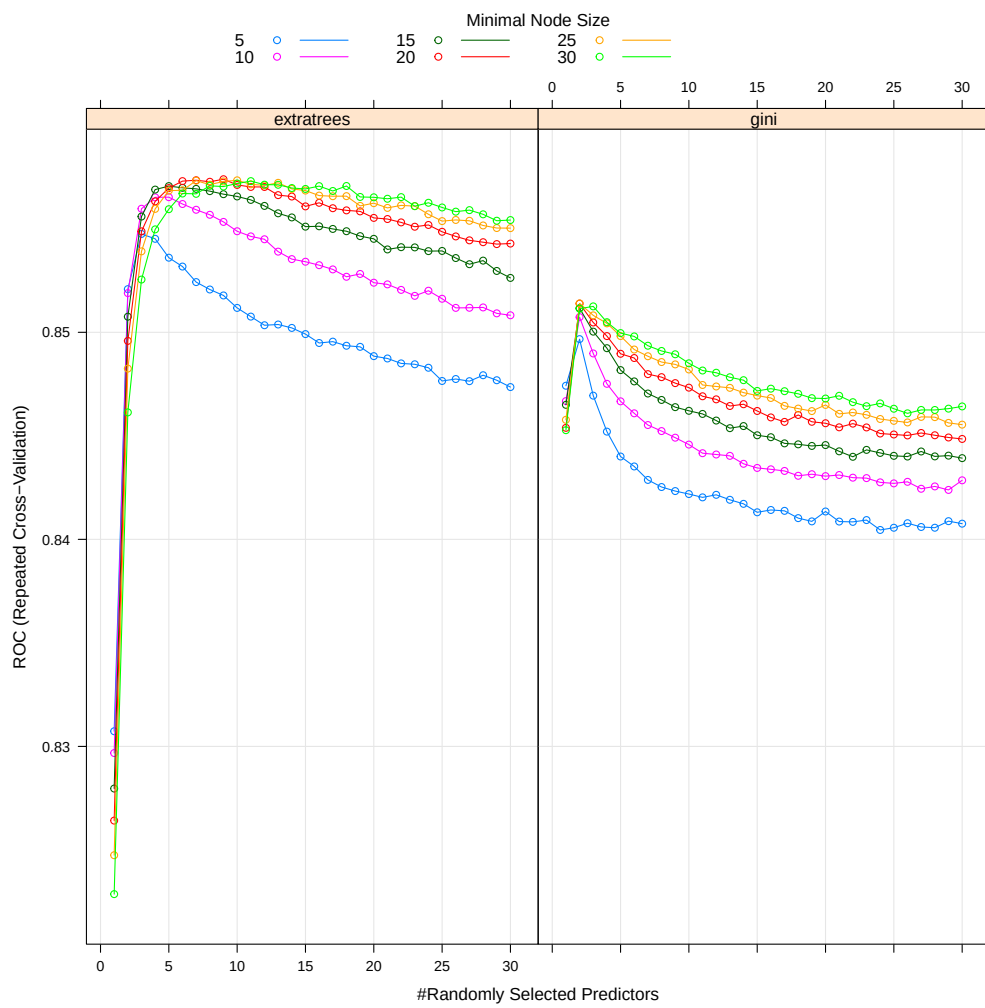


FIGURE C.2: Tuning parameter results of the repeated cross-validation procedure.

Confusion matrices

	Terrorism	NoTerrorism
Terrorism	1018	158
NoTerrorism	301	2242

	Terrorism	NoTerrorism
Terrorism	248	88
NoTerrorism	206	667

TABLE C.2: Confusion matrices for hard terrorism (permutation-based importance) in the training (left) and test data (right).

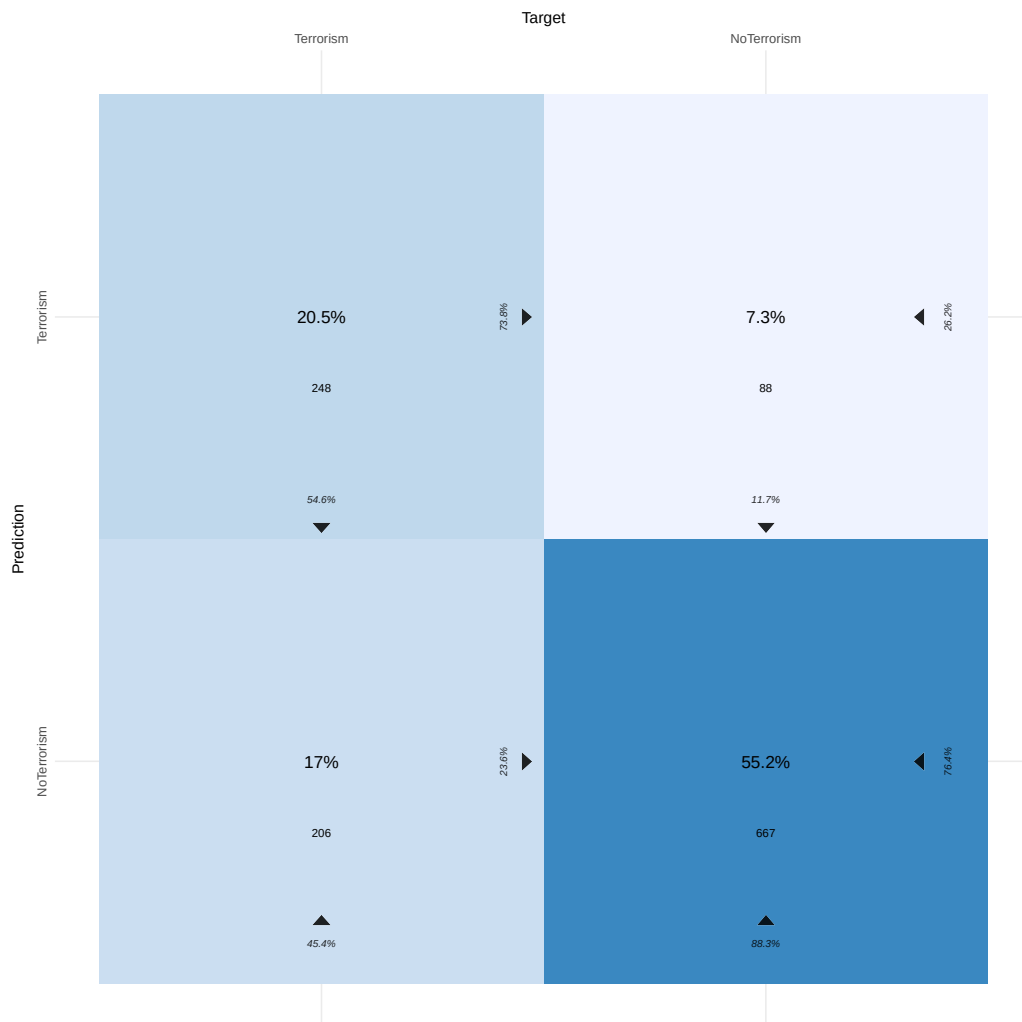


FIGURE C.3: Confusion matrix for terrorism against hard targets (test data).

Receiver-operatur curves

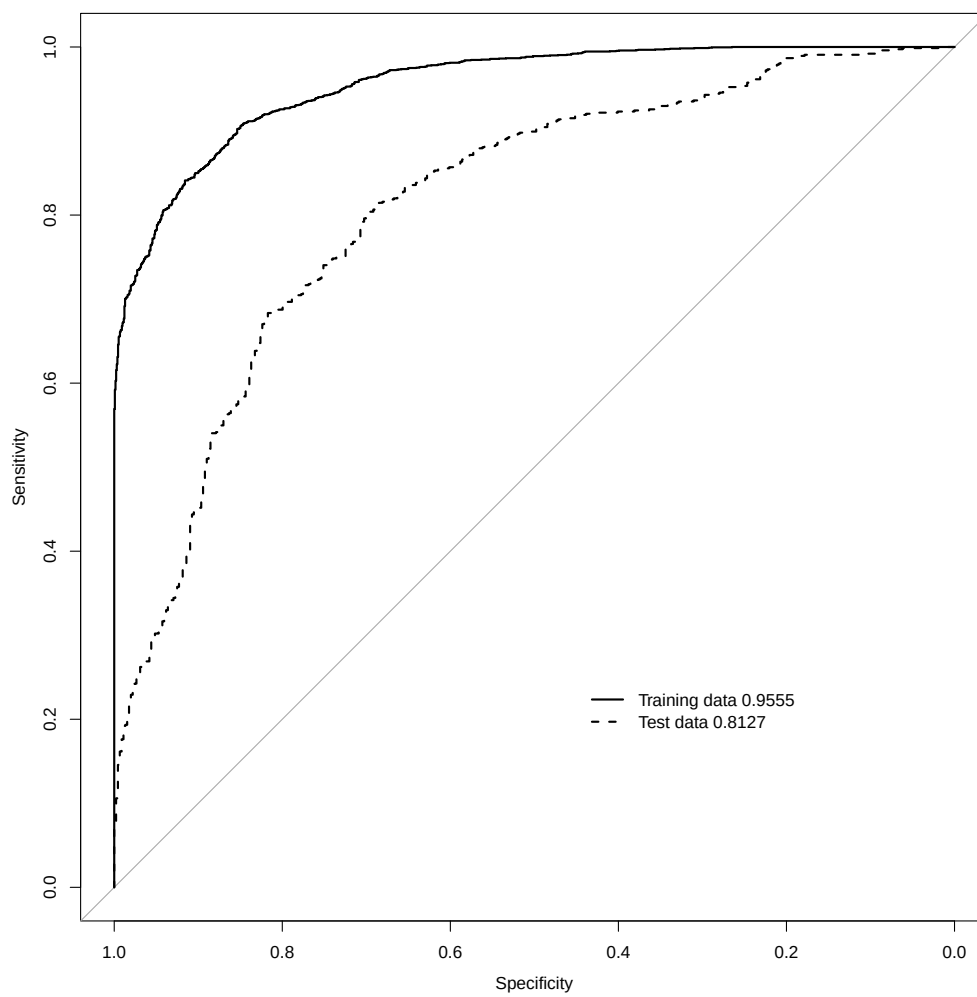


FIGURE C.4: Receiver-operator curves for terrorism against hard targets.

Additional performance metrics

TABLE C.3

Statistic	N	Mean	St. Dev.	Min	Max
Balanced Accuracy	1	0.715		0.715	0.715
Accuracy	1	0.757		0.757	0.757
F1	1	0.628		0.628	0.628
Sensitivity	1	0.546		0.546	0.546
Specificity	1	0.883		0.883	0.883
Pos Pred Value	1	0.738		0.738	0.738
Neg Pred Value	1	0.764		0.764	0.764
AUC	1	0.715		0.715	0.715
Lower CI	1	0.689		0.689	0.689
Upper CI	1	0.740		0.740	0.740
Kappa	1	0.453		0.453	0.453
MCC	1	0.465		0.465	0.465
Detection Rate	1	0.205		0.205	0.205
Detection Prevalence	1	0.278		0.278	0.278
Prevalence	1	0.376		0.376	0.376

Interaction plots

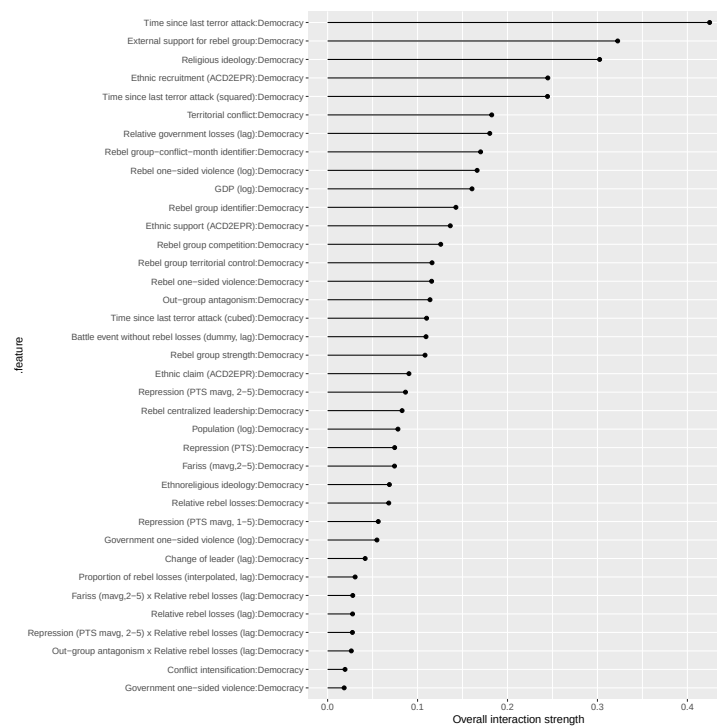


FIGURE C.5: Variable interaction strengths for terrorist incidence (permutation): Democracy.

Figure C.5 shows interaction strengths between democracy and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four pair of variables: democracy and time since the last terror attack, external support for rebel group, religious ideology, and ethnic recruitment, respectively.

