Dangerous Territory

A subnational study on how territorial control affects violence against aid workers in Africa.

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Master's Thesis Peace and Conflict Studies
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Spring 2017

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2017

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http://www.duo.uio.no

Print: Reprosentralen, University of Oslo

Word Count: 28,003

Abstract

Violence against aid workers has become a major concern for most humanitarian agencies. Adding to the destruction and chaos of conflict, deliberate attacks on humanitarian staff and facilities cause maximum damage to the health of populations. As long as they are being targeted, aid agencies cannot operate effectively and help the most vulnerable. This also poses a severe problem to the international community because deliberate attacks undermine the fundamental principles of humanitarian action. Irregular warfare, meaning governments fighting armed groups mostly in their own territory, has become the norm. These modern wars pose a challenge to the enforcement of international law and humanitarian principles.

This study shows that micro-dynamics leading to attacks against aid workers are closely related to territorial control of armed groups. Government and rebel groups greatly benefit from the services provided by humanitarian agencies. Most armed groups are highly dependent on support from the civilian population. The delivery of crucial services to civilians makes aid agencies important actors when securing the support of civilians for whichever actor controls a territory. Renouncing them from aid deliveries may undermine popular support. This thesis argues that violence against aid workers can be a strategy to undermine the enemy's civilian base of support and is thus less likely in territory where an armed group has full control. In contested territory, however, in which no armed group has full control and compete over popular support, violence against aid workers is more likely.

In order to study micro-dynamics in conflicts, a quantitative study on the subnational level in Africa is undertaken. The subnational level of the study is based on 0.5 longitude/latitude gid cells that rasterize the entire African continent. To ensure better comparability, the cells are pre-processed with coarsened exact matching. The results show that violence against aid workers is most likely in contested territory, as opposed to government- or rebel-held territory. The robustness prevails over a series of model specifications and robustness tests with alternative models. This analysis may help aid agencies to better plan their operations in conflict-affected zones[1].

[1]The datasets and R-Scripts for this thesis can be downloaded from the following Dropbox folder: https://www.dropbox.com/sh/899kr4bofq08l8w/AAAIh0XJzwbVm3M8NvRuirRqa?dl=0

Acknowledgements

First of all, I want to thank my supervisors Gudrun Østby and Håvard Mokleiv Nygård from the Peace Research Institute Oslo (PRIO). The meetings with you have always challenged me and motivated me to work beyond your or my expectations. You have pushed me above what I myself did not believe was possible.

I also want to thank Karim Baghat from PRIO. Although it was not your responsibility, you took the time to help me with all the issues I had with my data, and always tried your best to explain statistical modelling with gid cells to me.

Next, a vital person for the text in this thesis was Indigo Trigg-Hauger. You managed to check my writing errors in an incredibly short time, and have given me important input for the style in this thesis.

Many thanks go to my classmates from the PECOS family. It was an honor to study for two years with all of you in this program. Without you, this thesis writing process would have been a very lonely time. We discussed our ideas together, we provided input to each other, we laughed and suffered together, and we motivated each other.

A more general thank you goes to the many people with whom I discussed my ideas or problems in one way or another. Thank you for listening to me, thank you for motivating me, and thank you for being good friends.

Finis coronat opus.

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Chapter 1

Introduction

South Kordofan State is an oil-rich region in the south of Sudan. The area is highly contested with varying degrees of control by the Sudan People's Liberation Army-North (SPLA-N). Sudanese military forces have bombed 26 health facilities in the state since 2011. More than one million people live in the area, and are now dependent on the two remaining hospitals operating there (Amnesty International 2015).

Why would these government forces be interested in making the lives of civilians living in this conflict-affected region even more miserable by depriving them of health services? Are attacks against humanitarian facilities a strategy of armed actors who lost control over a territory?

The central question guiding this thesis is what micro-dynamics in conflicts determine violence against aid workers. More specifically, by looking at differences between contested and non-contested territory I want to assess whether territorial control impacts attacks against aid workers. In order to answer this question, I evaluate violence against aid workers using a theoretical framework which highlights civilian support of conflict actors.

Violence against civilians is a common consequence of armed conflict. Some of this violence is unintended and marks unfortunate cross-fire events. Some is produced by negative externalities of conflict, like famine, malnutrition, and disease. But much of the violence directed at civilians during conflicts is intended. This is something of a paradox, because in irregular warfare, rebels often merge with the civilian population, and as a consequence both government and rebel groups are somewhat dependent on the civilian population. Governments need civilians to find the rebels hiding among them, and rebels need civilians to not defect or give information to the enemy (Kalyvas 2006).

Humanitarian organizations provide material and technical assistance to people in need. The population generally benefits a great deal from this support. If an insurgent group takes over a territory, the government might not be willing to continue government-financed services, while insurgents might not even want government-run services in their territory (Mampilly 2009). Humanitarian organizations are supposed to deliver impartial aid to the population. Services local institutions are unable to offer, such as health care or development support, are being provided for free to the population (Uvin 1999). Cutting the population off from those services may undermine popular support. Civilians will blame whoever is in charge over the territory (Kalyvas 2006). Consequently, violence against aid workers may be counterintuitive. Then why are conflict parties targeting aid workers intentionally?

I argue that violence against aid workers is a strategy to undermine the enemy's civilian base. In territories in which an armed group has full control, violence against aid workers is less likely. In contested territory, in which one or more armed group compete over control, violence against aid workers is more likely because it weakens popular support for the enemy.

1.1 Motivation and relevance

Violence against aid workers has become an increasing challenge for humanitarian organizations in conflict regions. In 2016, Humanitarian Outcomes (2016), a specialist research group on humanitarian issues, counted 199 major attacks against aid workers, of whom 73 were killed, 63 wounded, and 63 kidnapped. The same year, cases of gang rape in South Sudan and deliberate attacks on medical centers and convoys in Syria drew significant media attention (Graham-Harrison 2016; The Guardian 2016).

Figure 1.1 shows the time trends in violence against aid workers, and whether they were internationals or nationals. There is a stark increase in attacks against national staff, with a peak in 2014. Attacks against international staff seem to have only marginally increased over the years.

2017 has already proven to be a deadly year for humanitarian workers. In January 2017 a refugee camp was bombed by the Nigerian army, an alleged mistake that led to the death of six Red Cross aid workers (BCC 2017). In February, six Red Cross staff were killed in Afghanistan by Taliban fighters. The attack led to a complete withdrawal of all Red Cross activities within Afghanistan (Al Jazeera 2017). One month later in March, six aid workers affiliated with UNICEF were killed in contested territory in South Sudan by armed militia groups (McVeigh 2017).

In recent years, Afghanistan has been the most dangerous country for aid workers, with a total of 167 incidents in 2013 alone. In Africa, South Sudan has been most

Figure 1.1: Global trend of violence against aid workers, by origin of staff, 1997 - 2015

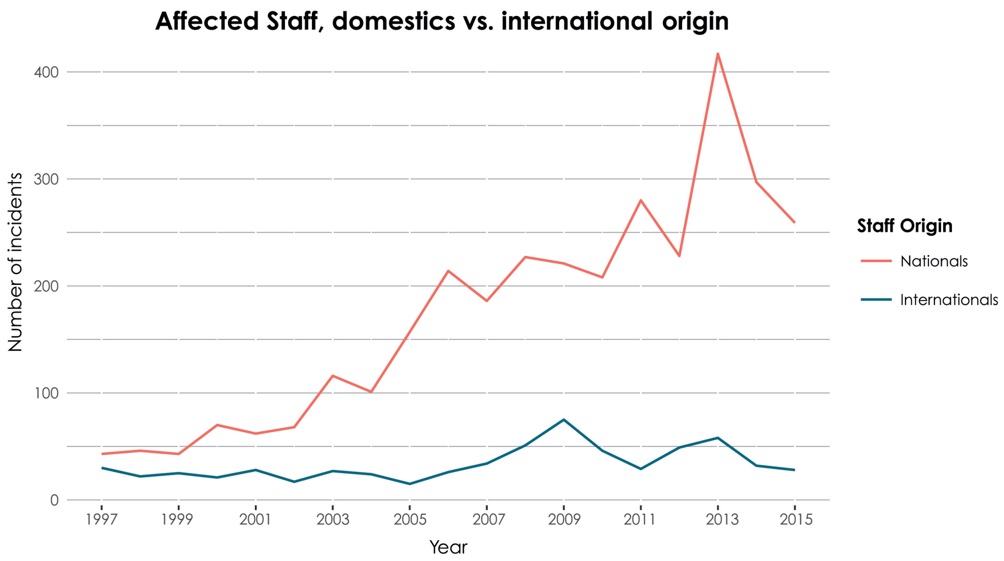


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

affected by violence against aid workers, with 230 cases between its secession in 2011 and 2016. Iran, Nigeria, Pakistan, and Yemen have the highest ratio of attacks against female aid workers. Figure 1.2 shows the different trends between killed, kidnapped, and wounded staff. For all three types the trend is steadily increasing.

The rules on paper are explicit: Attacks against humanitarians are forbidden (International Committee of the Red Cross (ICRC) 1949). Wars have rules, and protecting those who seek to provide humanitarian assistance is vital. Regrettably, there has been a decline in respect for international law and humanitarian principles.

The legal system protecting humanitarians is rooted in the protection of civilians in armed conflicts as described in the Hague and Geneva conventions[1]. These conventions do not mention humanitarian workers specifically, as they only address the legal protection of civilians. Only with the 1998 Rome statute[2] did intentional attacks against humanitarian personnel became institutionalized as war crimes.

[1] Protocol Additional to the Geneva Conventions of 12 August 1949, and relating to the Protection of Victims of International Armed Conflicts (Protocol I), (8 June 1977), 1125 UNTS 3, Article 48, and Protocol Additional to the Geneva Conventions of 12 August 1949, and relating to the Protection of Victims of Non-International Armed Conflicts (Protocol II),(8 June 1977), 1125 UNTS 609, Article 13

[2] Rome Statute of the International Criminal Court (last amended 2010), 17 July 1998, Article 8(2)(b)(iii) and(e)(iii)

Figure 1.2: Global trend of violence against aid workers by type of attack, 1997 - 2015

Figure made by author. Datasource: (Humanitarian Outcomes 2016)

Enforcing the legal framework that protects aid workers continues to be major challenge. Ensuring the safety of humanitarians is the responsibility of their respective governments[3]. But some governments are unwilling or unable to provide this protection. Sometimes government troops intentionally attack aid facilities because they suspect rebels may be hiding there. In other cases, governments do not have sufficient information about who is a civilian and who is a combatant (Fast 2014; Kalyvas 2006). When governments are on the side of the attacker they will always lack political will to hold themselves accountable.

Knowing whether attacks against aid workers are used as a large-scale war tactic or occur as unfortunate cross-fire events has severe legal implications. The latter, though still a crime, could be addressed by aid agencies themselves through improving their security management. The former, targeting humanitarians strategically, is a deliberate attack and thus a war crime. There is little aid agencies can do to avoid or protect their staff from such atrocities, and therefore it is the responsibility of the international community to bring perpetrators to justice. Nevertheless, understanding the conflict dynamics that lead to strategic attacks against aid workers can help aid agencies in

[3]Security Council resolution 1894 (2009) *on the protection of civilians in armed conflict.* S/RES/1894 (2009).

their operational decision-making process, and limit the risks to which they expose their staff.

The protection of aid workers is a pressing issue, not only on the humanitarian scene but also in the international political arena. In May 2016, the first ever World Humanitarian Summit was held in Turkey. A key goal was to fundamentally reform the aid industry to react more effectively to today's many humanitarian crises. In the same month, the UN Security Council adopted a resolution condemning attacks against health workers and facilities[4]. Only a few months earlier, Action Against Hunger started a campaign calling for a Special Rapporteur mandated by the United Nations to safeguard aid workers (*Ensuring the Protection Aid Workers: Why a Special Mandate Holder Is Necessary* 2015).

While many aid agencies are worried about the increasing safety issue for their staff, the topic remains rather unheard of among researchers. So far, mainly case studies and only one major (Hoelscher et al. 2015) quantitative cross-country study have been published on the topic. Case studies use anecdotal evidence from survivors and show what could have motivated the specific incident, leading to limited contextual conclusions. Hoelscher et al.'s study revealed it is indeed conflict-affected countries that pose the biggest risk for aid agencies and their staff. Yet we still do not know what dynamics in conflicts actually motivate attacks against humanitarians. The unit of analysis of previous studies on the nation state level does not allow for a detailed analysis of micro-dynamics in conflicts within countries.