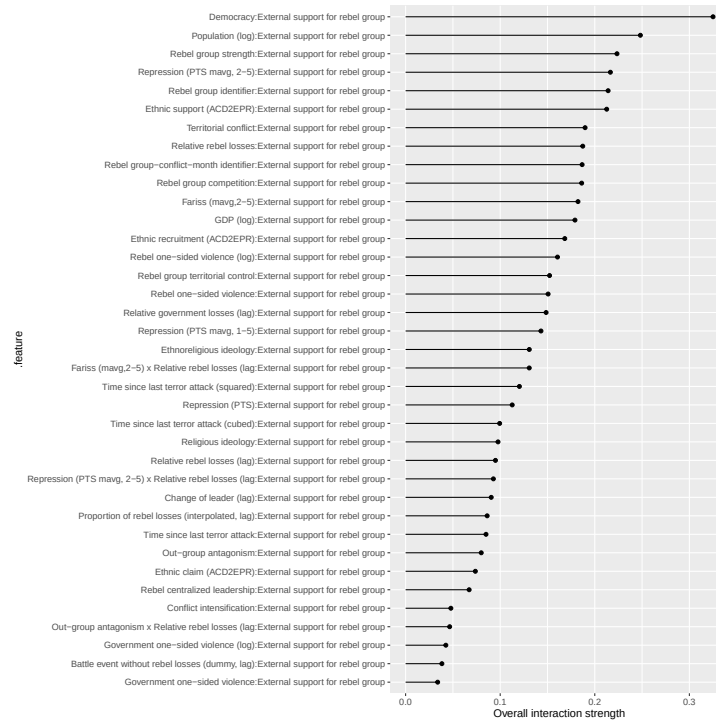


FIGURE C.6: Variable interaction strengths for terrorist incidence (permutation): External support for rebel group.

Figure C.6 shows interaction strengths between external support for a rebel group and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four pair of variables: external support and democracy, population size, rebel group strength, and repression (PTS), respectively.

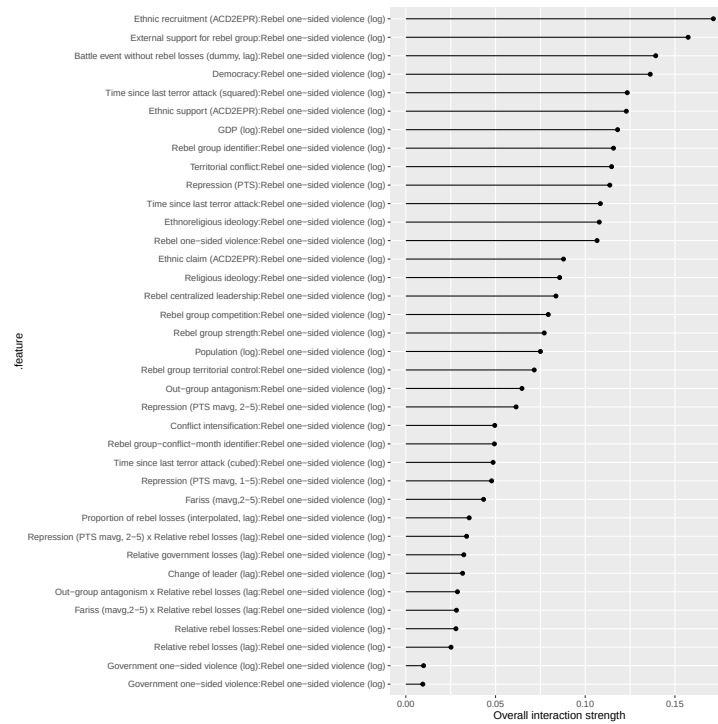


FIGURE C.7: Variable interaction strengths for terrorist incidence (permutation): Rebel one-sided violence (log).

Figure C.7 shows interaction strengths between rebel one-sided violence against civilians (log) and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects since the values are too low to justify further investigation for the purpose of this paper.

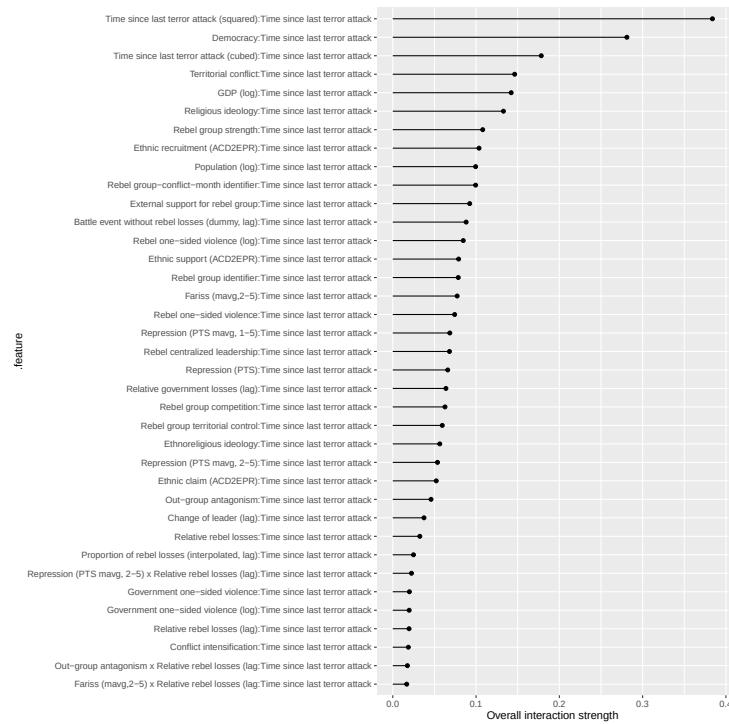


FIGURE C.8: Variable interaction strengths for terrorist incidence (permutation): Time since last terror attack.

Figure C.8 shows interaction strengths between time since the last terrorist attack and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects. The interaction with democracy is covered in the ALE plots on democracy and all other (relevant) features have too low values to justify further investigation for the purpose of this paper.

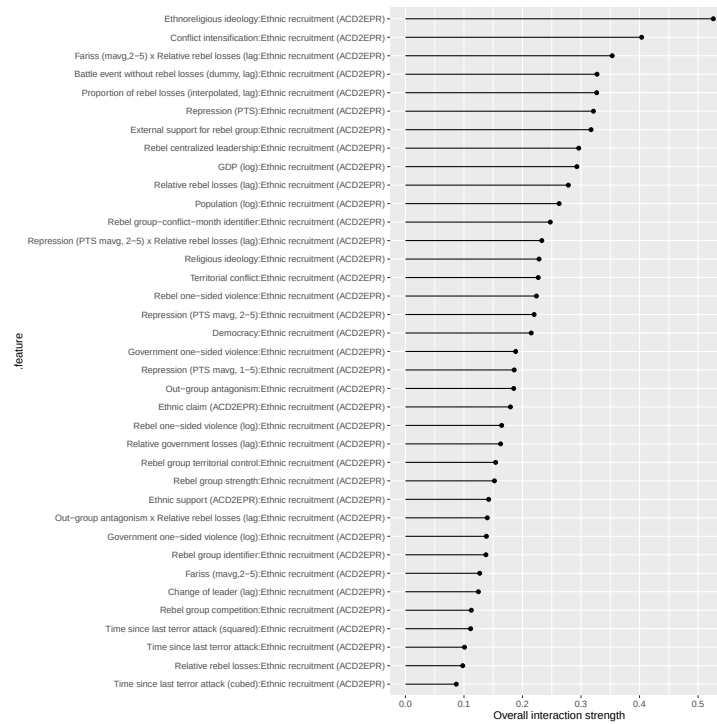


FIGURE C.9: Variable interaction strengths for terrorist incidence (permutation): Ethnic recruitment.

Figure C.9 shows interaction strengths between ethnic recruitment and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: ethnic recruitment and ethnoreligious ideology, conflict intensification, an interaction between repression (Fariss) and rebel losses, and battle event without rebel losses, respectively. An ALE plot showing the interaction effects are in the following subsection. Based on the H-statistics, further features would deserve further investigation but I leave that for future research. Suffice to note that ethnic recruitment seems to have interaction effects with a number of relevant variables, however.

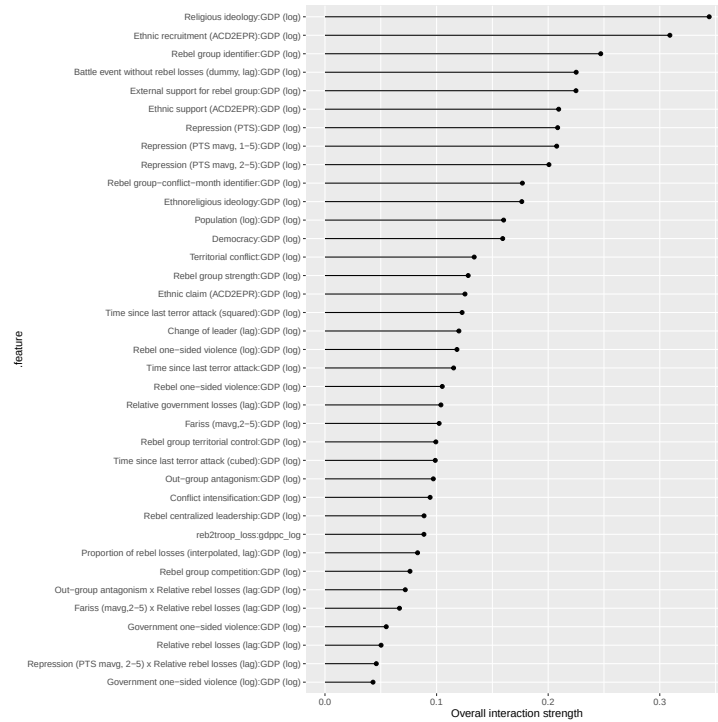


FIGURE C.10: Variable interaction strengths for terrorist incidence (permutation): GDP (log).

Figure C.10 shows interaction strengths between GDP per capita and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: GDP per capita and religious ideology, ethnic recruitment, battle event without rebel losses, and external support, respectively.

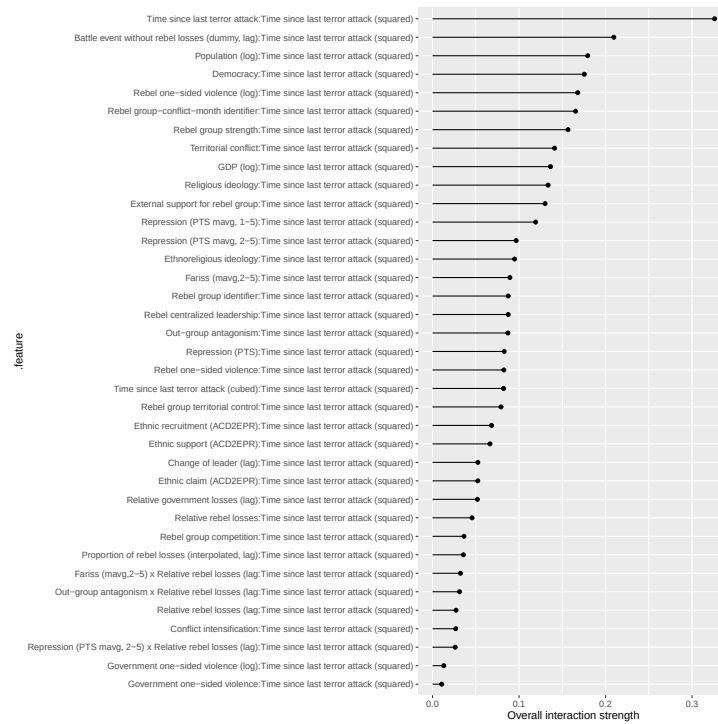


FIGURE C.11: Variable interaction strengths for terrorist incidence (permutation): Time since last terrorist attack (squared).

Figure C.11 shows interaction strengths between time since the last terrorist attack (squared) and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects with other features since values for (relevant) variables are too low for the purpose of this paper.

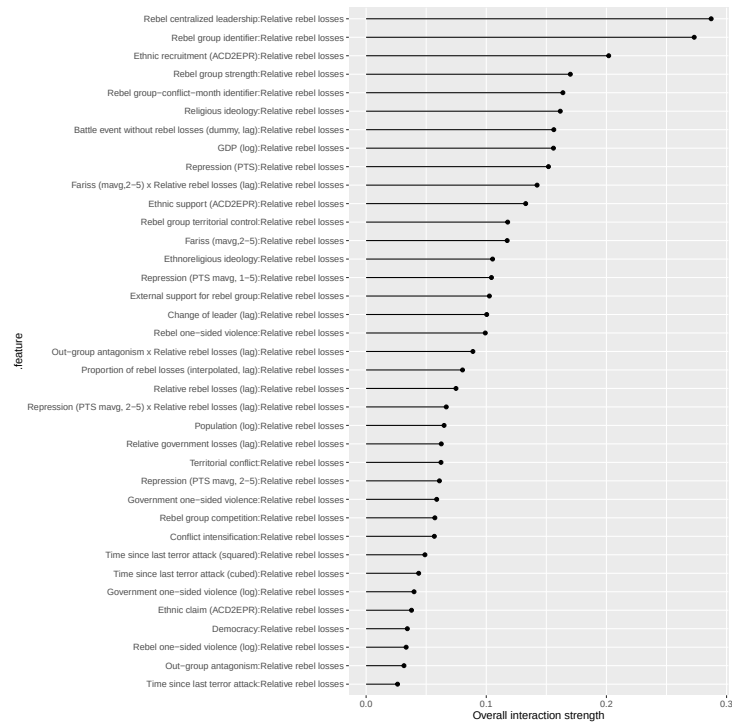


FIGURE C.12: Variable interaction strengths for terrorist incidence (permutation): Relative rebel losses.