1.2 Research question and approach

With this study, I want to further disentangle the conflict dynamics leading to attacks against aid workers. Because aid workers are not combatants, they are counted as civilian victims of conflicts. Thus, the role of civilians in conflicts is vital to understanding attacks against aid workers. Particularly in irregular warfare, conflict actors are highly dependent on the civilian population in order to maintain legitimacy over territorial control (Kalyvas 2006; Weinstein 2006). The delivery of crucial services to civilians makes aid agencies important actors when securing the support of civilians for whichever actor controls a territory. Aid workers become a tool to manipulate popular support. The very principle of neutrality and impartiality requires humanitarians to not take sides in hostilities, and to distribute aid to those most in need. In Liberia, for example, rebels

[4]Security Council resolution 2286 (2016) *on protection of the wounded and sick, medical personnel and humanitarian personnel in armed conflict.* S/RES/2286 (2016).

looted resources provided by aid organizations during the Liberian, with an estimated worth of $20 million USD (Anderson 1999).

Linking territorial control of armed actors to violence against aid workers is a new approach that has not been analyzed so far. The question guiding this thesis is *to what extent does territorial control in conflicts affect violence against aid workers?*

Modern conflicts are not usually fought between nation states, but rather between different conflict actors within a country or even across its borders. Frontlines and battle zones are spread across regions or countries, but hardly affect the country as a whole with the same intensity. Analyzing conflict dynamics with aggregated national level data makes it questionable whether incidents are really motivated by armed groups in active conflict zones. Territorial control within one country can be split between several armed groups. The problem is rooted in the ecological fallacy dilemma: a correlation on the nation-state level does not necessarily mean that the same result would yield in a more disaggregated study on the subnational level.

This is why I chose to approach the topic from a new methodological angle by moving beyond the nation-state level. Recent advancements in collecting conflict data on the incident level with geographic location information allows me to work with fine-grained subnational data to analyze the relationship between territorial control and attacks against aid workers in Africa. Working with subnational data, it is possible to allocate each violent incident against aid workers to a specific geographical location. This allows for a detailed quantitative analysis of the relationship between territorial control and attacks against aid workers.

My statistical approach is a negative binominal model due to the highly skewed count outcome. By applying advanced statistical techniques with pre-process matching, I ensure the results of my main analysis are robust.

1.3 Findings

As a preliminary analysis, I test the relationship between active conflict zones and attacks against aid workers. The findings support the theory that aid workers suffer a greater risk of being attacked in conflict zones.

In my main analysis, I find strong evidence that contested territory is the most dangerous for aid workers. The risk of being killed in contested territory is immensely higher as opposed to rebel- or government-held territory. This result holds throughout various model specifications and alternative models. Neither rebel- nor government-held territory show significant effects on violence against aid workers throughout the study. This means that non-contested territory is neither more dangerous nor more safe for aid workers than contested territory.

The results reveal that violence against civilians is a strong indicator for violence against aid workers. In territories in which conflict actors target civilians, the risk for aid workers being killed is much higher than in territory with no attacks against civilians. This shows how territorial control and violence against civilians are linked, and in turn affect violence against aid workers.

A further determinant for violence against aid workers is urban land. Aid workers seem to be more in danger in urban areas. However, this effect does not hold over all models tested.

1.4 Structure of the thesis

This thesis consists of seven Chapters. In the second Chapter, I present an overview of the relevant literature on violence against aid workers and civilians. I critically evaluate the weaknesses of previous studies as well as the research gap I aim to fill. Past research has showed that attacks against humanitarians seem to be more likely in conflict affected countries but the dynamics leading to these attacks are yet to be determined. For this, a more disaggregated study on the subnational level is needed.

The third Chapter presents the theory on which I base my analysis. I combine theories about territorial control in civil wars and violence against civilians in order to build my theoretical framework. The theory explains how violence against aid workers is a strategy armed groups use to undermine popular support of their enemy in contested territory.

Chapter four presents the data used in my quantitative analysis. First, I explain why I use disaggregated data on the subnational level and put my focus on Africa. After an overview of the combined datasets, I thoroughly explain all variables in the analysis. The independent variable, territorial control, went through a comprehensive recoding process which I show in detail. Additionally, the set of control variables is presented and an explanation is given for any potential relevant variables that are omitted in the study.

In the fifth Chapter, the research design and methods used are introduced. Because the dependent variable is a highly skewed count variable, a negative binomial model is applied. Threats to inferences and how they are dealt with are also explained. This includes multicollinearity, autocorrelation, and spatial dependence.

The sixth Chapter presents the analysis. First, a conflict model is introduced, testing the relationship between attacks against aid workers and active conflict zones. The second model which is also the main model tests the effect of territorial control on attacks against aid workers. A series of robustness tests with different model specifications are then excercised. Finally, pre-processing matching is applied in order to test the result for robustness in a more homogenous subsample. The results hold over all models and show strong evidence that operating in contested territory is most dangerous for aid workers.

The seventh Chapter sums up and draws conclusions about the results. I discuss the results from the analysis and what they mean for aid workers and humanitarian organizations on the ground. Furthermore, I discuss the strengths and weaknesses of the applied theory and methods in order to draw causal inferences. Lastly, the possibilities of future research is discussed.

Chapter 2

Literature review

Humanitarians have always been subject to violence as part of their job. Still, we know very little about patterns and trends, suggesting that further research is needed. In this Chapter, I assemble the existing literature on violence against aid workers. First, I give an overview of general findings on violence against aid workers. These findings show that violence against aid workers is indeed an increasing challenge for humanitarian organizations. Second, I introduce studies exploring the causes behind attacks against humanitarians. Third, I show how humanitarian aid and conflict dynamics play together. Last, I identify the gaps in research and show the gap I am trying to fill with this thesis.

2.1 Empirical findings on violence against aid workers

Violence against aid workers, even in the form of deliberate attacks, is not a new phenomenon. Fast (2014) presents evidence from attacks against aid workers that date back to the very beginning of the Red Cross movement. For example, in the war between Ethiopia and Italy in 1936, Italian forces deliberately attacked medical facilities, claiming they did not know about their existence, although the facilities were clearly marked with the Red Cross emblem. But recent research shows that intentional violence against aid workers is increasing (Stoddard et al. 2009, 2006).

In fact, Stoddard et al. (2009) show a majority of attacks are now intentional. This kind of violence is more dangerous for aid workers because it is usually lethal, and it also poses a severe problem to the international community because deliberate attacks undermine the fundamental principles of humanitarian action. Moreover, the authors say roadside attacks are the most common kind, meaning aid workers are often ambushed when they travel to field sites. However, their study only uses descriptive statistics. The authors process the data from the Aid Work Security Database (Humanitarian Outcomes 2016) and present the main trends without evaluating the effects.

Humanitarian aid commitments from member states of the Organisation for Economic Co-operation and Development (OECD) more than quadrupled since 2002, from \$4.589 million USD to \$21.885 million USD (OECD 2017). More than half of this humanitarian assistance was directed to conflict zones (Wood and Sullivan 2015). Hoelscher et al. (2015) show conflict does indeed expose humanitarians to violence. The more violent the conflict, the more dangerous it is for aid workers, and national staff often bear the greatest security risk burden. The higher number of domestic aid workers targeted could be a reflection of the fact that more national staff are deployed in the field.

Some agencies try to exclusively hire nationals in their field operations. In the last 20 years, there has been a major shift from internationally to locally hired staff, with up to 90 percent being local staff nowadays, although in emergency contexts and specialized agencies the proportion of international staff still tends to be higher (Fast 2014). Hoelscher et al. (2015) conducted one of the very few statistical analyzes on this topic. The authors found in general, aid workers experience more attacks in less-developed countries and in conflicts with peacekeeping forces present, whereas inequality seems to have no influence.

Other studies deal with the risk factors of regions and staff affiliation. Many emphasize the high absolute number of incidents in Africa. In her dissertation, Abbott (2006) collected her own data from media reports on fatal attacks against aid workers. She claims most fatalities occurred in Africa, and among staff from international governmental organizations (IGO). However, that might be because a higher proportion of aid workers operate in Africa. Abbott's main findings come from descriptive statistical data.

On the other hand, King (2002) presents a higher fatality rate among NGOs (59 percent) compared to UN staff (41 percent), and among locals (74 percent) compared to international staff (26 percent). King also collected his own data through reports on ReliefWeb, an online portal managed by the United Nations. Again, the analysis is descriptive, presenting the numbers only. Barnett (2004) suggests that a high number of deaths in a country may merely reflect the higher absolute number of aid workers deployed. Then again, a small number of incidents does not mean a country is not dangerous. Many humanitarian agencies remove their staff from zones deemed too dangerous. Abbott (2006) further notes that attacks are mostly executed by insurgent groups. Yet other studies found no evidence that rebel-governed territory, one-sided violence, or state fragility has a significant impact on attacks against aid workers (Hoelscher et al. 2015).

Most of these authors argue using findings from descriptive statistics. Only Hoelscher et al. (2015) conducted a thorough quantitative effects-of-causes analysis on the nation-state level. The relationship between incident and local conflict dynamics, however, cannot be examined on the aggregated country level.

In short, different studies have come to various, sometimes contradictory, conclusions. The identification of victims and their perpetrators seems a particularly ambiguous issue with great discrepancies in the existing research. The question of whether rebels are more likely to attack aid workers compared to government troops seems less clear, as different studies contradict each other. What seems undisputed, however, is that most aid workers killed are national staff, and there seems to be an upward trend in attacks. Generally, violence against aid workers is mostly intentional and takes place in conflict situations.

2.2 Why humanitarians are being attacked

The field of research around violence against aid workers remains troublingly underdeveloped. The contradictory empirical findings make it difficult for researchers to determine the causes of this violence. The available data is unreliable and conceptual challenges persist. For example, some organizations differentiate *security incidents* as acts of violence from *safety incidents* (accidents and illness), while others treat them as the same thing (Fast 2010). This makes it more difficult to disentangle the causes leading to intentional attacks.

Relief workers may be targeted for numerous reasons. As explained earlier, most attacks take place in conflict settings. With the rising number of asymmetrical conflicts, the nature of warfare is changing. Traditional command chains are treated with disregard. Civilians, including humanitarian personnel, are used as human shields. Attacks against aid workers may in some instances be part of a common pattern of violence towards civilians. In other instances, aid workers may be specifically targeted for attacks, either because of individual motivations or exogenous conflict dynamics (Fast 2014; Kalyvas 2006; Milton et al. 2013; Rubenstein and Bittle 2010).

2.2.1 Self-generated risks

One of the most comprehensive studies on violence against aid workers was undertaken by Fast (2014) in various forms of qualitative work. She emphasizes the impact of individual behavior of humanitarians on their security status. There are several ways behavior could become a factor. First, the average age of aid workers is decreasing due to the rising number of humanitarian emergencies, resulting in less-experienced and less well-trained staff in the field. Second, disrespect towards cultural or social rules and norms may lead to security incidents. It is mostly expatriate aid workers who are violating cultural norms. These are what Fast calls *explanations in the shadows*: self-generated risks linked to culture clashes, clothing issues, inappropriate behavior in terms of alcohol, sex and gender roles, crimes committed by aid workers such as diamond smuggling, and exploitation of power. Fast stresses that too few authors take individual behavior of aid workers into account, and are solely looking for causes of violence on the side of the perpetrator. The problem with the data at hand, as I will show in the subsequent data Chapter, is that it is impossible to take these external cultural, social, and political structures into consideration, especially in a quantitative study.

Furthermore, religious affiliation of humanitarian organizations or individual aid workers can cause offense among the native population, even without engaging in missionary activities. Salafist groups, for example, might be offended by the mere presence of Christian or atheist organizations (Fast 2014). Yet according to Stoddard et al. (2009), faith-based agencies are not targeted more than other humanitarian agencies.

2.2.2 Financial incentives and criminal behavior

Irregular wars are characterized by a high degree of crime. Financial incentives also motivate attacks. Insurgencies are expensive, and even ideologically motivated fighters need a basic income (Collier and Hoeffler 1998).