Figure C.12 shows interaction strengths between relative rebel losses and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: relative rebel losses and rebel centralized leadership, ethnic recruitment, rebel group strength, and religious ideology, respectively.

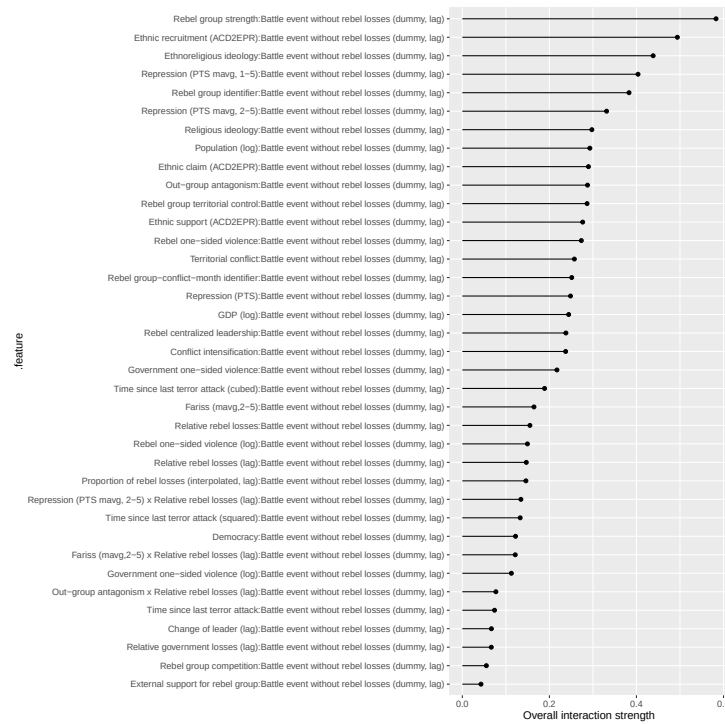


FIGURE C.13: Variable interaction strengths for terrorist incidence (permutation): Battle events without rebel losses.

Figure C.13 shows interaction strengths between battle event without rebel losses and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: battle event without rebel losses and rebel group strength, ethnic recruitment, ethnoreligious ideology, and repression (PTS), respectively. An ALE plot showing the interaction effects are in the following subsection. Based on the H-statistics, further features would deserve further investigation but I leave that for future research. Suffice to note that the absence of rebel losses seems to have interaction effects with a number of relevant variables, however.

Interactions (accumulated local effects plots)

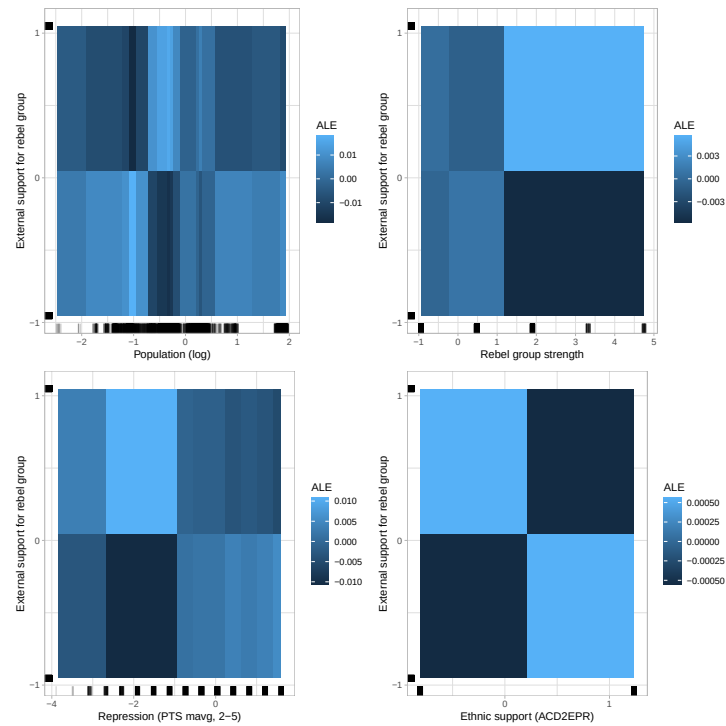


FIGURE C.14: Variable interaction strengths for terrorist incidence (permutation): External support for rebel group.

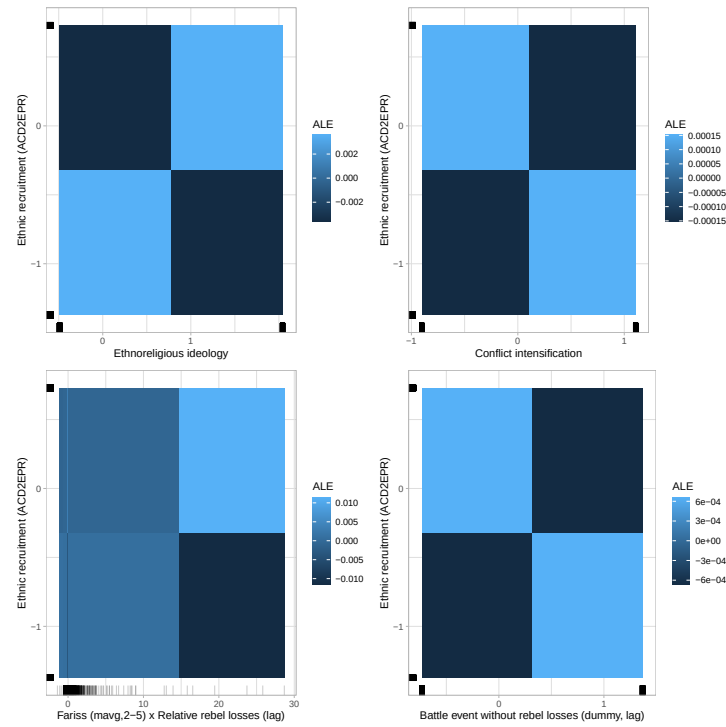


FIGURE C.15: Variable interaction strengths for terrorist incidence (permutation): Ethnic recruitment.

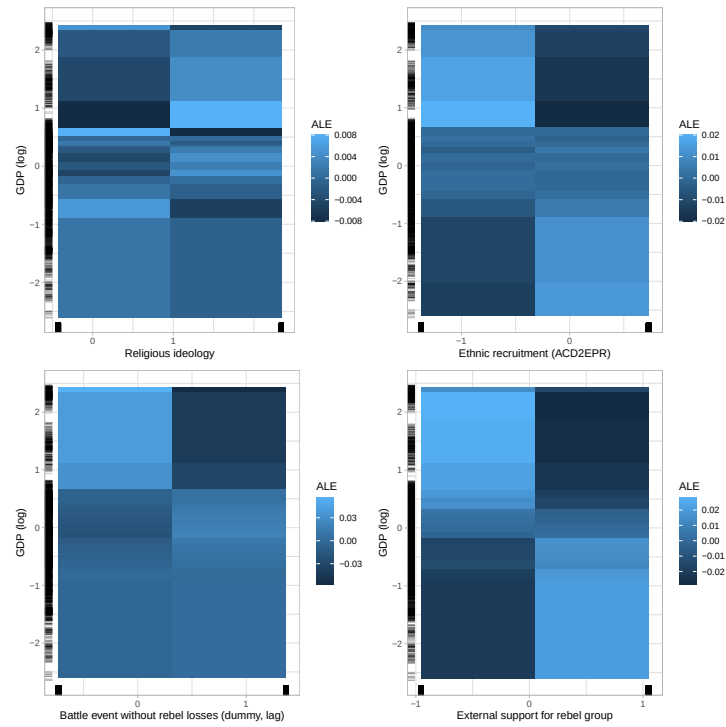


FIGURE C.16: Variable interaction strengths for terrorist incidence (permutation): GDP (log).

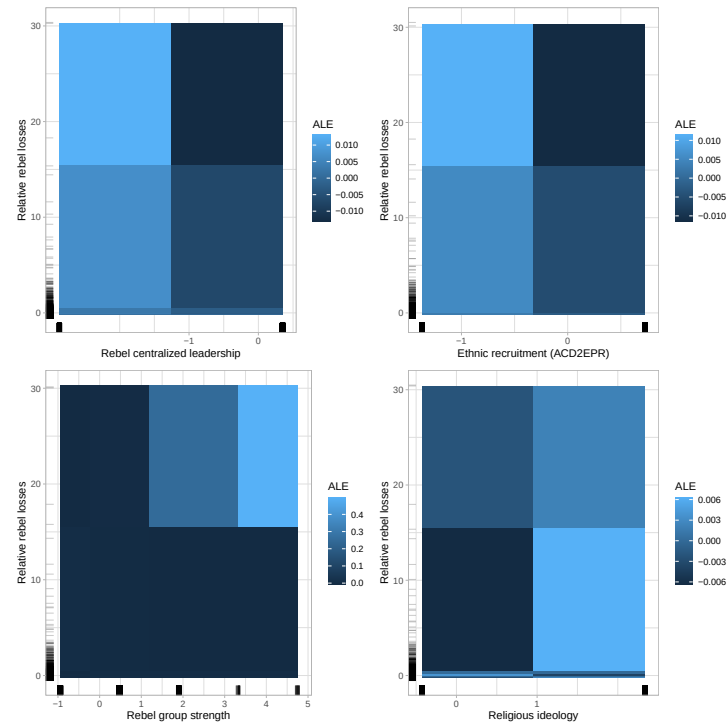


FIGURE C.17: Variable interaction strengths for terrorist incidence (permutation): Relative rebel losses.

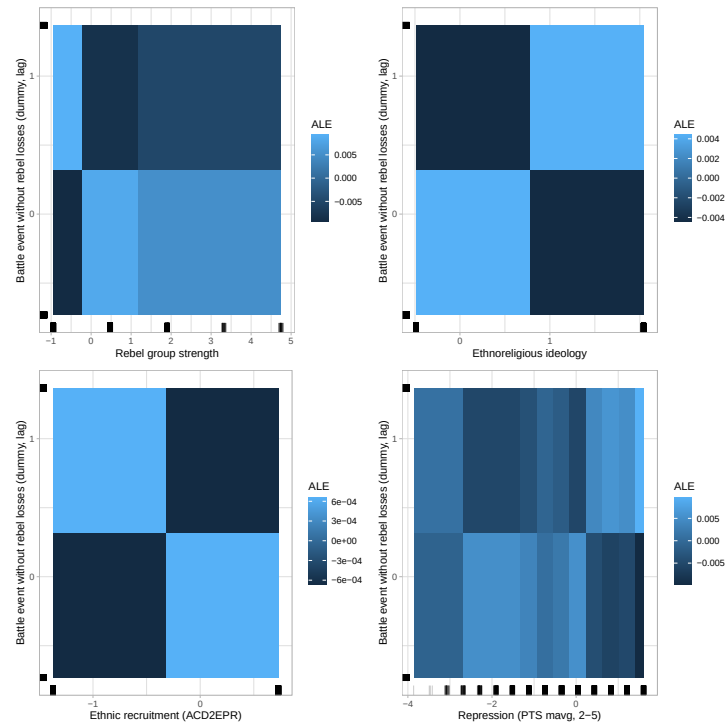


FIGURE C.18: Variable interaction strengths for terrorist incidence (permutation): Battle events without rebel losses.

C.1.3 **Terror soft - additional plots and tables**

This section presents tuning parameter search plots, additional performance metrics and confusion matrix and ROC curve plots, additional interaction plots and partial dependence plots.