Some authors claim it is criminal and not political violence that leads to most violent incidents against aid workers (Buchanan and Muggah 2005; Fast 2014). However, Hoelscher et al. (2015) and Wood and Sullivan (2015) find no evidence for this theory. Yet again, Fast (2014) clarifies that crimes do not always lead to violence. In so-called *pillaging strategies*, aid supplies are looted by underpaid soldiers as a source of income, or aid workers are asked to pay protection money. When humanitarian agencies ignore this looting, they directly contribute to prolonging the fighting, and help to legitimize the insurgents' cause (Torrenté 2004).

Kidnapping of international personnel and subsequent ransom demands are a lucrative source of income. Particularly new insurgent movements, which are vulnerable to incumbent forces, use this strategy to finance their activities. Kidnapping for ransom allows them to acquire large sums of cash with a low risk of being detected by government troops. In Africa, most ransom demands are managed through either Al Qaeda in the Islamic Maghreb and northern Africa, or Al Shabaab in Somalia. While local subgroups plan and organize the hostage taking, the negotiations are usually coordinated centrally through higher officers of any group (Loertscher and Milton 2015). These kidnap operations mainly target Western European citizens because their governments are often willing to pay high ransoms (Naylor 1997). International aid workers are high-profile targets, and are more vulnerable for ransom demands. The beheadings of international civilians, be it aid workers or not, draws prominent media attention. Therefore humanitarian operations make an easy target when trying to find suitable expatriates to kidnap for ransom (Stoddard et al. 2009, 2006). In the past three years, the number of aid workers kidnapped has more than tripled (Humanitarian Outcomes 2016).

Abductions of professional staff are sometimes motivated by a need for the skills doctors or other specialized workers possess. For example, the rebel movement during the civil war in Sierra Leone reigned with terror, and forced civilians to work in illegal diamond mines. Most civilians were unskilled workers, and the rebels lacked a competent workforce, such as doctors and teachers. In order to compensate, they abducted these specialized workers (Weissman 2004).

2.2.3 Politization

Chaotic situations during wartime may benefit groups that can take advantage of the prevailing instability. Humanitarian organizations, on the other hand, aim to enhance stability. These conflicting objectives can provoke violence. Aid agencies may also compete with rebels for the loyalty of the civilian population. Providing alternatives to what are usually government-supplied public goods, such as healthcare, is a strategy applied by opposition groups to gather popular support (Anderson 1999; Fast 2014; Lischer 2006; Narang and Stanton 2004; Uvin 1999).

When rebels perceive aid workers to be biased and a tool for the government, they are more likely to become hostile (Fast 2014; Stoddard et al. 2009; Terry 2011). In Afghanistan, for example, violence against western aid workers was connected with the general anti-West sentiments held by Taliban fighters (Rieff 2009). At times, governments try to expand control by winning the support of the local population with strategic aid projects. More recently, President Obama's special envoy to Afghanistan and Pakistan suggested that 90 percent of US intelligence about the Taliban originated from NGOs. After former Secretary of State Colin Powell's infamous statement about

NGOs being *force multipliers* for the US military in Iraq, the remaining organizations in Iraq have experienced increasing attacks, and threats from locals (Fast 2010).

This politicization of aid has severe implications regarding violence against aid workers. Stoddard et al. (2009, 2006) present statistical evidence showing most intentional attacks against aid workers have an underlying political motivation, with the aim of disrupting delivery of aid, or because of aid workers' organizational affiliation, nationality or agenda.

In recent years, there have been critiques about humanitarian aid becoming too politicized. Fast (2014) suggests the general public might sometimes be too tempted to look for exogenous explanations. In some cases, humanitarian agencies might make a security situation riskier for themselves, either because of their organizational ideas or their program. Christian organizations, for example, expose themselves to certain risks when operating in non-Christian territories.

Uvin (1999) recognizes that aid always creates benefits and losses for certain actors. Although humanitarian actors have always claimed to be politically neutral with the sole objective of saving lives on all sides, aid has always had political impacts. Aid agencies should thus recognize their political nature as a matter of fact, and evaluate the perception the population has of them, as much as they evaluate the impact of their projects. This means the amount of aid might be less important compared to who the recipients are. In some cases, less efficiency might lead to more stability.

The politicization of aid often comes together with increased militarization and securitization, providing additional explanations for violence against aid workers (Fast 2014). Humanitarian aid is often linked to international interventions. Problematically, this relies heavily on assuming the international community is indeed intervening in the most conflict-affected zones. Torrente (2004) emphasizes the most common international response in conflicts is deliberate neglect. Therefore, only providing aid to zones where military or security personnel from external forces are present neglects the people most in need.

Furthermore, the overrepresentation of domestic aid workers might not always be an advantage. Although they bear fewer self-generated risks in terms of cultural discrepancies, they can be exposed to more politicized risks. Domestic workers are cheaper labor and need less cultural training. In some conflict settings this can be problematic. Perpetrators might perceive national staff as part of the other conflict party for example, because of their ethnicity. In such cases it is not possible for domestic aid workers to present themselves as independent and impartial humanitarian actors (Fast 2014).

The subject of the aforementioned studies is mostly the victims. The authors point out various reasons as to why aid agencies and workers alike expose themselves to risks. However, these risks are very context-specific, and might only hold for the respective cases. The studies have little generalizability in terms of wider patterns. For example, why are religiously affiliated staff attacked in one place but not in another? Or, why do some insurgent groups perceive a specific aid organization as a government tool, while other insurgent groups have a different perception of the same organization?

2.3 Humanitarian aid in civil wars

Adding to the destruction and chaos of conflict, deliberate attacks on health care facilities and health workers cause maximum damage to the health of populations (The PLOS Medicine Editors 2014). For example, in September 2013, the Independent International Commission on the Syrian Arab Republic, mandated by the UN, stated that Syrian health workers and facilities have been deliberately and systematically targeted (Safeguarding Health in Conflict 2014).

In civil wars, rebels often merge with the civilian population in order to hide from their enemies (Kalyvas 2006). The blurred lines between civilians and combatants in irregular wars impose new security risks to aid workers. However, Fast (2014) calls for a more nuanced viewpoint, because this underestimates the intelligence of perpetrators. Another problem is the knowledge about and respect for International Humanitarian Law (IHL). Irregular wars are too often fought by child soldiers who are less knowledgeable about the rules of war (Lischer 2007).

Kalyvas (2006) explains that because of the blurred lines in civil wars, both conflict sides are somewhat dependent on civilians, either because they need to hide among them, or because they need to find their enemy among them. Any armed group with de-facto control over a territory needs to provide some security and services to the population (Arjona et al. 2015). Humanitarian organizations provide health care and other services for free to the benefit of the population and the group controlling that territory. Depriving the population from these services might have consequences for the group in control. Civilians are unlikely to continue supporting a group that cut them off these services if the territory is contested (Mampilly 2009; Uvin 1999).

Lischer's (2006) primary concern lies with the role of humanitarian agencies and other international actors, who often indirectly or directly provide aid to militants. For example, giving aid to the civilian base of rebel groups indirectly strengthens the rebel movement. Ignorance of the political context can aggravate violence. A number of studies show humanitarian aid can induce negative externalities, for example violence against civilians. In some instances, aid even prolongs the conflict (Anderson 1999; Duffield 1997; Narang and Stanton 2004). Fast (2014) calls this the *Sophie's choice* of humanitarian actors, meaning sometimes the delivery of aid ultimately fuels war and overall suffering. The problem is rooted in the reality that aid is often used as a strategy to reward or sanction the actions of certain actors involved in a conflict. This is a problematic misconception because aid does not create peace or prolong conflict (Torrenté 2004). Wood and Sullivan (2015) analyzed the effect of aid on rebel violence in a subnational study on a dozen African countries and found the presence of aid projects does indeed intensify rebel violence in that territory. However, their analysis suffers from reverse causality; aid projects might be located where the most severe conflicts are ongoing.

These studies show aid projects might indeed have strategic value for armed groups in conflict settings. Yet it seems unclear what is cause and what is effect: whether aid agencies are targeted because they help the wrong actors, or because they provide security and services to the civilians, and whether the provision of aid prolongs conflicts or helps create peace.

2.4 The gap to fill

This literature review shows that research on violence against aid workers is an emerging field with little conclusive findings behind the dynamics leading to this violence. Overall, there are three patterns of explanations for violence against aid workers.

One stream of literature emphasizes that violence against aid workers is mostly rooted in individual wrong-doing by aid workers themselves. These micro-level explanations consider cultural, criminal, gender, and economic factors in order to analyze who the targets are, and what they did to become a target. A second branch of literature explores individual motivations of perpetrators, linked to opportunistic crime activities. The third stream of literature explores deep causes that are exogenous, namely the politicization of aid and the changing nature of violence in irregular wars. The focus lies on macro-level or global trends linked to humanitarian action as a whole. All three describe the victims as carefully-chosen targets.

Most of these studies are qualitative, on the case study or comparative case study level (Anderson 1999; Duffield 1997; Fast 2010, 2014; Lischer 2006; Narang and Stanton 2004; Torrenté 2004). This means the findings might hold for the respective cases, but there is little we can infer for a wider population. It might be true that in Afghanistan the Taliban attacks aid workers because of a general prevailing anti-West sentiment, but in Kenya, for example, this claim might not hold. It is not clear what dynamics in conflicts lead to one outcome or the other.

Empirical studies have shown that violence against aid workers is indeed an increasing trend and countries in conflict are most affected. However, there is a clear lack of large-N analysis on the topic. Neither plentiful cross-sections nor longitudinal designs have been applied to the study of the factors impacting violence against aid workers. It is not clear what dynamics in conflicts cause violence against aid workers.

Some of the quantitative analyzes suffer from reverse causation (Wood and Sullivan 2015), while others are on an aggregated level, making claims about micro-dynamics in conflict settings unviable (Hoelscher et al. 2015). Civil wars are often fought on the regional level. Aggregated data on a cross-country level does not reveal whether aid workers are actually targeted in active conflict zones or in other parts of the country. Studying the topic on a subnational level could reveal a wealth of more in-depth information.

Although various researchers have tried to identify perpetrators and their motivations, or victims and their wrong-doings, there is no study linking conflict dynamics to security risks for humanitarians. This thesis analyzes how conflict dynamics in terms of territorial control between armed groups affect the safety of humanitarians on the subnational level. With disaggregated data on the subnational level, it is possible to pinpoint each incident to a specific location, highlight the subsequent conflict dynamic in this place. Although it will remain a challenge to identify perpetrators without thorough reports from affected organizations, a subnational study can identify what group was in control of the territory in which the respective incident took place. This gap is important to fill because it extends the grounds for inference about generalizable causal relationships. To do so, I work with data on the subnational level because it allows more detailed information about the location of incidents and armed group dynamics in these specific locations.

Analyzing the micro-dynamics of conflicts and their relationship to violence against aid workers is of strategic importance for aid agencies when planning their operations. Knowing in which situations humanitarians are most at risk will also allow us to further disentangle the motivations of perpetrators. And, ultimately, this will help humanitarian organizations to better secure their personnel.

Chapter 3

Theoretical argument

In this Chapter, I first define concepts often used in the theory that follows. Second, I develop a theoretical framework drawing on contributions from Kalyvas' (2006) theory on the use of violence against civilians in civil wars. Understanding violence against aid workers may also help us understand the logic of violence in general. Kalyvas suggests that violence against civilians becomes inevitable when combatants merge with the civilian population, creating an identification problem for the enemy. In irregular warfare, the strength of an armed group is highly dependent on the solidity and support of its civilian base. The aim of armed groups is to weaken their enemy, and this is best achieved by weakening their civilian base. Humanitarian organizations, on the other hand, contribute to the strengthening of this civilian base. For this reason, aid workers can become targets themselves.

In the third part I illustrate under what circumstances government troops might be likely to attack aid workers. In territories where they have little control, government troops might resort to attacking civilians, including aid workers. State forces might want to stop aid deliveries to rebel movements. Attacking humanitarian facilities might serve as a force multiplier to undermine the civilian base of the rebel movement. Thus, government troops are most likely to attack aid workers in contested territory.

In the fourth part, I illuminate why rebel groups might attack aid workers. Because rebels are dependent on popular support, they are unlikely to attack those who help them maintain their civilian base. In contested territory however, it might not be clear to civilians what side is providing these services. If humanitarian organizations influence a positive outlook toward the government, rebel groups might be more likely to attack aid workers.

In the fifth part, I summarize the points given and present an overview of my core argument. My argument suggests that territorial control is a determinant for violence against aid workers, as a strategy for armed groups to strengthen their own support, or undermine their enemy's popular support.