Tuning parameter search

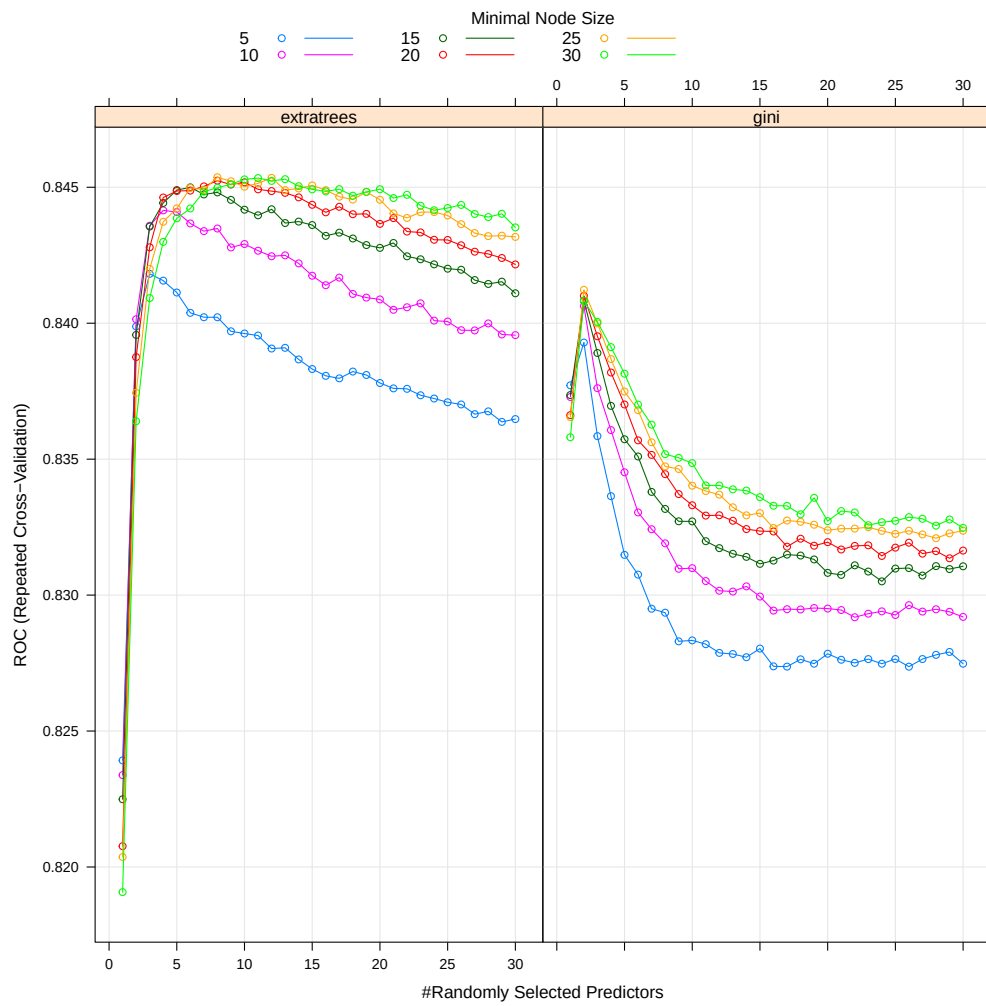


FIGURE C.19: Tuning parameter results of the repeated cross-validation procedure.

Confusion matrices

	Terrorism	NoTerrorism
Terrorism	551	82
NoTerrorism	379	2707

	Terrorism	NoTerrorism
Terrorism	88	22
NoTerrorism	246	853

TABLE C.4: Confusion matrices for training (left) and test (right) data with permutation importance.

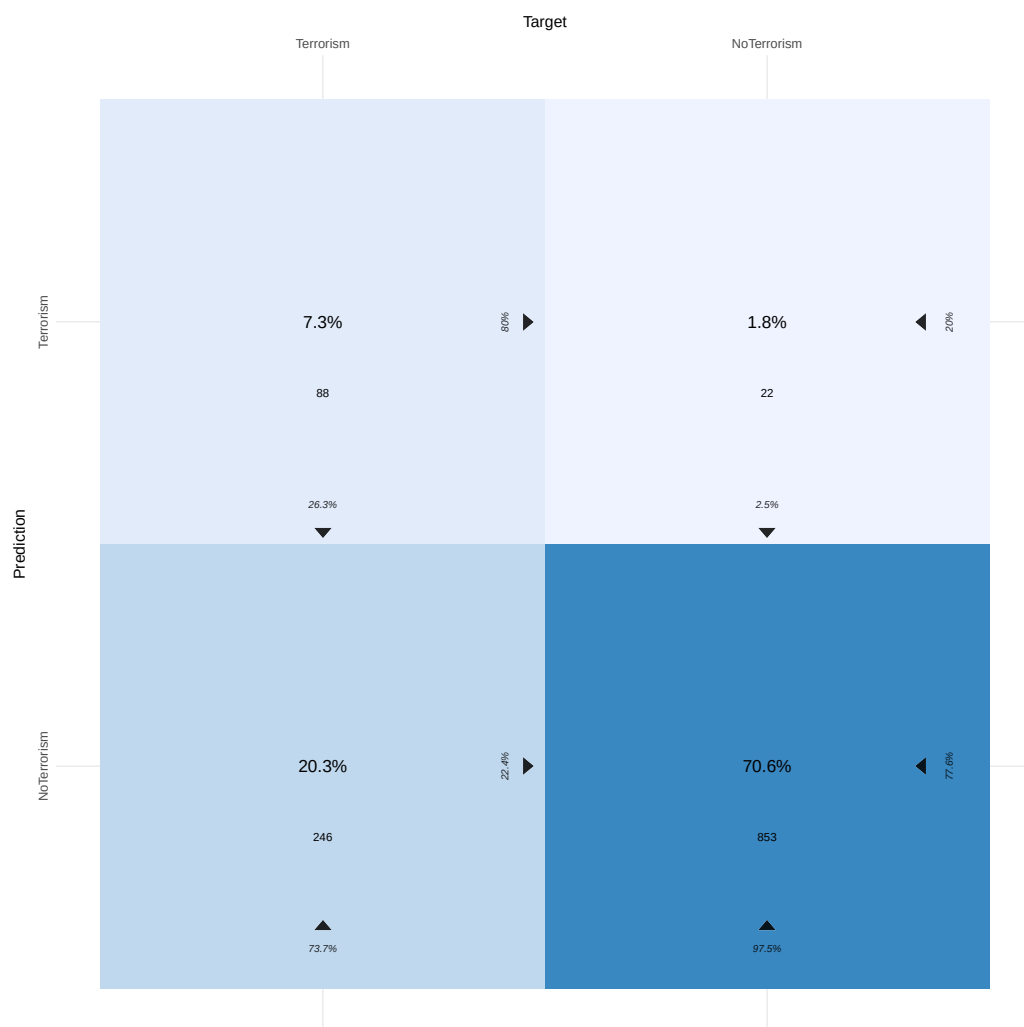


FIGURE C.20: Receiver-operator curves for terrorism against soft targets.

Receiver-operatur curves

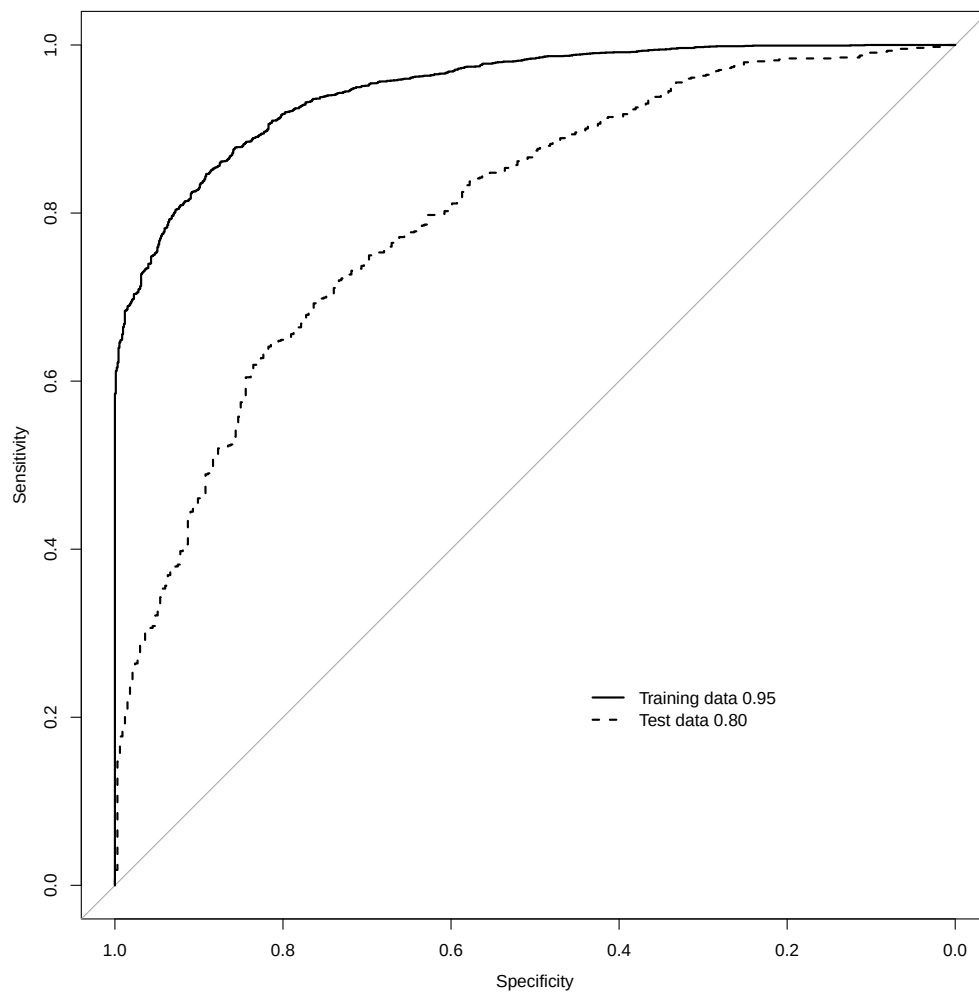


FIGURE C.21: Receiver-operator curves for terrorism against soft targets.

Additional performance metrics

TABLE C.5

Statistic	N	Mean	St. Dev.	Min	Max
Balanced Accuracy	1	0.619		0.619	0.619
Accuracy	1	0.778		0.778	0.778
F1	1	0.396		0.396	0.396
Sensitivity	1	0.263		0.263	0.263
Specificity	1	0.975		0.975	0.975
Pos Pred Value	1	0.800		0.800	0.800
Neg Pred Value	1	0.776		0.776	0.776
AUC	1	0.619		0.619	0.619
Lower CI	1	0.595		0.595	0.595
Upper CI	1	0.643		0.643	0.643
Kappa	1	0.301		0.301	0.301
MCC	1	0.371		0.371	0.371
Detection Rate	1	0.073		0.073	0.073
Detection Prevalence	1	0.091		0.091	0.091
Prevalence	1	0.276		0.276	0.276

Interaction plots

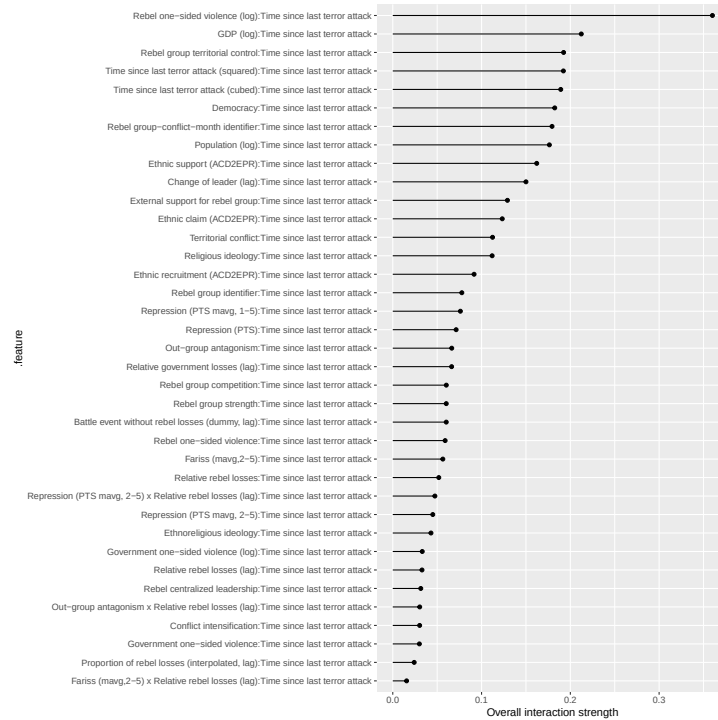


FIGURE C.22: Variable interaction strengths for monthly soft terrorist incidence (permutation): Time since last attack.

Figure C.22 shows interaction strengths between time since the last attack and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: time since the last attack and rebel one-sided violence (log), GDP per capita, rebel group territorial control, and democracy, respectively.