3.1 Definitions

Before continuing, I want to clarify for the reader the main concepts guiding this work. **Civilians**: Civilians are non-combatants that are not official representatives of either conflict party. There is no universally accepted definition of civilians in an armed conflict. The Geneva Convention (1949, Article 3), defines civilians in conflicts as:

> *"Persons taking no active part in the hostilities, including members of armed forces who have laid down their arms and those placed hors de combat by sickness, wounds, detention, or any other cause, shall in all circumstances be treated humanely, without any adverse distinction founded on race, colour, religion or faith, sex, birth or wealth, or any other similar criteria."*

This makes any person not actively part of an armed group a civilian.

Humanitarian aid workers: According to the Geneva Conventions' (1949) definition of civilians, aid workers are civilians even though they are serving actively in conflict. The crucial distinction is that aid workers do not carry weapons. More specifically, the Aid Work Security Database (AWSD) defines aid workers as:

> *"the employees and associated personnel of not-for-profit aid agencies (both national and international) that provide material and technical assistance in humanitarian relief contexts. This includes both emergency relief and multi-mandated (relief and development) organizations ... and does not include UN peacekeeping personnel, human rights workers, election monitors or purely political, religious, or advocacy organizations."* (Humanitarian Outcomes 2016)

As I will be working with the AWSD dataset for my analysis, I use this definition of humanitarians.

Conflict: Conflicts are a form of organized violence. Because my analysis will be based on data from the Armed Conflict Location and Event Data Project (ACLED), I follow their definition of politically violent events as my concept for conflicts.

> *"violent and non-violent actions by political agents, including governments, rebels, militias, communal groups, political parties, rioters, protesters and civilians ... ACLED covers violent activity that occurs both within and outside the context of a civil war, particularly violence against civilians, militia interactions, communal conflict and rioting."* (Raleigh et al. 2009: 3-4)

This definition allows for the inclusion of conflicts fought not only against a government, but also between any politically organized groups.

Insurgency and insurgents: The term insurgency is subject to a variety of interpretations and interchangeable terms, such as irregular warfare, unconventional warfare, revolutionary warfare, rebellion, guerrilla warfare, and terrorism. As a consequence, insurgents may be called guerrillas, rebels, terrorists, revolutionaries, and extremists. Moore (2007) offers a definition of insurgencies that I use for the remainder of this paper:

> *"An insurgency is a protracted violent conflict in which one or more groups seek to overthrow or fundamentally change the political or social order in a state or region through the use of sustained violence, subversion, social disruption, and political action."*

3.2 The role of civilians in civil wars

In order to understand violent actions in civil wars, it is important to grasp the logic behind insurgencies and counterinsurgencies. Attacks against aid workers are a less-understood aspect of conflict, primarily because they constitute a smaller proportion of the overall number of violent incidents against civilians. Although theories explaining violence against general civilians cannot fully grasp the separate causes behind violence against aid workers, there should be some overlap in the logic behind violence against civilians and violence against aid workers, because aid workers are a subgroup of civilians. This theory shows how armed groups use violence against aid workers as a tool to maximize damage to the civilian population. It is therefore important to assess the civilian role in conflicts.

The notion that civil wars are more violent than regular interstate wars developed with the reality that these wars dissolve the classic spatial division between battlefield and non-battlefield, and are characterized by the absence of direct boundaries.

By breaking down the state's monopoly of violence, civil wars change the essence of sovereignty. In insurgencies, there is no distinction between politics and war, incarnating the Clausewitzian claim that war is a continuation of politics (Clausewitz 1989; Kalyvas 2006; Krulak 1999).

Waghelstein (1985: 42) calls irregular civil wars *total war at grassroot level* because society itself serves as the battlefield. Mao Zedong (1961), one of history's most influential strategists on guerrilla warfare, famously wrote that guerrillas are *fish swimming in the sea*. The point of the analogy is that one cannot distinguish guerrillas from civilians. The fact that every citizen of the war-torn area becomes part of the conflict, whether he or she wants to be part of it or not, makes irregular wars particularly cruel. Insurgents need civilians and therefore cannot allow them to stay neutral (Balcells 2010; Galula 2006; Weinstein 2006). When combatants merge with the civilian population, more civilians become victims of violence. This intermingling with civilians has the consequence of civilians becoming part of the battlefield, and therefore intentional victims of war-time violence (Kalyvas 2006; Weinstein 2006).

Insurgents are dependent on the support of the local population for a number of reasons. State forces usually have access to vast government resources, creating an asymmetry among insurgent and government capacities. Rebel groups rely on civilians to provide them with much-needed resources, such as shelter, information, and food. The capacity of the whole rebel movement depends largely on the extent of support from the civilian population. Furthermore, the conflict parties face an identification problem. Who is a combatant, and who is a civilian? Who is guilty, who is innocent? In irregular war, the most precious good is information about individuals and who they support. With their ability to withhold vital resources or information, civilians have some degree of power over the conflict parties (Galula 2006; Guevara 1968; Kalyvas 2006; Kilcullen 2011; Mason 1996; Migdal 2015; Scott and Clark 1970).

Kalyvas (2006) builds a comprehensive framework on the logic of violence in civil war. In this framework, control is the decisive factor for actors when choosing between indiscriminate and discriminate violence. Discriminate violence targets individuals for specific reasons. Indiscriminate violence describes random acts of violence against anyone living in a specific area. These random acts of violence are based on the principle of *guilt by association* and induce irrational fear because it cannot be predicted.

But indiscriminate violence has two severe drawbacks for any conflict actor. First, in most conflicts people usually have a choice of actor they support with their resources. The availability of this choice decreases the utility of indiscriminate violence. When individuals face an equal risk of being targeted regardless of whether they stay loyal, the relative risk of defection increases. Second, the ability to move freely among the civilian population is important for the insurgents' venture. If civilians are not sympathetic toward the cause of an armed group, they will provide information about their whereabouts to the enemy. This argument also holds the other way around. If civilians feel threatened by government troops, they are less likely to betray the insurgents. This is why it is not favorable for any conflict actor to target civilians indiscriminately if other options are on the table (Kalyvas 2006; Weinstein 2006).

Some governments rely on militias to commit violence against civilians in order to avoid being held accountable. These so-called paramilitaries are armed groups usually operating alongside the governments' security apparatus, or sometimes independently. Their aim is supposedly to protect local populations from insurgent violence. Unfortunately, some militias have repeatedly engaged in violence against civilians. The Civil Defense Forces in Sierra Leone for example were initially formed to protect the population against attacks by the Revolutionary United Front rebels, but later turned their back on the local population and became the main perpetrators (Jentzsch et al. 2015).

Control and collaboration are interlinked. The more control a group has over a territory, the easier it is to establish its own social order and shut other armed groups out of the area. Rebel governance emerges when rebels control a territory (Arjona et al. 2015; Kalyvas 2006). Territorial control allows insurgents to move freely among the population and control the population through more standard procedures. This sends a signal of strength to the civilians. As a consequence, indiscriminate violence is not necessary to control the population. Rebel organizations with a strong leadership structure are capable of overseeing their organization and are able to detect and punish individuals who disobey orders (Arjona et al. 2015; Johnston 2007; Kalyvas 2006; Staniland 2012; Weinstein 2006).

Consequently, the use of indiscriminate violence may only be useful for actors who cannot identify their enemies (Kalyvas 2006; Weinstein 2006). Again, territorial control is a crucial factor. In contested territory, none of the actors can fully control the population. This leads to an information gap for both sides. Yet information is key in executing discriminate or selective violence. In this situation, indiscriminate violence against all civilians serves as a more effective strategy (Kalyvas 2006).

3.3 Why government troops attack aid workers

Government forces are known for exercising the worst violence against civilians in civil wars, sometimes because they are unable or unwilling to identify insurgents among the civilian population (Valentino et al. 2004). But how does that transfer to aid workers?

Humanitarian organizations pose a number of challenges for government forces. Insurgents might be hiding in these facilities, disguised as normal civilians (Stoddard et al. 2009). This could, for example, affect refugee camps or health centers. Additionally, because of the impartial nature of humanitarian operations, aid not only goes to civilians but also to insurgents. The impartial and non-discriminatory mandate of most humanitarian organizations might create a problem insofar as government troops do not accept this very impartial treatment of insurgents. This politicization of aid decreases the humanitarian space in which impartial delivery is feasible (Fast 2014). Linked to this problem, the services humanitarian organizations provide improve the social well-being of civilians and therefore also strengthen the civilian base for insurgents (Torrenté 2004).

Government forces have two main reasons to target humanitarians. Drawing on Kalyvas' framework, we can first see that the information asymmetry drives armed groups to use violence against civilians indiscriminately. For government troops this is the case when they cannot differentiate rebels from civilians. This is most likely to occur in or around areas where aid is distributed, such as refugee camps or health centers. These places are sometimes used by rebels to merge with the civilian population. Particularly in medical clinics and refugee camps, rebels can hide easily among civilians while simultaneously profiting from the available resources and services (Lischer 2006). The ability to hide among civilians is not only insurgents' greatest strength but also their greatest weakness. As a consequence of this, government troops may use indiscriminate violence because they are unable or unwilling to differentiate between civilian refugees and rebels. In some instances, insurgent groups deliberately create refugee flows in order to loot aid goods. Fighters return during night time to eat the food and use the medical supplies provided by aid agencies (Barber 1997; Lischer 2006; Salehyan and Gleditsch 2006). In this case, the interests of humanitarian organizations and government forces conflict. Although government troops usually do not compete with aid agencies, they might disapprove of the provision of aid to rebels. Government troops might deliberately target aid workers and facilities to stop them from supporting rebel movements.

Secondly, government troops use violence against aid workers as a force multiplier in the strategic targeting of the civilian base of rebels. In order to fight guerrillas, one has to cut off their civilian base of support. By committing cruel atrocities against civilians and cutting them off from life-saving services, civilians are forced to flee that territory. This in turn isolates insurgents and deprives them from the resources and shelter provided by their civilian base (Azam and Hoeffler 2002; Valentino et al. 2004). Valentino et al. (2004) found evidence that mass killing is often a calculated military strategy used by regimes attempting to defeat major guerrilla insurgencies.

In an attempt to draw a line between civilians and insurgents, government forces direct their violence towards aid workers as a force multiplier. Instead of attacking all civilians indiscriminately, it can be more convenient to only focus on humanitarians. That way, the state can destabilize the internal social order of rebel movements by depriving civilians of the basic services they need to survive. This allows government troops to undermine the civilian base of rebels in a relatively efficient manner without directly targeting civilians.

The attacks against health centers in Sudan by military forces mentioned at the beginning of this thesis might be understood through this lens. By eliminating the medical care of a whole region, the government can induce a massive exodus of the civilian population. Attacking only a limited number of health centers draws less international attention, versus slaughtering thousands of civilians.

Attacking aid workers in rebel-held territory might be less optimal for the following reasons: Firstly, if government troops target civilians randomly, but rebels are able to offer credible protection, these civilians are more likely to support the rebels (Zambernardi 2010). In rebel-held territory, rebels can offer more credible protection to civilians as compared to in contested territory. Secondly, attacking aid facilities in rebel-held territory makes it less easy to obscure the issue of who is to blame. As mentioned in the legal overview in the introduction, intentional violence against aid workers is a war crime. Governments, and especially democratic regimes, have an interest in not being seen by their own population or the international community as the perpetrator (Hultman 2008). Therefore, I argue that government troops are more likely to attack aid workers in contested territory as compared to rebel-held territory.

A fundamental rule of relief work is that organizations only enter a country or territory upon agreement with the ruling government. This makes it unlikely for government troops to attack humanitarians in territory they control, as they have invited them to operate there.

Following that reasoning, I argue that government troops are most likely to attack aid workers in contested territory. Firstly, because they cannot identify the insurgents, and suspect to find them particularly among aid facilities. Secondly, as a force multiplier to deprive the insurgency of its civilian base.

3.4 Why rebel groups attack aid workers

Even in the most destructive wars, rebels are likely to install quasi-institutions and local order. Rebel governance only takes place in conflict settings, and as such is always linked to coercion and violence. Arjona (2014) uses the term *rebelocracy* to describe situations where insurgents become de-facto rulers over a territory and as a consequence face the need to establish social order in these areas. Rebel institutions usually emerge when a movement gains territorial control (Weinstein 2006; Wood 2010). Rebels try to win civilian support by offering them a certain degree of order and security through their quasi-institutions. With these structures for social order, insurgents can build trust among the local population. This social order can be seen as an attempt to overcome the collective action problem faced by all rebellions (Arjona et al. 2014; Kasfir 2015; Lichbach 1998).

In that sense, humanitarian organization can be of strategic importance for rebelocracies. Humanitarian organizations provide vital services to the civilian population and as such strengthen the civilian base of rebel groups. If rebels alienated aid workers in their territory and deprived the civilian population from their services they would weaken their own base of support. Why then are humanitarians under attack from rebel groups?

Although it is more beneficial for rebel groups to co-exist with humanitarian organizations, every rebel movement consists of opportunistic individuals who want to gain individual benefits, and humanitarian organizations provide easily lootable resources. During conflict episodes, shortages in resources such as food and medical supplies are common. Looting these resources from aid organizations helps overcome short-term shortages (Stoddard et al. 2009; Weinstein 2006). According to Narang (2013), rebel violence against aid workers induces a within-group collective action problem. If rebel methods become too violent towards aid workers, humanitarian organizations might withdraw entirely from the region, taking with them not only lootable resources, but also vital and life-saving support for the civilians. As a consequence, civilian support dwindles. Only rebel leaders who built a centralized structure that allows them to impose disciplinary measures to their members are able to resolve this collective action problem. Centralized structures and control are not achievable without a minimum of territorial control. In October 2016 for example, an international aid worker was killed by rebels in South Sudan. The incident took place in the region of Eastern Equatoria and was part of a series of armed robberies specifically targeted at humanitarian convoys (UNOCHA 2016). Although the motivation for these attacks has not been recorded, it seems the aid convoys were specifically targeted in order to loot their resources.

Rebels may also attack when they perceive aid workers as a government tool. If the local population believes humanitarian aid is provided through the government, civilians will be more likely to support the cause of that government. A study on rebel violence in Iraq for example found that aid projects can enhance local security, and as such increase support for government forces (Fast 2014). This provokes insurgents to see humanitarian organizations as a challenge to their authority because of dwindling popular support for the insurgency. Humanitarian organizations might thus be a threat to rebels' most vital resource: the support of the local population. This argument is based on the zero-sum nature of loyalty. Civilians are either loyal to insurgents or government forces (Wood and Sullivan 2015).

Essentially, if rebels do not hold full control over a territory humanitarian organizations are their competitors. When their control or territory is threatened, rebels are more likely to punish aid workers for their declining civilian support dilemma.

3.5 Core argument and hypothesis

Violence against aid workers can be understood in more general terms as competition for popular support. This in turn is closely related to control over territory. Control over and support of the civilian population is a decisive factor for armed groups in civil conflicts. Any armed group with full control over a territory can establish a quasi-system of social order and therefore provide some degree of security. Civilians support actors who increase their wellbeing and care for their safety, and they defect from groups who cannot guarantee their security. Aid organizations may be of strategic importance by alleviating the suffering of the local population, making it less necessary to flee the conflict zone.

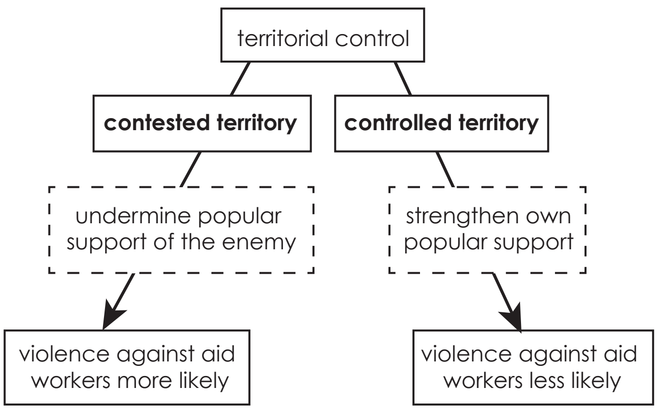
In contested territory, on the other hand, two or more armed groups are competing over control and neither group has full control over the population. Indiscriminate violence against all civilians might introduce other negative externalities. Large-scale violent attacks are not easy to cover up, and as a consequence civilians know who the perpetrator is, and can deprive support. Furthermore, these attacks attract the attention of the international community, which may have severe political consequences.

Humanitarian organizations strengthen the civilian base. Yet in contested territory, it is key to undermine the civilian base of the enemy. For government forces, attacking aid workers can be a force multiplier for weakening the civilian base of rebels. Furthermore, it allows them to target insurgents in aid facilities. In January 2017 the Nigerian military bombed a refugee camp, allegedly by mistake. Prior to that, the area saw a drastic increase in attacks by Boko Haram (Searcey 2017). It seems to be no coincidence that the target was in an area with increasing rebel activity.

For rebel groups, attacking aid workers only makes sense when their group suffers from a collective action problem or is threatened by politicized aid agencies. Both reasons concern contested territory in which the group is not able to establish its own effective control.

Undermining the work of humanitarian organizations serves as an effective alternative to weaken the civilian base of the enemy. Violence against aid workers leads to the withdrawal of regional or nation-wide humanitarian operations. Depriving an area of humanitarian services hits civilians the worst, and might either motivate civilians to flee the territory or reduce support for the group they expected security from. Because the benefits from humanitarian organizations outweigh the drawbacks for any armed actor, violence against aid workers is a useful strategy in contested territory only. Figure 3.1 shows the causal graph for that argument.

Figure 3.1: Causal graph: The path from territorial control to violence against aid workers



In other words, territorial control affects control over civilians. Attacking aid workers weakens the civilian base and as such undermines popular support for the enemy. It is therefore an efficient strategy to weaken the enemy's strength in places with no full territorial control.

Based on the competition for civilian support that is vital for either conflict actor, I formulate the following hypothesis, which is depicted in figure 3.1: *H_1: Violence against aid workers is more likely in contested territory than in non-contested territory.*

In my analysis, I test whether aid workers suffer from a greater number of violent incidents in contested territory, as opposed to in territory which is either under government or rebel control.

Chapter 4

Data

In this Chapter I explain the operationalization of the data. First, I give a brief overview of which datasets are being used and how they are combined. Additionally, I give an explanation about my unit of analysis. Second, I discuss the dependent variable and its definition as used in the dataset at hand. Third, I introduce the independent variable and its operationalization based on the conflict dataset and how I re-coded it. Fourth, control variables are discussed. Last of all, I explain why potential control variables are excluded.

4.1 Dataset and unit of analysis

Most modern conflicts are fought on a regional, not national, level. As a consequence, some regions within a country might be severely affected by conflicts, while other regions within the same country are relatively peaceful. In other instances, conflicts go beyond the borders of nations (Buhaug and Lujala 2005; Cederman and Gleditsch 2009). For example, Sudan shows a high rate of violence against aid workers. After the secession of South Sudan, a high-conflict area of the country was removed from that unit. To account for that issue, this study is based on subnational data. This is in contrast to many previous quantitative studies on conflict dynamics that are based on standard panel data accounting for country years. These studies fail to take regional differences within countries into account.

Studies on the regional level are challenging when deciding on the unit of analysis. Regional measures, such as states and districts, are not static concepts and may change over time, especially when affected by conflicts. This is not ideal for a panel study that analyses trends over a given time period. If the composition of the unit changes over the years, it is not internally comparable. These challenges prevail for all regional entities bound to exogenous political influences that might affect the entity.

A solution to this problem lies in spatio-temporal units that allow for the analysis of regions without being bound to the political entity of nation states, and are therefore not affected by exogenous factors. The Peace Research Institute Oslo (PRIO) provides a dataset based on gid cells (Tollefsen et al. 2012). The cells are the size of 0.5 degrees in latitude and longitude intervals that rasterize the entire terrestrial area (Tollefsen 2012). The size and location of the cells is fixed over time. The data is available up until 2014.

The global gid matrix consists of 259,200 cells, and multiplying them over years for panel data would lead to several million observations (Tollefsen et al. 2012). Therefore it makes sense to subset the data and limit the analysis to certain regions. Most severe cases of violence against aid workers take place in Africa and the Middle East. Afghanistan, Somalia, and Sudan account for more than 60 percent of attacks against aid workers (Stoddard et al. 2009). Chaotic conflict situations in the Middle East resulted in data shortages on that region. Furthermore, Afghanistan, Iraq, and Syria have experienced extraordinary numbers of attacks against aid workers. These conflicts are in that regard clearly special outliers. Including them in a study for general trends might bias the results. As I will discuss in the seventh Chapter, these conflicts might have different underlying dynamics leading to violence. I chose to work with the ACLED (Armed Conflict Location and Event Data Project) dataset to account for violent events (Raleigh et al. 2010). The dataset includes all violent events, even if they are not part of an active conflict. This is different from other conflict datasets such as the Uppsala Conflict Data. ACLED only provides panel data for the African continent dating back to 1997. Thus, my choice to limit my study on Africa is merely based on biases due to outliers and data shortcomings. For my dependent variable, I use the aid work security database (AWSD) that counts attacks against aid workers (Humanitarian Outcomes 2016). The advantage of the ACLED and AWSD datasets are that both contain geographic information for each incident and are therefore mergeable with the cells from the PRIO GRID dataset. ACLED provides a dataset that already includes the gid cell code for each incident up until 2013.

To sum up, the unit of analysis is the cell year level, with gid cells covering the entire African continent between 1997 and 2013. The African continent consists of 10,674 cells, resulting in 181,473 cell observations within the 17 years of the analysis. During that time, a total of 319 aid workers were attacked, of whom 181 were killed.

4.2 Dependent variable: Violence against aid workers

Generally, information concerning violence against aid workers is patchy, and consequently no comprehensive dataset exists. Attacks on health care providers are among the most extensively reported. The World Health Organization (WHO) recognized the problem of underreported attacks and started its own data gathering program. However, they did not manage to standardize the reporting procedures or bring the various humanitarian actors together (WHO 2012). As a consequence, the project failed in producing any valuable information. Meanwhile, more than ten other independent organizations are simultaneously gathering their own data on attacks against health care providers[1]. Some of them are limited to the countries they operate in, while others, such as Amnesty International, are working with a more holistic approach. The numbers show great discrepancies among all actors. Humanitarian Outcomes, an independent research organization, manages the AWSD dataset, which is to date the only existing international database on attacks against all humanitarian personnel (Humanitarian Outcomes 2016).

The AWSD reports major security incidents affecting aid workers, which are defined as killings, kidnappings, and serious injuries. The unit of observation, as in the ACLED dataset, is based on the incident level and provides exact geographical data for each event. AWSD defines incidents as

> *"reports on major security incidents involving deliberate acts of violence affecting aid workers."* (Humanitarian Outcomes 2016)

Information is either collected through systematic media filtering or voluntarily provided by aid organizations yet without standardized reporting procedure. Each incident indicates date, country, specific location including geocodes, number of aid workers affected (victims), gender of victims, institutional affiliation of victims if known, type of staff (national vs. international), outcome of the incident, means of attack, attack context, and location details such as office, roadside etc. Figure A.1 in the appendix shows the code key of the dataset.

[1] Amongst others: Safeguarding Health in Conflict Coalition, Center for Strategic and International Studies, PLOS Medicine, Merlin, Médecins Sans Frontières International, Afghanistan Analyst Network, Pack Health Worker Team, Amnesty International, Violations Documentation Center in Syria, Human Rights Watch, Physicians for Human Rights

4.2.1 Operationalization of violence against aid workers

The variables in the AWSD dataset indicate each separate incident and the number of victims, giving information about time and location. I aggregate the counts of *Total aid workers killed* for each cell year entity. Incidents that count wounded and kidnapped aid workers are excluded from these analyses for the following reasons: As explained in Chapter 2, I assume kidnaps are either motivated by economic or professional needs. Therefore, the causal argument based on popular support may not apply to the same extent for these kinds of attacks. The exclusion of wounded aid workers from the analysis is based on the assumption that these attacks could be more opportunistic, and therefore are difficult to isolate without knowing the details. For example, there could be a violent robbery initiated by a perpetrator aiming for individual gain. Although an aid worker might still be chosen on purpose, for example because the person is an expatriate and assumed to be carrying more valuable goods, the attack is not connected to the overall strategy of an armed group.

With help of PRIO, I can work with a modified dataset in which the gid cells are already included. That means the geographic information from the AWSD dataset is assigned to its respective gid cell from the PRIO GRID dataset. This allows me to merge the AWSD dataset with the PRIO GRID dataset according to gid and years.