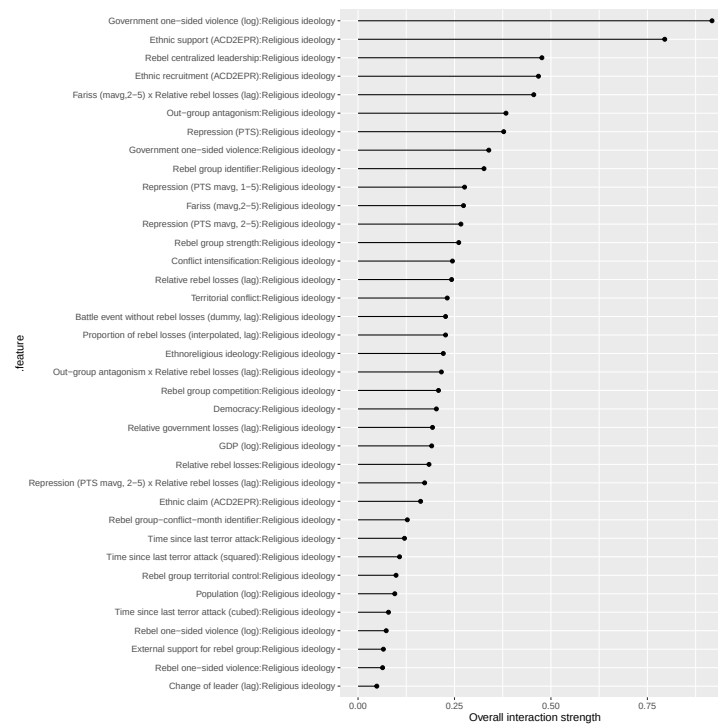


FIGURE C.23: Variable interaction strengths for monthly soft terrorist incidence (permutation): Religious ideology.

Figure C.23 shows interaction strengths between religious ideology and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: religious ideology and government one-sided violence (log), ethnic support, rebel centralized leadership, and ethnic recruitment, respectively.

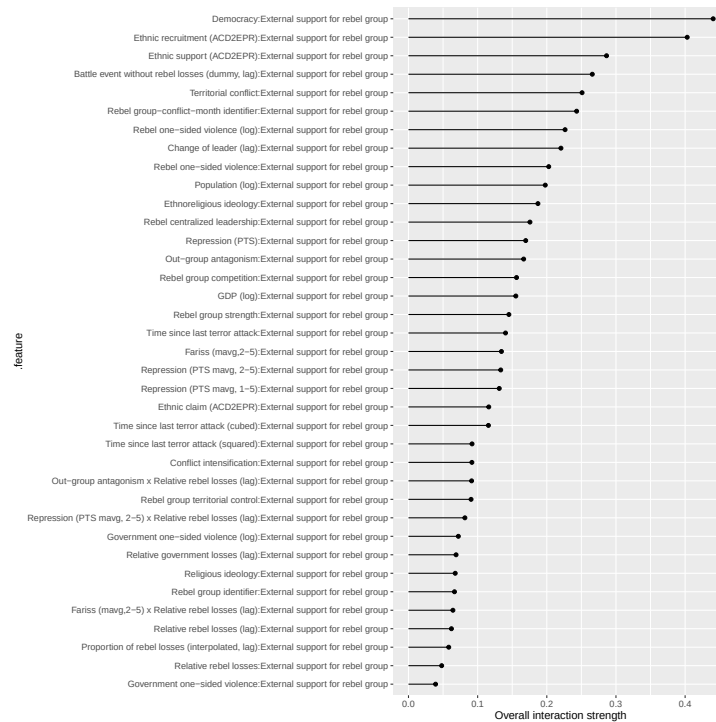


FIGURE C.24: Variable interaction strengths for monthly soft terrorist incidence (permutation): External support for rebel group.

Figure C.24 shows interaction strengths between external support for a rebel group and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: external support for a rebel group and democracy, ethnic recruitment, ethnic support, and battle event without rebel losses, respectively.

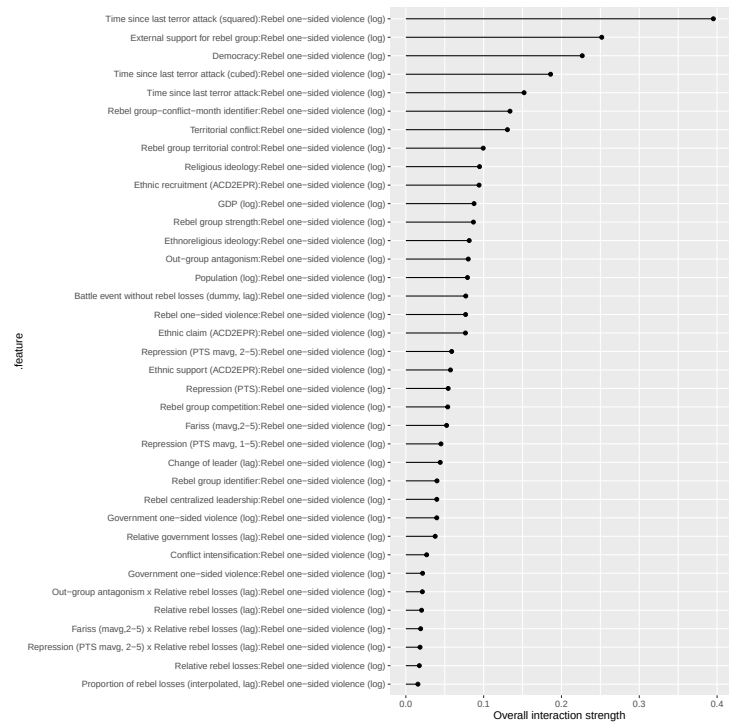


FIGURE C.25: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel one-sided violence (log).

Figure C.25 shows interaction strengths between rebel one-sided violence (log) and all other features in the data. Based on Friedman’s H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: rebel one-sided violence (log) and time since the last attack, external support for a rebel group, democracy, and time since the last attack (cubed), respectively.

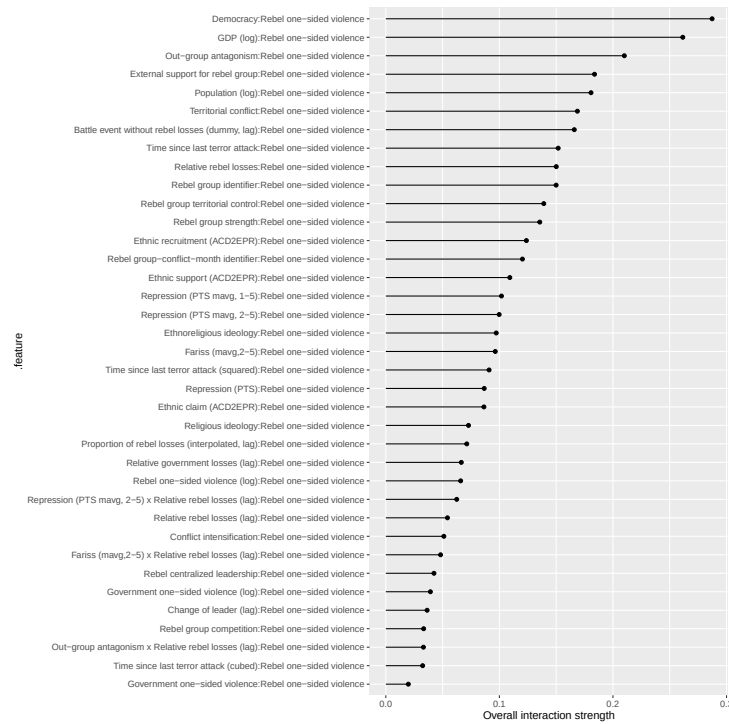


FIGURE C.26: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel one-sided violence.

Figure C.26 shows interaction strengths between rebel one-sided violence and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: rebel one-sided violence and democracy, GDP per capita, out-group antagonism, and extern support for a rebel group, respectively.

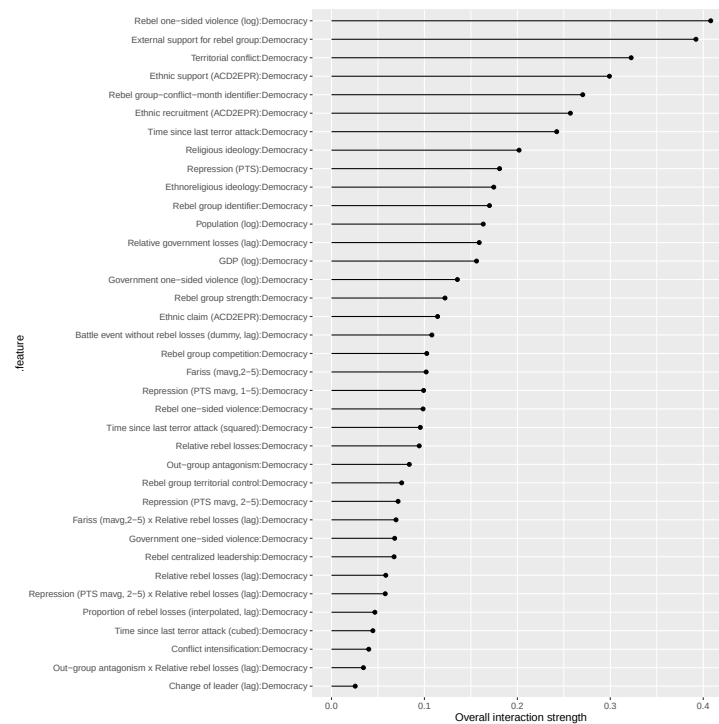


FIGURE C.27: Variable interaction strengths for monthly soft terrorist incidence (permutation): Democracy.

Figure C.27 shows interaction strengths between democracy and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: democracy and rebel one-sided violence (log), external support for a rebel group, territorial conflict, and ethnic support, respectively.

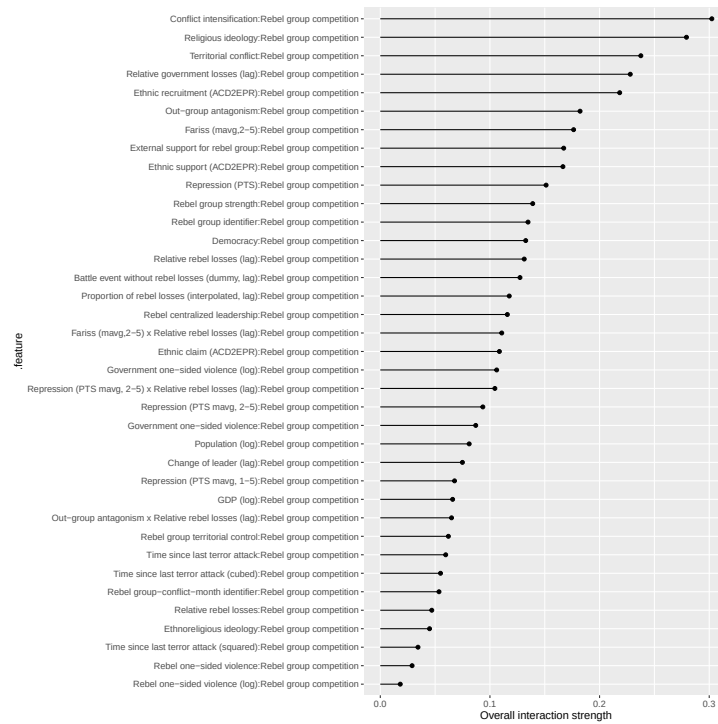


FIGURE C.28: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel group competition.

Figure C.28 shows interaction strengths between rebel group competition and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: rebel group competition and conflict intensification, religious ideology, territorial conflict, and relative government losses (lag), respectively.

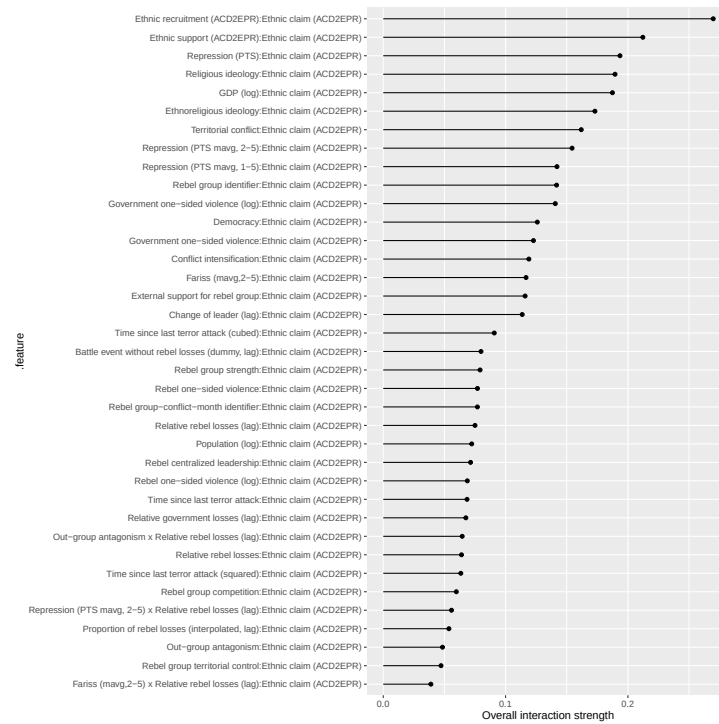


FIGURE C.29: Variable interaction strengths for monthly soft terrorist incidence (permutation): Ethnic claim.

Figure C.29 shows interaction strengths between ethnic claim and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects since values for meaningful features are too low to justify further investigation.