I follow a study from Buhaug et al. (2011) where they excluded gid cells with fewer than 10 people in each cell. It makes sense to only include cells in which something can happen. Areas with no or low population are unlikely to see any human activity. This elimination process excludes 864 gid year observations in my dataset. After isolating cells with fewer than 10 people, I cross-checked with the data on violence against aid workers as well as the number of total fatalities from ACLED; no incidents were affected by the elimination of the cells.

Between 1997 and 2013, 208 out of 180,607 cells were affected by violent incidents against aid workers, and only 101 cells were affected by deadly incidents against aid workers, as shown in Table 4.1.

Table 4.1: Deadly attacks against aid workers in Africa, 1997 - 2013

	Count
Cells affected by deadly attacks	101
Aid workers killed	181

In their study on violence against civilians, Eck and Hultman (2007) found that the mechanisms explaining incidences of violence against civilians are somewhat different from the mechanisms explaining the magnitude of violence against civilians. To account for this, I built a second model with a binary dependent variable. The variable is coded 1 if at least one aid worker was killed and 0 if no attacks occurred. As deducible from Table 4.1, the number of 1s for the dummy variable is 114. In Table 4.2 below, I present summary statistics from the violence against aid worker attacks. My main analysis will be based on total aid workers killed, but I will use the other variables for robustness checks. The dummy variable *attacks* indicates the incidence of any deadly attack against an aid worker.

Table 4.2: Summary statistics, dependent variable *violence against aid workers*

Statistic	Mean	St. Dev.	Min	Max	N
Attack yes/no	0.001	0.02	0	1	180,607
Killed aid workers	0.001	0.1	0	10	180,607

One can see that the dependent variable aid workers killed does not show a normal distribution because it is not symmetric around its mean (Stock and Watson 2015: 82). The mean value, clearly towards 0, shows that the mode of the count variable lies at 0. This leads to skewed data that suffers from heteroscedasticity.

4.2.2 Data issues and shortcomings

Inferences based on the data at hand can be misleading because of a number of validity shortcomings in the dependent variable. First, the definition of an aid worker is nebulous. Do private contractors supplying aid agencies belong to that category? Where is the line between missionaries and aid workers? As long as the definition of humanitarian is not standardized, information solely based on media reports will be severely biased. Some media outlets have repeatedly described missionaries and human rights activists as humanitarians (Fast 2014). Second, the level of detail in the information provided reflects that some agencies take their reporting duties more seriously than others. This affects the reliability of the data. Third, media reports might be biased. In conflict-affected countries, journalists might not be able to name perpetrators, or provide accurate numbers or origins of victims because the media is controlled by the government. Cross-referencing with data from other institutions sheds light on the massive discrepancies. For example, in a 16-country case study, the ICRC (2011) found more than twice as many attacks against medical personnel alone. It is also important to mention that the value 0 does not necessarily mean there was no attack, only that there was no attack reported.

4.3 Independent variable: Territorial control

My objective is to develop a systematic measure that can reflect levels of territorial contestation in order to test the effect of territorial control on violence against aid workers. It follows that the independent variable needs to grasp de-facto control or contestation of armed groups over a territory.

The Cunningham/Gleditsch Dataset on Non-State Actor Data would provide comprehensive information about insurgent groups and the territory they control. Unfortunately, the dataset comes in country years, not indicating the exact coordinates of the rebel territory location. As briefly mentioned before, the ACLED dataset contains information about each politically motivated violent event, including geographically exact information. The unit of observation is a single event, initiated by one of their pre-defined actors. The gid cells that match with the PRIO GRID dataset are already included. The ACLED definition of an event is

> *"a single altercation where often force is used by one or more groups for a political end, although some instances - including protests and non-violent activity - are included in the dataset to capture the potential precursors or critical junctures of a conflict."* (Raleigh et al. 2009: 4)

One or more events can occur in the same location on the same day. If two similar events occur in the same location on the same day between the same actors they are reported as a single event. If another event type occurs, it is coded separately. For example, if a rebel group fights against the military but also kills civilians in this fight, violence against civilians is reported separately from the fight between the rebels and the military troops.

Furthermore, ACLED actors are defined as the following (Raleigh et al. 2009: 5):

> *(1) "Governments are defined as internationally recognized regimes in assumed control of a state".*
>
> *(2) "Rebel groups are defined as political organizations whose goal is to counter an established national governing regime by violent acts. Rebel groups have a stated political agenda for national power ... [and] are acknowledged beyond the ranks of immediate members".*

(3) "Political militias are a more diverse set of violent actors, who are often created for a specific purpose ... and for the furtherance of a political purpose by violence. These organizations are not seeking the removal of a national power, but are typically supported by, or allied with a political elite and act towards a goal defined by these elites or larger political movements".

(4) "Identity militias are armed and violent groups organized around a collective, common feature including community, ethnicity, region, religion or, in exceptional cases, livelihood".

For the purposes of this study, insurgent and rebel groups are defined as non-state armed actors. The following paragraph explains what *event types* from the ACLED dataset are used to build the independent variable *territorial control*. The ACLED dataset includes the variable event type, which is composed of nine different types of events: *Battle-No change of territory, Battle-Non-state actor overtakes territory, Battle-Government regains territory, Headquarters or base established, Strategic development, Riots/Protests, Violence against civilians, Non-violent transfer of territory and Remote violence*. Most of the variables are self-explanatory. The event type *Battle-Non-state actor overtakes territory* describes events in which *"after fighting with another force, a non-state group acquires control, or if two non-state groups fight and the group that did not begin with control acquires it'* (Raleigh et al. 2009: 8). *Headquarters or base established* describes events in which the respective group establishes headquarters or bases in the assigned territory. Strategic development *"records activity by rebel groups/militia/governments that does not involve active fighting but is within the context of the war/dispute. For example: recruitment drives"*. (Raleigh et al. 2009: 9).

4.3.1 Operationalizing territorial control

I develop a nominal measure of territorial control to account for territorial contestation among armed groups, deduced from the information provided by ACLED.

By including all politically motivated violent incidents, the dataset grasps events outside of recognized conflict zones. This allows for better tracking of territorial changes in control. I constructed a new variable *territorial control* based on the following ACLED event types: *Battle-No change of territory, Battle-Non-state actor overtakes territory, Battle-Government regains territory, Headquarters or base established, Strategic development and Non-violent transfer of territory.* Riots and protests, violence against civilians, as well as remote violence are not considered in the coding of the variable because the incidents do not describe events related to territorial control and any changes.

The independent variable (IV) *territorial control* is coded into nominal categories 1 for government-controlled territory, 2 for rebel-controlled territory and 3 for contested territory. ACLED further provides information about what actor was the main actor or the *winner* of the battle. This allows for disentangling territorial control on a yearly base according to the coding scheme in Table 4.3.

Category 1: Government territory

Category 1 describes government territory following the events of *Battle-Government regains territory, Headquarters or base established, Strategic development and Non-violent transfer of territory.* If an actor initiates strategic development, such as major recruitment efforts, I assume a certain degree of control over the given territory. This accounts for both government and rebel territory.

The variable is assigned to government territory for any of the above-mentioned events in which the military was the main actor. Following variable assignment, the cell year units are filled down with this category until rebels gain control over the territory.

Furthermore, the variable is coded 1 for any cell that does not fall in one of the two subsequent categories, because government territory delineates the base of the variable. This is in line with ACLED coding that *assumes that the government is in control and holds all territory under its internationally recognized mandate* (Raleigh et al. 2009: 10).

Category 2: Insurgent territory Category 2 identifies territories in which insurgents hold (de-facto) control, following the events *Battle-Non-state actor overtakes territory, Headquarters or base established, Strategic development and Non-violent transfer of territory.* Category 2 is assigned to any of these events in which a rebel force, a political militia, or an ethnic militia is the main actor. The category applies to each incident in which a non-state actor overtakes territorial control, either through military or non-violent means. After category 2 is implemented the subsequent cell year units are also assigned to category 2 until the respective cell is recaptured by government troops.

Category 3: Contested territory Category 3 identifies territories that are contested among two or more groups. This could either mean a dispute between govern-

Table 4.3: Coding independent variable: Territorial control

IV: Territorial control	**ACLED event type**	**ACLED actor1**
Government territory	Battle-Government regains territory	1- military
(Category 1)	Non-violent transfer of territory	1- military
	Headquarters or base established	1- military
	Strategic development	1- military
Rebel territory	Battle-Non-state actor overtakes territory	2- Rebel force
(Category 2)		3- Political militia
		4- Ethnic militia
	Non-violent transfer of territory	2- Rebel force
		3- Political militia
		4- Ethnic militia
	Headquarters or base established	2- Rebel force
		3- Political militia
		4- Ethnic militia
	Strategic development	2- Rebel force
		3- Political militia
		4- Ethnic militia
Contested territory	Battle-No change of territory	1- military
(Category 3)		2- Rebel force
		3- Political militia
....		4- Ethnic militia
If more than one	Battle-Government regains territory	1- military
change within a year	Battle-Non-state actor overtakes territory	2- Rebel force
		3- Political militia
		4- Ethnic militia
	Non-violent transfer of territory	1- military
		2- Rebel force
		3- Political militia
		4- Ethnic militia
	Headquarters or base established	1- military
		2- Rebel force
		3- Political militia
		4- Ethnic militia
	Strategic development	1- military
		2- Rebel force
		3- Political militia
		4- Ethnic militia

ment troops and insurgents, or a dispute between two or more non-state actors. The category is coded 3 for the event *Battle-No change of territory*. Additionally, any of the events mentioned above from category 1 and 2 fall into category 3 if more than one change within a year occurs in the same cell. Unlike categories 1 and 2, no fill down for the cell year unit is implemented. This is because I assume territory to be contested only if active competition is in place.

4.3.2 Overview of IV operationalization

The categorization of the independent variable *territorial control* leads to the following allocation. 83,746 out of 180,607 cell year units are in government control, 92,268 cell year units are in rebel control, and 4,593 cells are contested territory, as shown in Table 4.4.

Table 4.4: Distribution of independent variable

Category	Number of cells
1: Government territory	83,746
2: Rebel territory	92,268
3: Contested territory	4,593
Dummy contested territory 1	4,593
Dummy contested territory 0	176,014
Total cells	**180,607**

The coding of the independent variable makes it easy to construct an additional binary variable for a robustness check. The variable is coded 0 for non-contested territory, controlled by any actor according to category 1 and 2 of the main independent variable, consisting of 176,014 cells. 1 describes contested territory according to category 3 of the territorial control variable, consisting of 4,593 cells as in category 3. In Table 4.5 below I present the summary statistics of the independent variable.

Table 4.5: Summary statistics, independent variable

Statistic	Mean	St. Dev.	Min	Max	N
Territorial control	1.6	0.5	1	3	180,607
Contested territory	0.03	0.2	0	1	180,607

4.3.3 Shortcomings

The validity of the ACLED dataset is stronger compared to the AWSD dataset, but it also has a number of shortcomings. Territory that is assumed to be under government control is coded as such, even when the rebels control the area during night time (Raleigh et al. 2009). Following the coding of my independent variable, I would assign these cases to category 3, contested territory. However, I cannot post-extract this information from the ACLED dataset. Another problem might be the accuracy of territorial control according to gid cells. Although ACLED provides the cell information for each incident and therefore transfer of territorial control, I doubt that the full range of control is always covered. For example, if an armed group takes control over a village by violent means, it is also likely to hold control of some of the neighboring, but low-populated, areas. This should be coded as non-violent transfer of territory following the violent transfer of territory.

4.4 Control variables

With a set of suitable control variables one can account for omitted variable bias (OVB). OVB means that alternative mechanisms, unmeasured variables, are at work. Other mechanisms such as the severity of a conflict or general violence against civilians might influence the effect of violence against aid workers.

In a cross-sectional comparison, the treatment effect can be estimated under the requirement that all relevant covariates are identified. The control group is then a good counterfactual because it controls for all the covariates that make these units different from the treatment group. Precondition for that is a strong theoretical framework for control variables. The reason we need to control for potential other causes becomes apparent when looking at the counterfactual framework. The ceteris paribus question in this context is whether aid workers are targeted strategically, and by which group of perpetrators. The question highlights the fundamental problem of causal inference. Either an aid worker is attacked or not, but he or she cannot experience both at the same time. If, for example, we have data on one region in which government troops attacked aid workers and data from another region in which insurgent groups did not attack aid workers, we cannot infer that there is a relationship between attacks and government troops because the counterfactual data is missing (Angrist and Pischke 2014). The problem is illustrated in Table 4.6.

Table 4.6: Unknown counterfactuals

		actor	
		government	insurgent
region	A	attacks	
	B		no attacks

Consequently, a good control group reveals the counterfactual fate of the treated group as if it was not treated. This is only possible in an ideal experiment with perfect random assignment. Only then could we perfectly control for alternative causal effects as well as endogeneity.

4.4.1 Conflict intensity

Incidents of heavy fighting and large-scale battle increase the likelihood that people who do not belong to the battle will become victims of the fighting. Unfortunately, this means that civilian victims, among them aid workers, are sometimes hit. This can, on the one hand, be due to unfortunate cross-fire events. As tragic as such incidents are, the victims are not intentional targets, but rather merely in the wrong place at the wrong time. On the other hand, some groups aim to maximize violence on and off the battle field as a means to demonstrate power. Civilian victims, among them aid workers, are targeted intentionally in order to increase damage and grievances.

The ACLED dataset provides a count for total fatalities of each violent incident (Raleigh et al. 2009). This helps measure the intensity of a conflict: the more fatalities, the more violent the conflict. But one of the shortcomings is that all observations are on the incident level. There could be incidents with very few fatalities in a generally very violent conflict, or the other way around, with less intense conflicts showing disproportionally high fatalities. One should keep that in mind when interpreting the results of the analysis.

Alternatively, the UCDP conflict intensity measure would indicate minor and major conflicts according to their yearly or overall fatality rates. But the UCDP data only considers active conflicts while ACLED includes all sorts of violent events, including those outside of active conflict zones.

4.4.2 Violence against civilians

Combatants are more likely to use indiscriminate violence against all civilians if the number of civilian fatalities is already high (Eck and Hultman 2007). Aid workers are thus more likely to be targeted in conflicts with a high degree of violence against civilians. The ACLED dataset unfortunately only provides the count of total fatalities without differentiating between combatants and civilians. It is therefore not possible to control for the degree of violence against civilians. I include a dummy variable that accounts for any attack on civilians, derived from the ACLED event type *Violence against civilians*, coded 1 for every incidence of violence against civilians.

4.4.3 Urban land

Urban areas may be more prone to violence linked to social unrest and crimes. Developing countries in particular have difficulties keeping up with population growth, and therefore also the needs for jobs and social services. Economic inequalities, insufficient welfare services, and competition over scarce resources in densely populated urban areas may induce violence (Urdal 2008). Aid workers may be the target of that violence like any other inhabitant. To control for urban area, I include a PRIO GRID measure for percentage area of the cell covered by urban land, based on ISAM-HYDE land use data (Meiyappan and Jain 2012). The data only provides measures for 1995, 2000, and 2005, it is therefore necessary to interpolate the data for a yearly estimate.

4.4.4 Economic measure: Nightlight emission

Low income in general is an indicator for low development (The World Bank 2017). As such, low income might indicate fewer educated people such as doctors, as well as poor health services in the respective region. Furthermore, low income generally indicates high rates of poverty. A low-income indicator may control for opportunistic violence against aid workers. There are different ways to measure low income in subnational units. Gross domestic product (GDP) is the monetary value of all the goods and services produced within a country's borders. The World Bank measures GDP annually in US dollars. GDP gives an overview over the overall economic performance of a country. The PRIO GRID dataset provides the gross cell product (GCP) for each cell. Estimates are only available for the years 1990, 1995, 2000, and 2005 (Tollefsen 2012). Again, the data would need interpolation for yearly estimates. The problem is that GCP is derived from GDP and as such is not necessarily the most precise data for a subnational unit.

Satellite pictures from nightlight emissions can offer an alternative measure to economic performance. Nightlights indicate different levels of consumption and production activities and are thus a good proxy for economic activity. The data is available for entities for which standard GDP measures are not, such as sub-national units as well as entities that cross national borders. This is therefore particularly relevant for a subnational analysis on the gid cell level. The satellite data provides a more accurate measure, because the nightlights are directly related to a specific location (Henderson et al. 2011). Another advantage is that the satellite data is readily available for each gid cell.

The advantages to using nightlights seem to outweigh the drawbacks compared to the gross cell product. Thus, I control for economic activity with the PRIO GRID nightlight measure that accounts for the average night time light emission of each cell (Weng 2014).

4.4.5 Population density

One crucial factor to control for is population density, because it might influence violence against aid workers through several channels. Countries with larger populations tend to be more prone to civil war outbreaks (Hegre and Sambanis 2006). This increases the need for more aid workers. Firstly, simply because more people need assistance. Secondly, conflicts increase the need for humanitarian assistance. Furthermore, since population is accounted for per cell, it might be possible to grasp other confounding facts. For example, refugee camps are usually densely populated and also have a high number of aid workers present.

PRIO GRID provides a variable for population size per cell (Center for International Earth Science Information Network (CIESIN) and Centro Internacional de Agricultura Tropical (CIAT) 2005). The estimates are available for the years 1995, 2000, and 2005, and indicate the number of persons within the respective gid cell. Again, the data needs interpolation to work with the yearly averages. To obtain the population density, the variable further needs to be divided by the accompanying land area variable that measures the total area of land (in square kilometers) in each cell (Weidmann et al. 2010).

4.4.6 Conflict

Since my independent variable only tests for territorial control but not for active conflict, I constructed another dummy variable that is supposed to control for any active fighting per cell year. The events *Battle-No-change of territory, Battle-Non-state actor overtakes territory and Battle-Government regains territory* from the ACLED dataset are used to construct this variable. If any of the aforementioned events takes place in a gid year unit, the variable is coded 1. Table 4.7 presents the summary statistics of the control variables.

4.4.7 Excluded variables

I want to shortly explain which variables should ideally have been included in the study but could not be due to data restrictions. The set of possible control variables is limited

Table 4.7: Summary statistic, control variables

Statistic	Mean	St. Dev.	Min	Max	N
Violence against civilians	0.04	0.2	0	1	180,607
ongoing conflict	0.1	0.3	0	1	180,607
Conflict intensity	4.1	278.6	0	64,787	180,607
Nightlights	0.05	0.03	0.01	1.0	180,607
Urban area	0.1	0.9	0.0	51.7	180,607
Population density	46.8	714.4	0.004	107,090.3	180,607

due to the chosen unit of analysis on the cell year level. Many variables exist only for the country year level.

The AWSD lacks one very fundamental control variable, namely the number of aid workers deployed in any given location. A rise in the number of attacks may merely reflect the higher absolute number of aid staff deployed. The biggest shortcoming in this study is that there is no data on how many aid workers are deployed, and as such the data at hand on violence against aid workers only provides absolute numbers but no ratios. This is a serious problem when it comes to inferences based on AWSD data. However there is little I can do to overcome these problems other than taking them into account when interpreting the results of my analysis.

The OECD (2017) tracks all humanitarian donations from its member states on an annual base. This would be a great opportunity to make up for the lack of information about the numbers of aid workers deployed. Unfortunately, the numbers are only provided on a national basis, indicating how much a country received but not where the money goes. It is highly likely that there are severe differences between regions and that payments are allocated on a project base. With the data at hand I could only assign the national value to each cell within that country. Yet there might be large differences between the cells, leading to a severely biased control variable.

The risk profile of a region would be a good indicator to assess the overall risk situation of an operation. Hoelscher et al. (2015) show that higher-risk countries also pose more risk for aid workers. Here again the problem lies in the detail of aggregated national data unsuitable for my study. Although the overall risk profile of a country is a valid indicator to draw conclusions on the risk of specific regions, it is not sufficient. Many conflict-affected countries suffer from particularly risky regions, usually the frontlines of a conflict. However, that does not mean that every region in that country is equally affected. The exclusion of this variable might be less severe, since I control for conflict and fatalities, and these variables already serve as an indicator for the overall risk.

Chapter 5

Research design and methods

Quantitative research designs explain general relationships in an *effect-of-causes* approach (Mahoney and Goertz 2006: 229). By tracking the variation of observations across time and space, the quantitative design estimates the effect of the independent variable on the dependent variable across a large population. The goal of statistical analysis is to find out whether there is a causal relationship between a predictor and the outcome.

Causal inference describes the process of using facts we do know to infer to facts we do not know (G. King et al. 1994: 119). To do so, we need to eliminate the non-causal portion of an association between the predictor and the outcome. Regression attempts to uncover the causal effect by conditioning on other variables. Regressions compare treated and control groups with the same observed characteristics, by assuming that the key observed variables have been identified and made equal across the treatment and control groups. A regression estimates the weighted average of multiple matched comparisons. Due to the fundamental problem of causal inference I explained earlier, it is impossible to calculate individual-level causal effects. We can only calculate the average treatment effect of the whole population (Angrist and Pischke 2014). The problem is, our data only reveals associations that are a combination of causal and non-causal (spurious) components. Without a priori assumptions, we cannot separate the causal component from the non-causal component. It is therefore important to identify a suitable research design (Keele 2015).

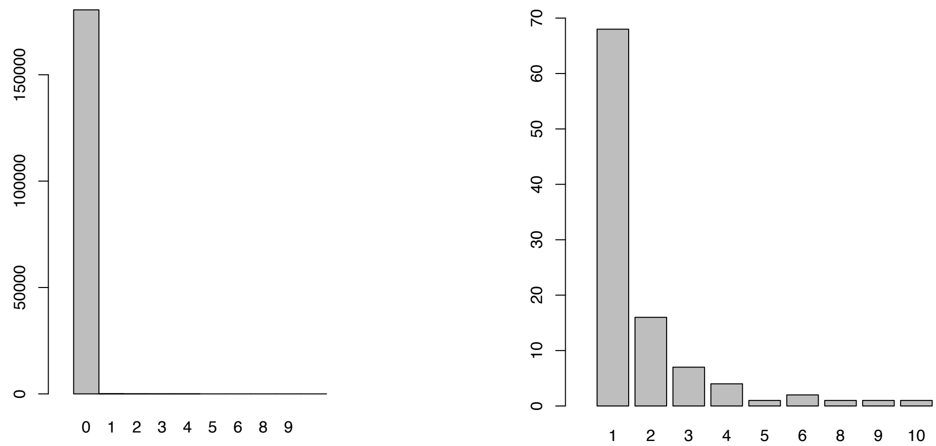
In this Chapter, I explain the model I chose for my research design. First, I explain why a negative binomial model is best when dealing with overdispersed count variables. Second, I show other potential threats to inferences, namely collinearity, autocorrelation, and within-unit differences, and how I attempt to overcome them.

5.1 Choice of model

The dependent variable counts the total number of aid workers that were killed in a cell year. Applying a linear regression model such as the ordinary least squares (OLS) to a count outcome can lead to inconsistent, inefficient, and biased estimators. OLS relies on false assumptions for count outcomes. It assumes that true values are distributed normally around the expected value and can take any real value, positive or negative, integer or fractional (Long 1997). Count variables are often highly skewed, but extreme skew violates the normality assumption of OLS regression. This is the case with my dependent variable, as shown in the summary statistics in Table 4.2. The mean value is very close to the minimum value, showing a skewed distribution of the values that is not symmetric around the variables mean (Stock and Watson 2015).

Figure 5 shows the plots of the dependent variable's frequency distribution. The x-axis denotes the value of the dependent variable aid worker attacks and the y-axis denotes the count of the respective value in the dataset. The left plot in Figure 5.1a shows that the mode of the data clearly lies at zero and the distribution is skewed. This is why an OLS model is not suitable to test the data at hand. Figure 5.1b shows the plot of the frequency distribution without the zero values. Still, the distribution is skewed with most values at one. The actual numbers are shown in Table 5.1.

Figure 5.1: Plots frequency distribution dependent variable *killed aid workers*



(a) distribution with zero values

(b) distribution without zero values

Figures made by author

Table 5.1: Frequency distribution dependent variable *killed aid workers*

Attacks against aid workers	0	1	2	3	4	5	6	8	9	10
Frequency	180,506	68	16	7	4	1	2	1	1	1

5.1.1 Dealing with count outcomes

In statistics, there are a couple of models that deal with count outcomes. One such model is the Poisson regression model (PRM). A crucial factor of the PRM is that events of the outcome are independent, meaning the occurrence of one event does not influence future events. Additionally, the mean of the distribution is a function of the independent variables, thereby accounting for heterogeneity (Long 1997: 217-218).