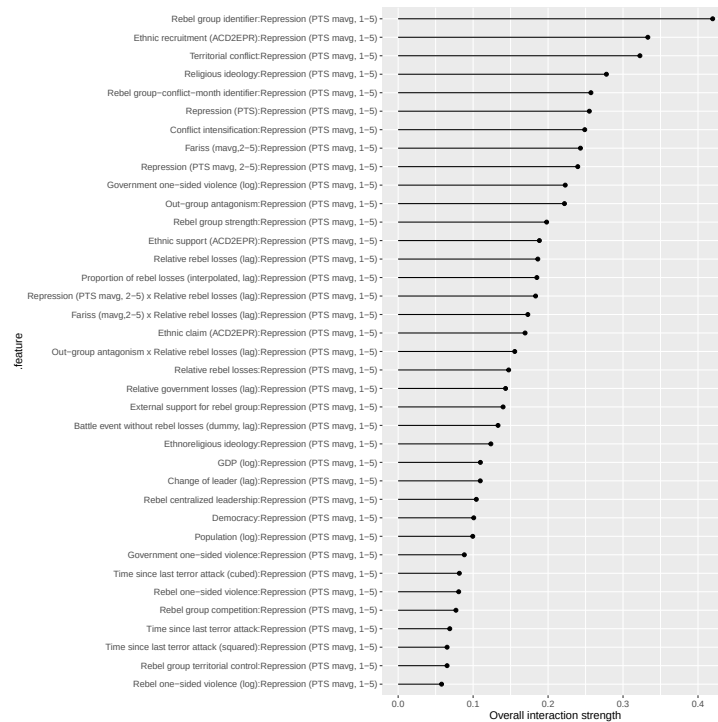


FIGURE C.30: Variable interaction strengths for monthly soft terrorist incidence (permutation): Repression (PTS, five year moving average).

Figure C.30 shows interaction strengths between repression (PTS, five year moving average) and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: repression (PTS, five year moving average) and ethnic recruitment, territorial conflict, religious ideology, and conflict intensification, respectively.

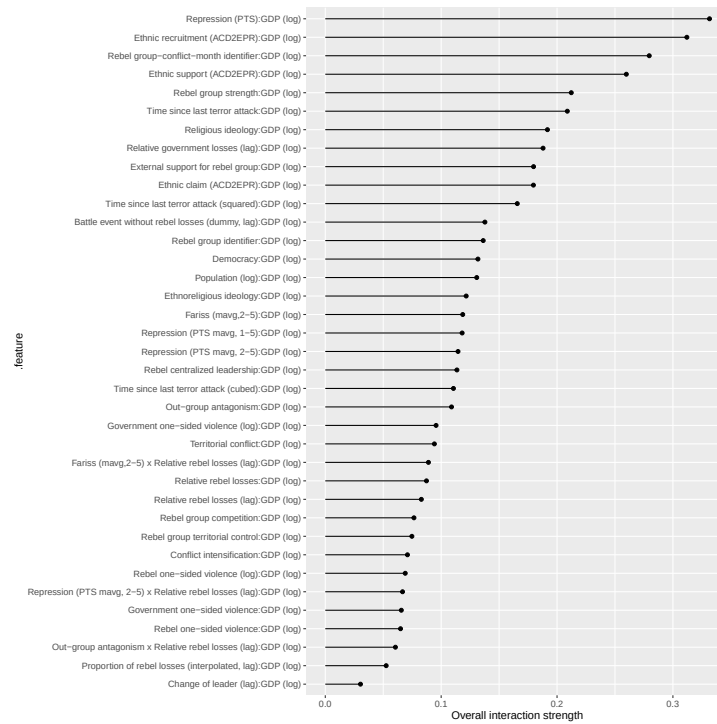


FIGURE C.31: Variable interaction strengths for monthly soft terrorist incidence (permutation): GDP per capita.

Figure C.31 shows interaction strengths between GDP per capita and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: GDP per capita and repression (PTS), ethnic recruitment, ethnic support, and rebel group strength, respectively.

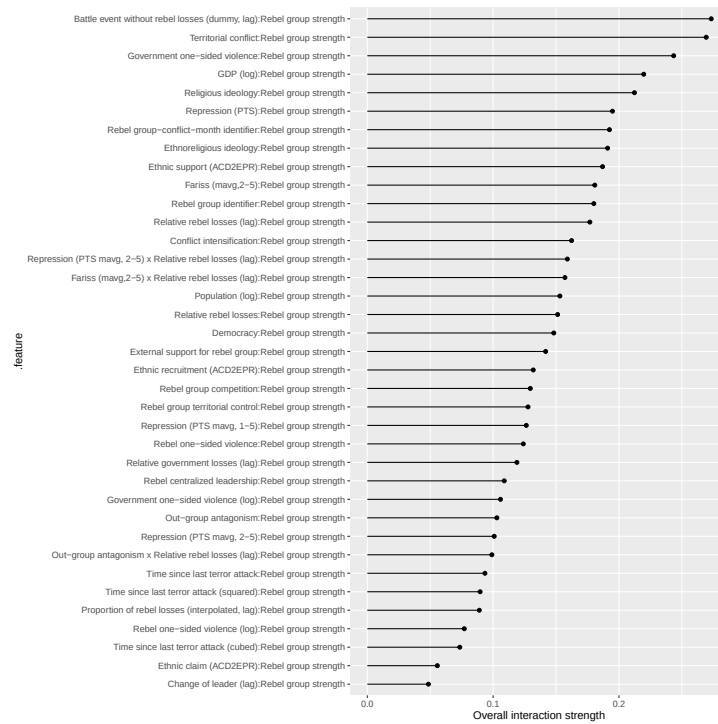


FIGURE C.32: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel group strength.

Figure C.32 shows interaction strengths between rebel group strength and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: rebel group strength and battle event without rebel losses, territorial control, government one-sided violence, and GDP per capita, respectively.

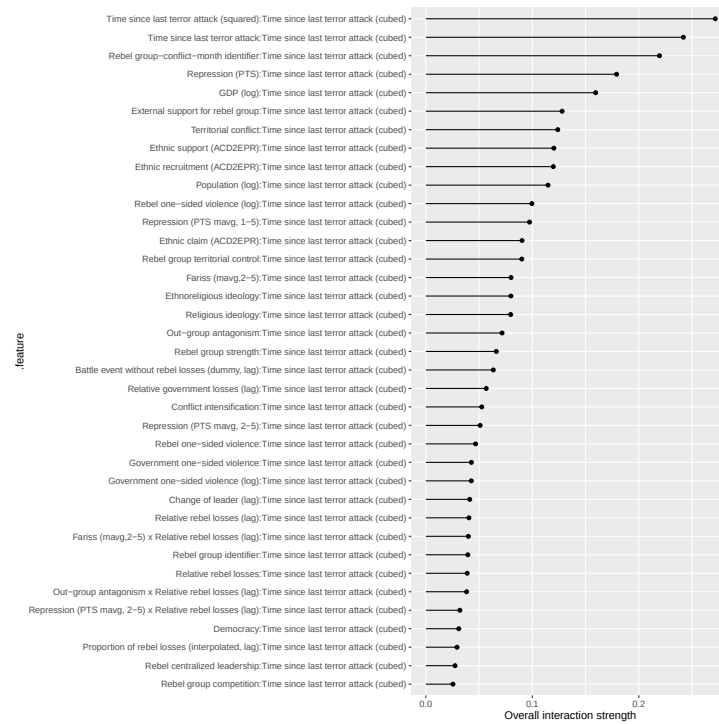


FIGURE C.33: Variable interaction strengths for monthly soft terrorist incidence (permutation): Time since last attack (cubed).

Figure C.33 shows interaction strengths between time since the last attack (cubed) and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects since values for meaningful variables are too low to justify further investigation.

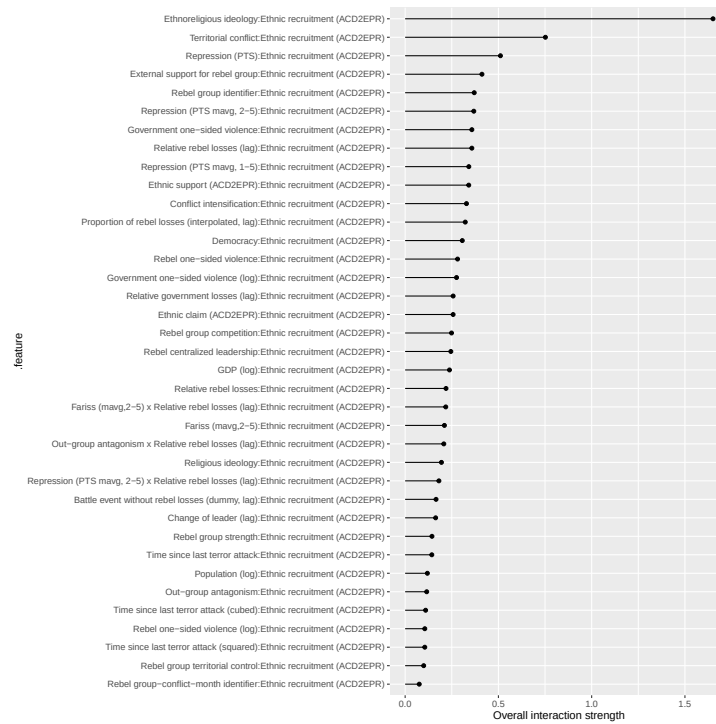


FIGURE C.34: Variable interaction strengths for monthly soft terrorist incidence (permutation): Ethnic recruitment.

Figure C.34 shows interaction strengths between ethnic recruitment and all other features in the data. Based on Friedman’s H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: ethnic recruitment and ethnoreligious ideology, territorial conflict, repression (PTS), and external support for a rebel group, respectively.

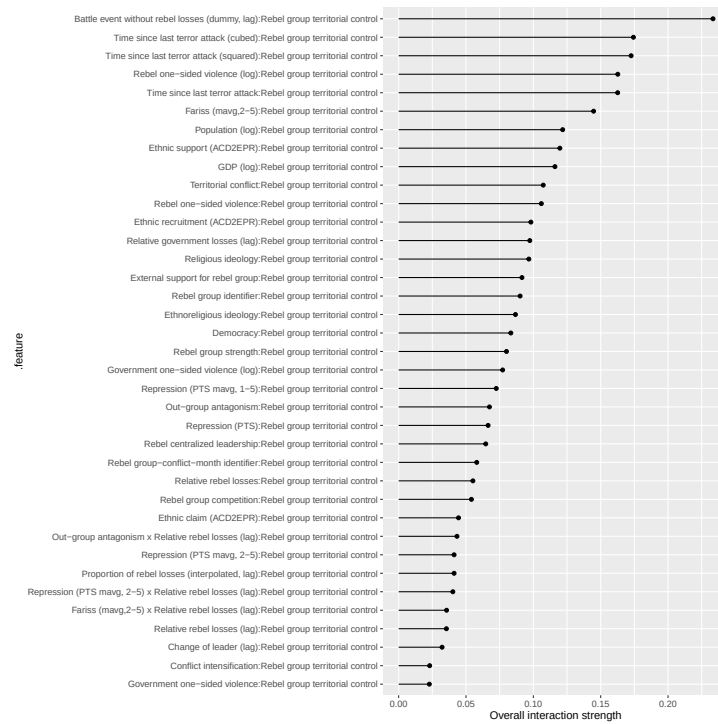


FIGURE C.35: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel group territorial control.

Figure C.35 shows interaction strengths between rebel group territorial control and all other features in the data. Based on Friedman's H-statistics, I do not look into interaction effects since values for relevant variables are too low to justify further investigation.

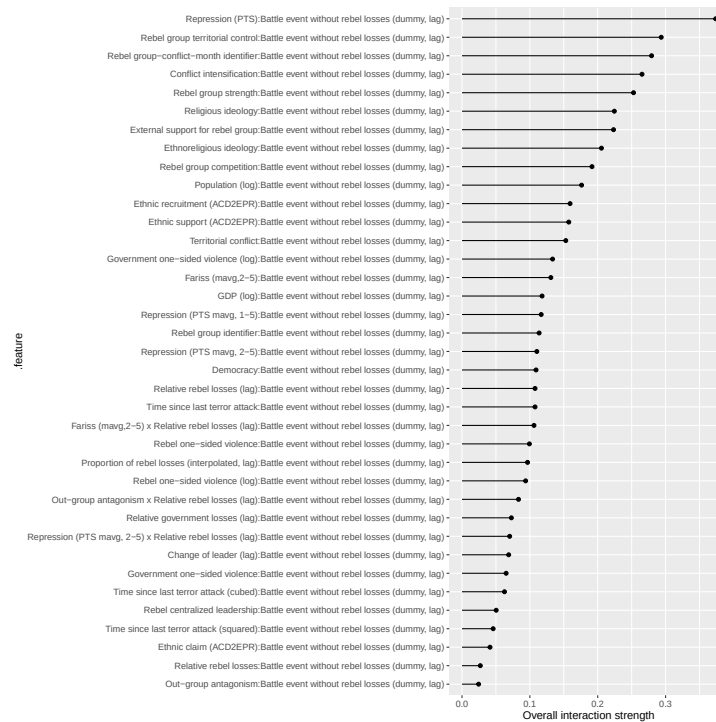


FIGURE C.36: Variable interaction strengths for monthly soft terrorist incidence (permutation): Battle event without rebel losses.

Figure C.36 shows interaction strengths between battle event without rebel losses and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: rebel event without rebel losses and repression (PTS), rebel group territorial control, conflict intensification, and rebel group strength, respectively.

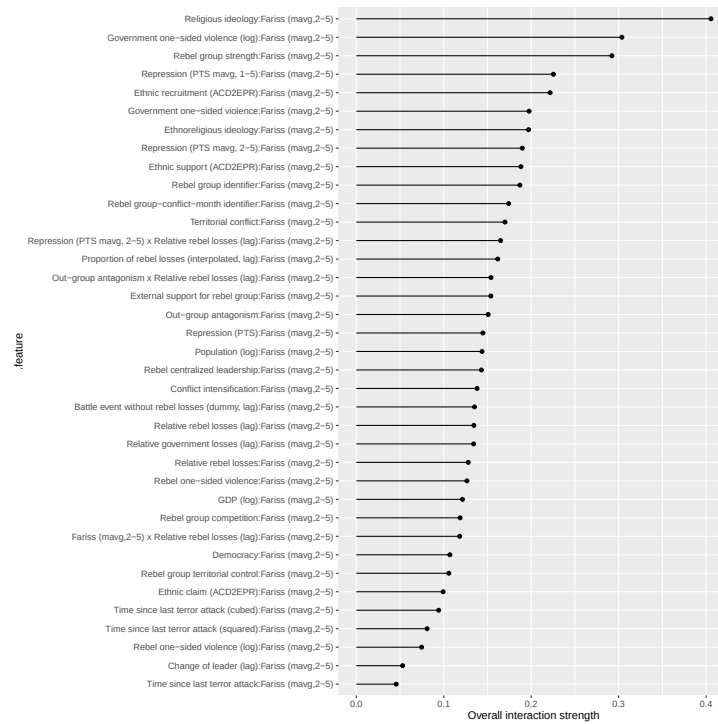


FIGURE C.37: Variable interaction strengths for monthly soft terrorist incidence (permutation): Repression (Fariss).

Figure C.37 shows interaction strengths between repression (Fariss) and all other features in the data. Based on Friedman's H-statistics, I look into interaction effects for the first four (meaningful) pairs of variables: repression (Fariss) and religious ideology, government one-sided violence (log), rebel group strength, and ethnic recruitment, respectively.

Interactions (accumulated local effects plots)

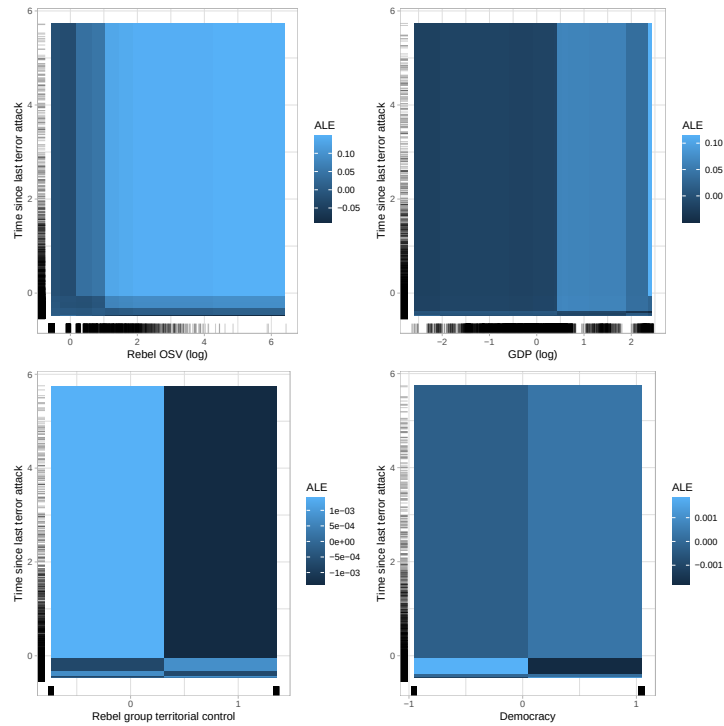


FIGURE C.38: Variable interaction strengths for monthly soft terrorist incidence (permutation): Time since last attack.

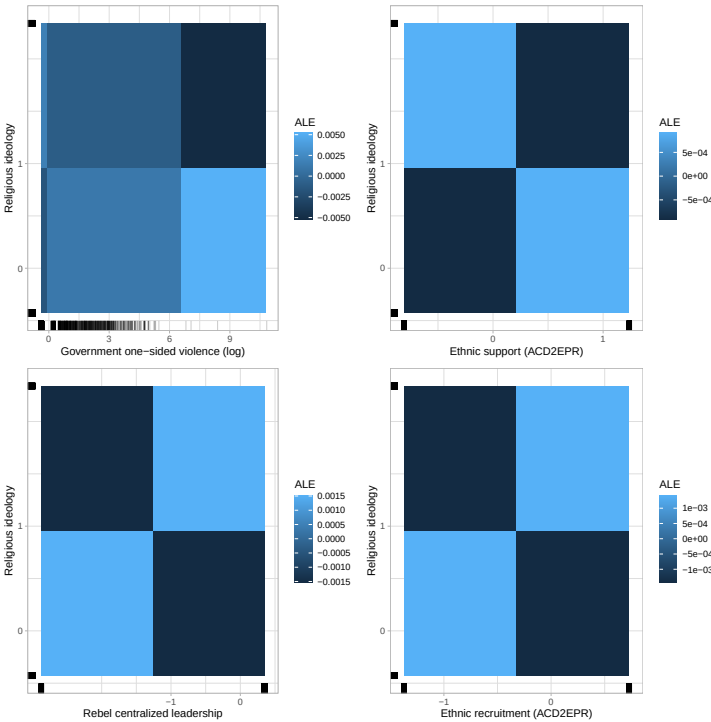


FIGURE C.39: Variable interaction strengths for monthly soft terrorist incidence (permutation): Religious ideology.

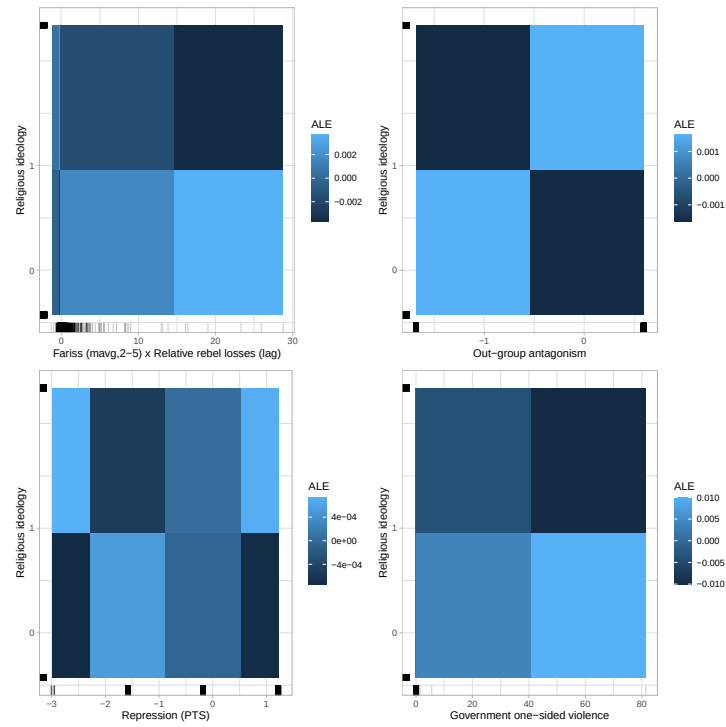


FIGURE C.40: Variable interaction strengths for monthly soft terrorist incidence (permutation): Religious ideology.

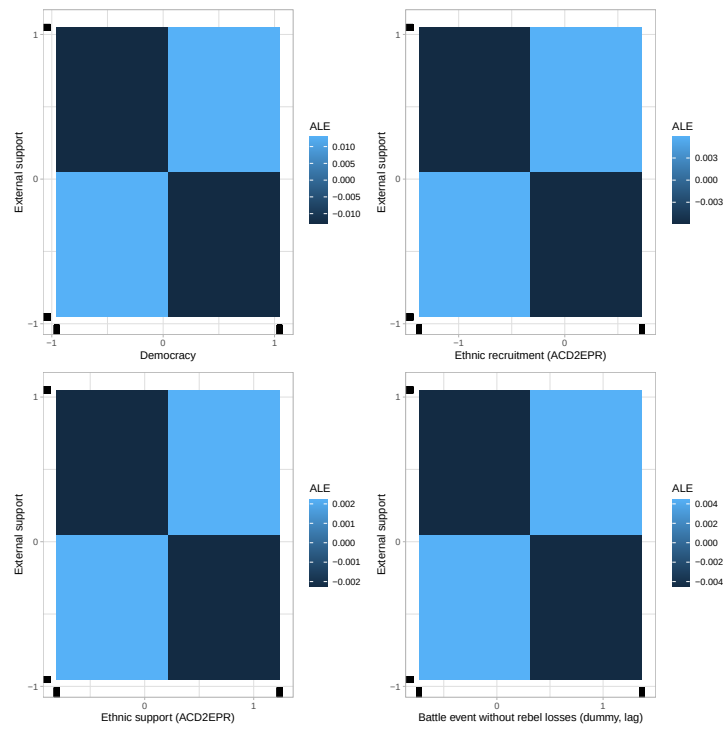


FIGURE C.41: Variable interaction strengths for monthly soft terrorist incidence (permutation): External support for rebel group.

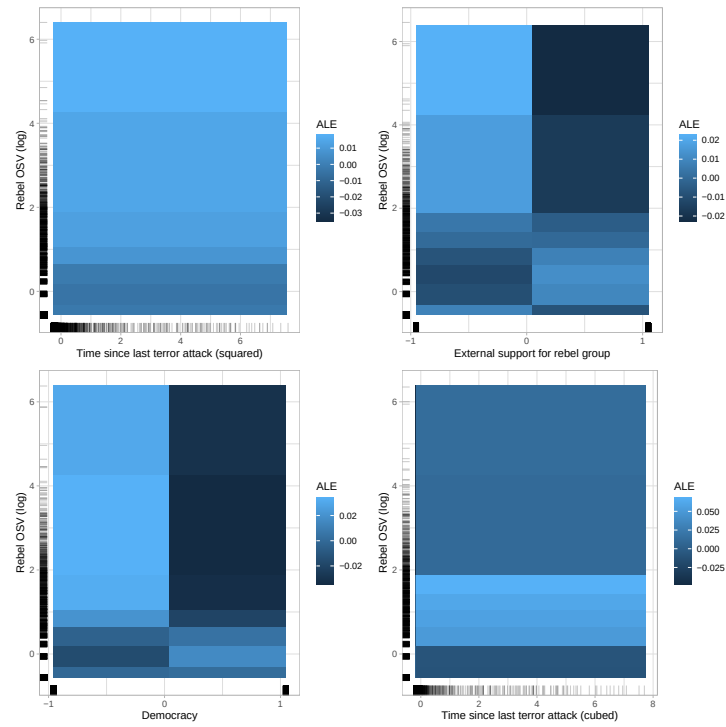


FIGURE C.42: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel one-sided violence (log).

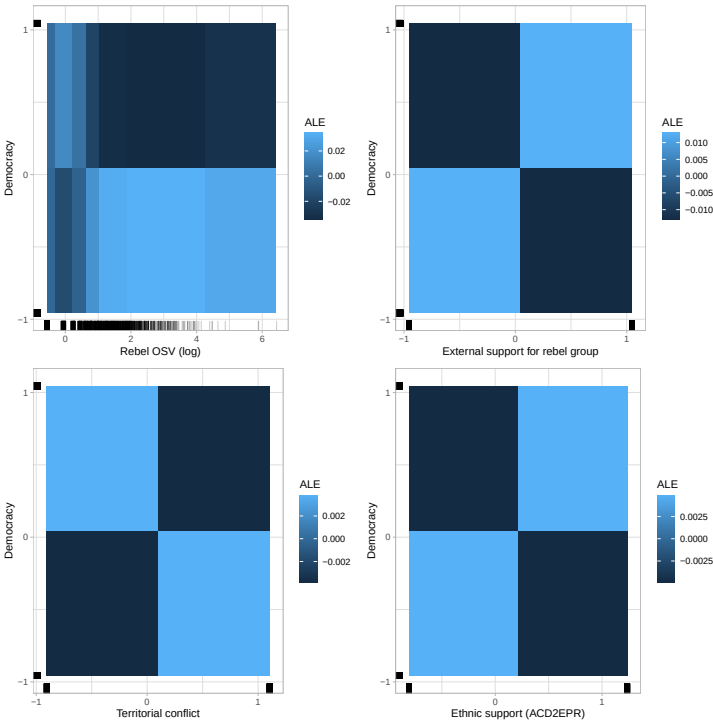


FIGURE C.43: Variable interaction strengths for monthly soft terrorist incidence (permutation): Democracy.

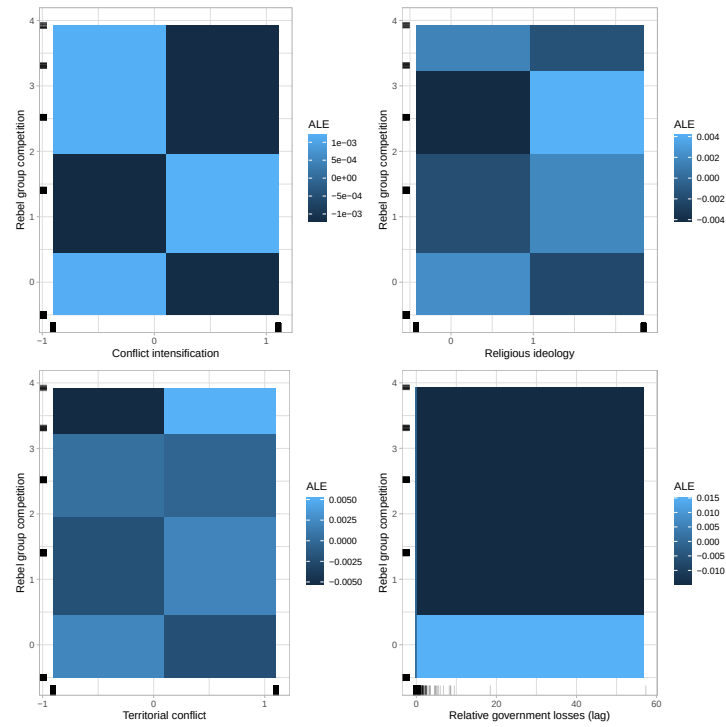


FIGURE C.44: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel group competition.

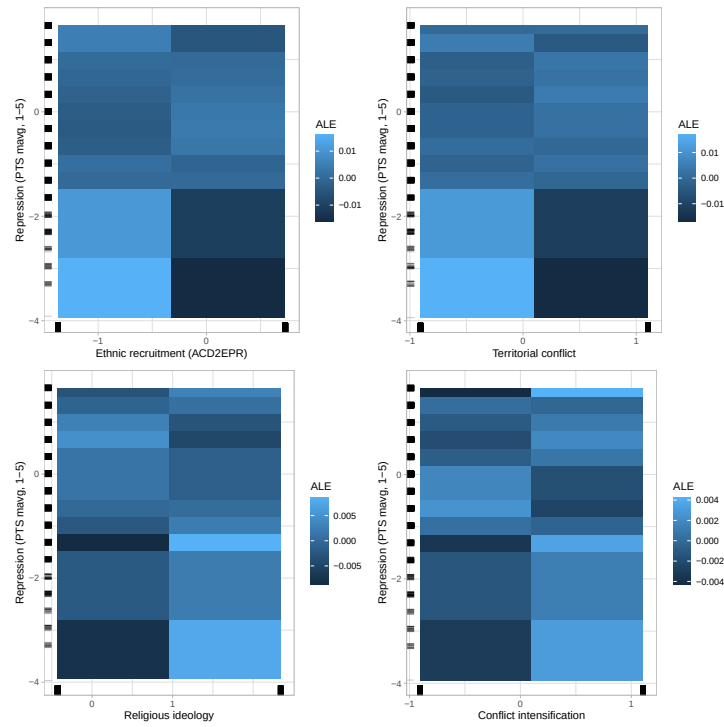


FIGURE C.45: Variable interaction strengths for monthly soft terrorist incidence (permutation): Repression (PTS, five year moving average).

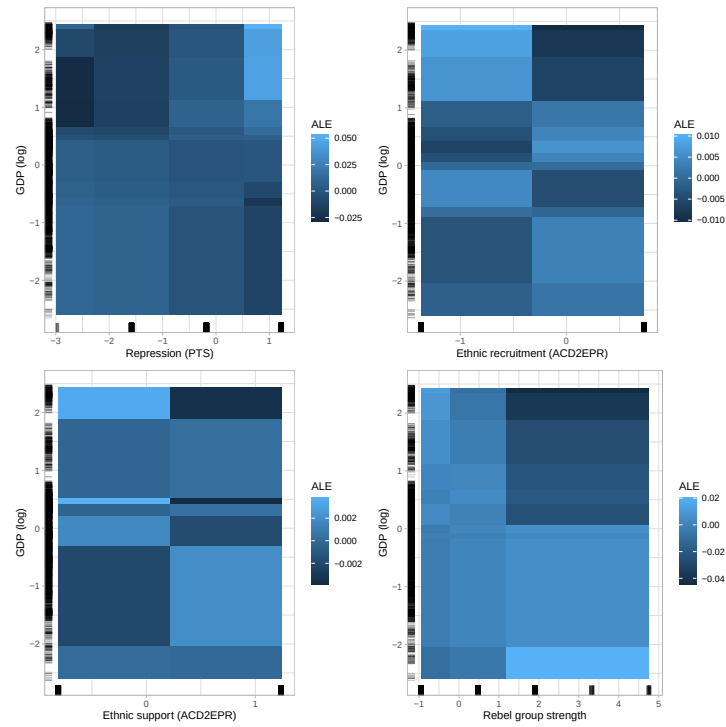


FIGURE C.46: Variable interaction strengths for monthly soft terrorist incidence (permutation): GDP per capita.

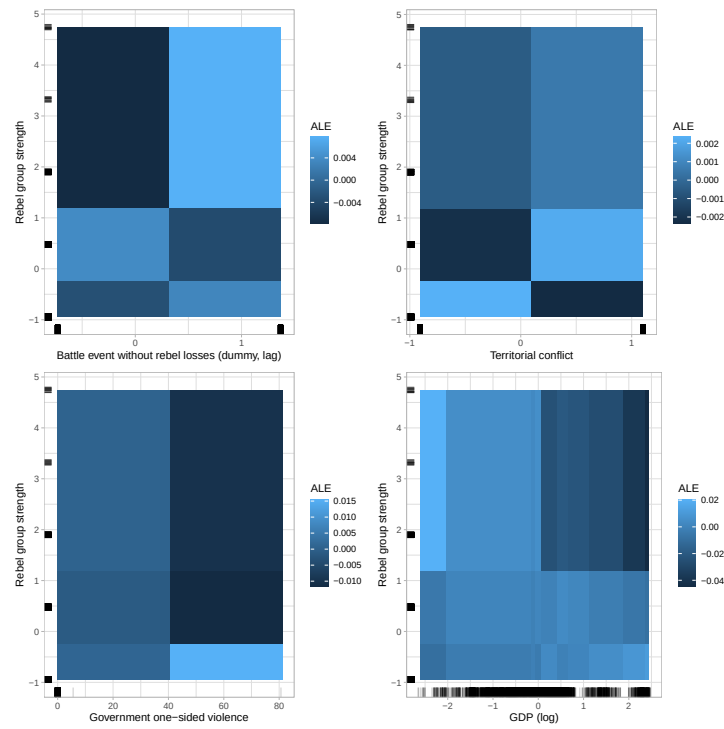


FIGURE C.47: Variable interaction strengths for monthly soft terrorist incidence (permutation): Rebel group strength.

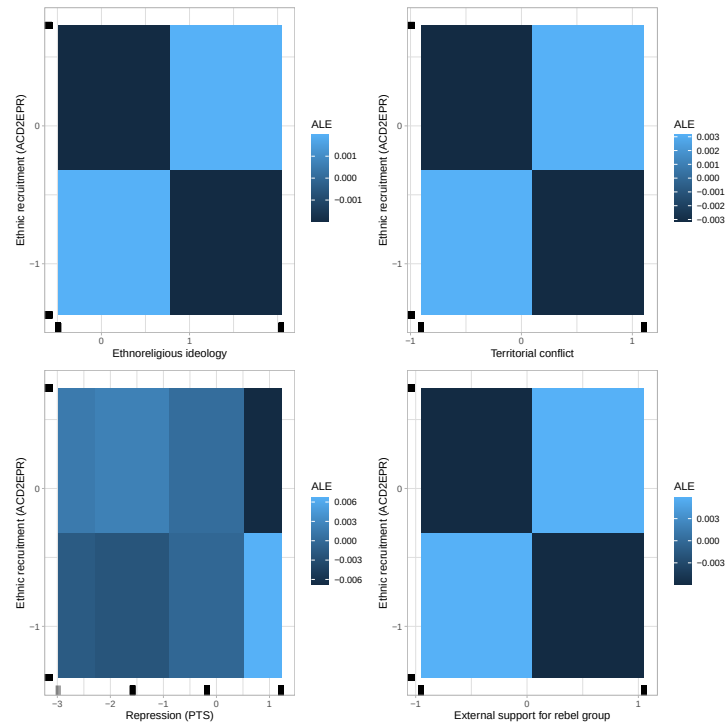


FIGURE C.48: Variable interaction strengths for monthly soft terrorist incidence (permutation): Ethnic recruitment.

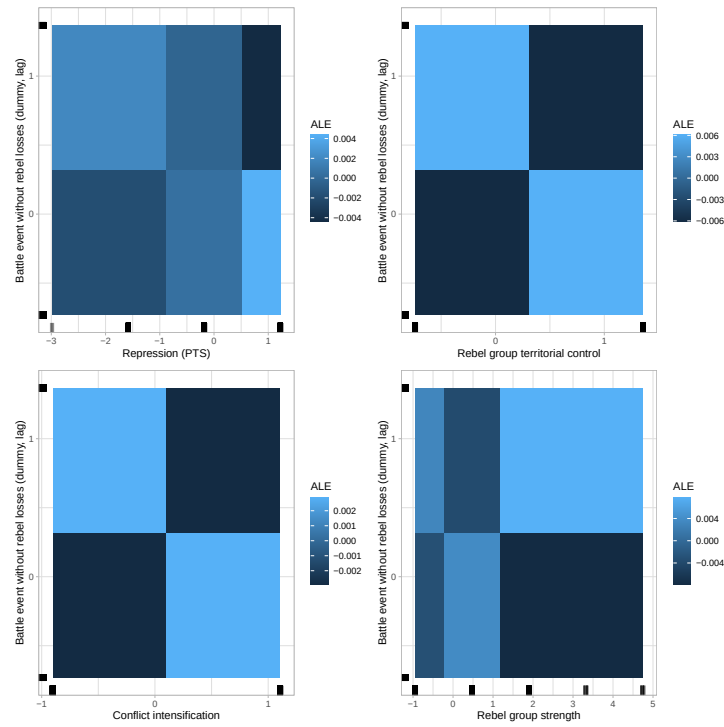


FIGURE C.49: Variable interaction strengths for monthly soft terrorist incidence (permutation): Battle event without rebel losses.

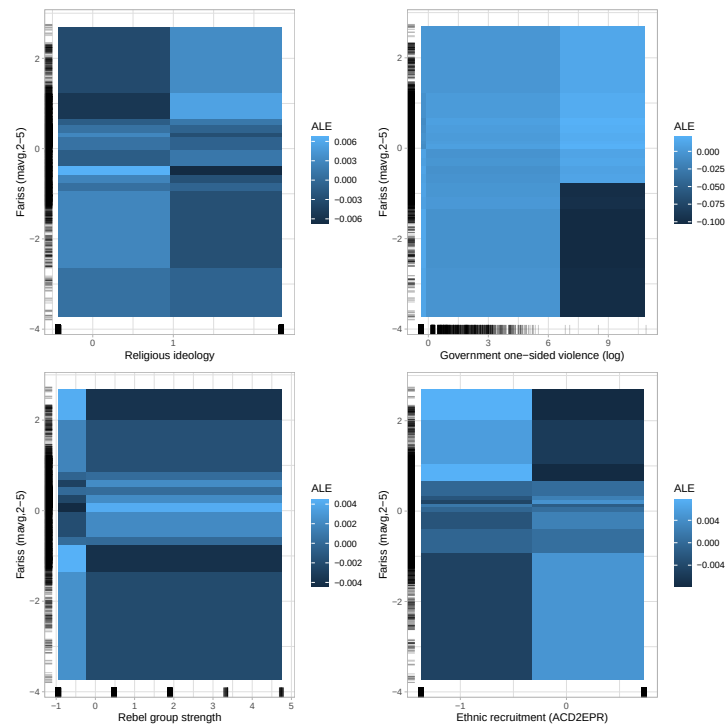


FIGURE C.50: Variable interaction strengths for monthly soft terrorist incidence (permutation): Repression (Fariss).

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