The underlying assumption of the PRM is that the conditional variance of the outcome equals the conditional mean, also known as equidispersion. As the mean increases, so does the variance. This in turn decreases the predicted zeros because the distribution around the expected values becomes approximately normal (Long 1997: 223). To test for equidispersion, a PRM model needs to be run first. In a second step, a one-tailed z-test testing for the difference between the mean and the variance can be done. The null-hypothesis of the test states that $\alpha = 0$ and is accepted when the conditional mean equals the conditional variance (Long 1997: 237). In doing so, the test rejects the null-hypothesis with an alpha value of 1.8, identifying overdispersion and thus making the PRM rather unsuitable. Applying a PRM when overdispersion is present can lead to inefficient estimates (Long 1997: 230). Efficiency means our estimate is close to the right one (G. King et al. 1994). Inefficiency then, for example, can mean that the significance of variables is overestimated.

When the conditional mean exceeds the conditional variance, a negative binomial regression model (NBRM) based on a Poisson distribution can help to overcome that problem. The NBRM estimates the probability of a count. The parameters of the model are still linear but the expected response is not linearly related to them. The NBRM accounts for observed and unobserved heterogeneity in the conditional mean. Heteroscedasticity is no longer an issue because the variance is a function of the mean and therefore varies with the predictors. When the variance exceeds the mean, as required by the NBRM, smaller counts show higher probabilities (Long 1997). This can balance the many zeros from cells in which no aid workers were deployed in the first place.

Overdispersion is a property of the distribution and also accounts for outliers. With the z-test from before I have already shown that the model is overdispersed in terms of skewed distribution. Although the NBRM resolves the problem of overdispersion, I still want to check the model for outliers. A Bonferroni-adjusted outlier test shows that there are indeed a number of outliers in the model (Cook and Prescott 1981). This, again, confirms that the NBRM is the right model choice. Since the model accounts for the outliers, I do not need to worry about them.

5.2 Threats to inferences

Threats to inferences can occur during various stages in research, such as during data collection, measurement errors, the choice of a badly fitting research method or model, and when interpreting the results. While causal inference describes the process of using the facts we know to infer to facts we do not know, causality is focused on the theory. King et. al (1994: 76) define causality as;

> "a theoretical concept independent of the data used to learn about it."

This means that threats to causal inferences can happen either on the theoretical or empirical level, whereas causality itself is limited to the theoretical level. However, the two are interdependent since the concept of causality will have an effect on the inferences drawn.

Multicollinearity

When predictors correlate with each other, there is not enough independent variation in each variable to estimate its effect on the outcome confidently. Perfect collinearity occurs when two variables linearly correlate with each other, while multicollinearity occurs when more than two do so. This means the predictors account for the same part of the variance in the outcome. Imperfect collinearity can still lead to biased estimates and affect the significance of the variables (Kennedy 2008). The problem is depicted in Figure 5.2.

When running a regression with multicollinear predictors, the estimated impact on the dependent variable tends to be less precise when controlling for the other variables. If predictors are highly correlated, then a unit change in one variable is not independent of a change in the other correlating variable. This overfitting leads to larger standard errors and thus imprecise estimates (Stock and Watson 2015).

With a correlation matrix one can estimate unconditional associations between variables. Table 5.2 shows the correlation between the variables in my main model. The correlation coefficient does not have a unit and is thus difficult to interpret as a number.

Figure 5.2: Collinearity between predictors

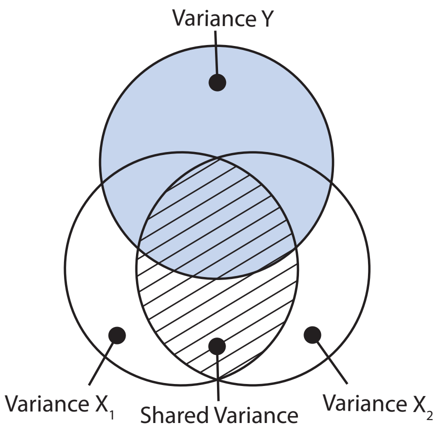


Figure made by author.

The closer the number is to 1, the higher the correlation. Fortunately, my main predictor variable territorial control does not correlate with any of the other variables. The correlating variables are violence against civilians, active conflict, and conflict intensity. I will discuss the implications of this in the Section 5.2.3.

Table 5.2: Correlation matrix predictors

	Aid work. killed	Territorial control	Viol. ag. civilians	Conflict dummy	Conflict intensity	Night-lights	Pop. density
Aid work. killed							
Territorial control	-0.22						
Viol. ag. civilians	-0.30	-0.11					
Conflict dummy	-0.38	-0.05	0.90**				
Conflict intensity	-0.33	0.00	0.86**	0.90**			
Nightlights	-0.27	-0.43	-0.27	-0.26	-0.30		
Pop. density	-0.37	-0.30	-0.09	-0.04	-0.12	0.06	
Urban land	-0.36	-0.36	-0.08	-0.03	-0.11	0.14	0.38

With a variance inflation factor (VIF) analysis one can test more formally whether the predictors suffer from collinearity. The VIF is the inverse of a correlation matrix. This is done by regressing one independent variable against the other independent variables. In practice, this means first running a linear model and then applying the VIF function. It measures the amount by which the estimate of the independent variable increases due to its collinearity with the other predictors. VIF values that are higher than 10 indicate collinearity (Kennedy 2008: 199).

Table 5.3: Variance inflation factors

	GVIF	Df	GVIF^(1/(2∗Df))
Territorial control	1.515	2	1.109
Conflict	2.753	1	1.659
Intensity	1.009	1	1.004
Violence against civilians	2.080	1	1.442
Nightlights	1.526	1	1.235
Population density	1.029	1	1.015
Urban area	1.489	1	1.220

According to the VIF test, the predictors do not show strong collinearity. Furthermore, Kennedy (2008: 100) notes that correlated predictors should not necessarily be excluded from a model. Excluding one of the two predictors gives the remaining predictor full credit for the overlapping variance. This can lead to a biased estimate because it accounts for lower variance in the prediction.

5.2.1 Autocorrelation

Most tests assume that units are independent of one another. Autocorrelation means that a variable is correlated with itself over time or space. This is due to the assumption that units that are close to each other are more likely to have similar values, as opposed to units far away (Stock and Watson 2015).

Autocorrelation in time

The OLS assumption that observations are supposed to be time-independent also accounts for Poisson distributions (Long 1997: 218). Panel data is often vulnerable to this time-dependence, also called autocorrelation, because the outcome is typically related to its value from the past and the future (Stock and Watson 2015: 586). This means that if an attack against an aid workers took place in a specific cell year unit, this cell year unit will be more likely to experience another attack in the following year. This makes sense because the same groups might have a specific strategy of attacking aid workers. Furthermore, units with no attacks, for example because they are in non-conflict affected countries, are more likely to remain peaceful in the following years. I account for this potential bias by including a one-year lag of the outcome as a control variable.

Spatial autocorrelation

The logic of spatial autocorrelation is very similar to time dependence, assuming that attacks are more likely in cells close by cells that already experienced an attack. To control for that, I use the number of attacks in all first-order neighboring cells. This means I have to calculate the number of attacks in all eight cells surrounding a specific cell in the raster, for every year. Courtesy of PRIO, I have received a dataset that identifies the first-order neighbors for each cell. I then had to match them to the cells in my dataset in order to assign the number of attacks to each first-order neighbor. In a second step, I summarized the number of attacks in all first-order neighbors. This *number of attacks in first-order neighbor's* is my control variable for spatial autocorrelation.

5.2.2 Fixed effects: Within-unit dependence

Pooled panel data are observations from different units in different time periods, as is the case with this study based on a gid year sample. This implicitly assumes that every unit has the same baseline, that predictors control for all differences between units, and that inferences can be drawn equally across space and time. Yet fixed but unobserved differences, or heterogeneity, is ignored. There are always a number of unobserved differences between units that can influence an outcome, for example prevailing cultural attitudes. These omitted variables would cause each unit to have its own baseline. Ignoring this bias can lead to over- or under-estimated predictors (Stock and Watson 2015).

When running a regression with pooled data one assumes that all units have the same intercept. An intercept is the expected value of the outcome when all the predictors equal zero. This would mean I would not acknowledge that the countries differ from each other in certain unmeasured ways. No matter which country I picked, they would all have the same intercept. By including fixed effects (FE) across units instead, every country is assigned its own intercept. This allows to control for omitted variables that differ across units but not over time (Green et al. 2001).

In terms of appliance, fixed effects can either be conditional or unconditional. Unconditional FEs construct a dummy variable for each intercept. This is only suitable for a limited number of cross-sectional units. In my case, applying unconditional FEs to several thousand gid cells is out of question. Conditional FEs, on the other hand, still adjust for all cross-sectional units but condition the separate intercepts out of the model estimation (Hilbe 2011). Unfortunately, there is no such function available for the negative binomial regression up to date. Thus, I work with unconditional FEs in my analysis to control for within-country effects.

5.2.3 Uncontrolled threats to inferences

Although correlating variables should not necessary be excluded from an analysis, I still want to come back to the correlation between the three aforementioned variables of active conflict, violence against civilians, and conflict intensity, because there could be a potential collider bias. Colliders are variables that are caused by the treatment and should not be controlled for (Morgan and Winship 2007). This means that the variance of the dependent variable explains the variance in the predictors, as explained above. The three of them are derived from the ACLED dataset, and even more, violence against civilians and active conflict are both recoded from ACLED event types. Thus, looking at it from a theoretical angle, violence against civilians and conflict intensity might be consequences of conflict. Without active conflict, there are no conflict fatalities, let alone violence against civilians. As such, it is likely that conflict works as a selection into treatment for conflict intensity and violence against civilians. But this is not entirely true, because conflict is merely a precondition for violence against civilians and conflict intensity, but not necessarily a determinant. Since it is a precondition, the variance of conflict accounting for the variance in violence against aid workers should be overlapping with the two other variables. This is why I decided to run my main territorial model without the conflict dummy.

Backdoor variables that influence selection into treatment impose a potential threat (Angrist and Pischke 2014). The treatment variable, territorial control, might potentially be influenced by other variables, such as military strength or foreign interventions. For example, a government with a powerful military is more likely to defend its territorial control against rebel groups. This bias is difficult to control for because there is no local-level data on the strength of rebel groups.

Endogeneity, namely reverse causation, is another issue. This would mean the outcome was causing the treatment (Angrist and Pischke 2014). I touched on this briefly in the literature review. Some authors claim the presence of aid workers prolongs conflicts by sustaining rebel groups. Rebel groups with more resources are also more likely to hold territorial control. Violence against aid workers can, obviously, only take place where aid workers are present. Thus, there is a possibility that the presence of these aid workers actually influences territorial control of armed groups. However, this is a theory that has not been tested thoroughly and there is little I can do besides taking this into consideration.

Chapter 6

Analysis

In this Chapter I present the results from my statistical analysis. First, I give an overview of the relevant descriptive trends in the data at hand.

Second, I present the results from my regression analysis. The first model is a plain conflict model that estimates the effect of active conflict zones on attacks against aid workers. The second model is my main territorial model, with the three-level territorial control predictor. What follows are a number of robustness tests with alternative models and specifications. First, the independent variable is replaced with a binary territorial contestation variable. Second, the dependent variable is replaced with a binary incidence variable, requiring a logistic regression model. Third, two kinds of conflict-zones only subanalysis are undertaken. The first one tests the effect of contested territory with an interaction term based on the conflict dummy. The second one shows the same model specification as in the main territorial model but is run on a subset of the data with conflict affected cells only.

Third, I present a new analysis with a priori matched data in order to improve causal inference claims. Contested territory shows a robust positive effect over all models.

6.1 Descriptive main trends

Before proceeding with the statistical analysis, it is worthwhile to have a descriptive view of the data. This reveals the tendencies and time trends of the data and helps to avoid inferential errors from the statistical analysis.

Figure 6.1 shows the trend over time in deadly attacks against aid workers, including all attacks in Africa between 1997 and 2013. The figure tells a somewhat different story than that of Figure 1.2 in the introductory Chapter, which depicted the global trend in attacks against aid workers. The global trend showed a steady increase, with some minor ups and downs. Deadly attacks against aid workers in Africa however saw a

Figure 6.1: Trend of deadly attacks against aid workers in Africa, 1997 - 2013

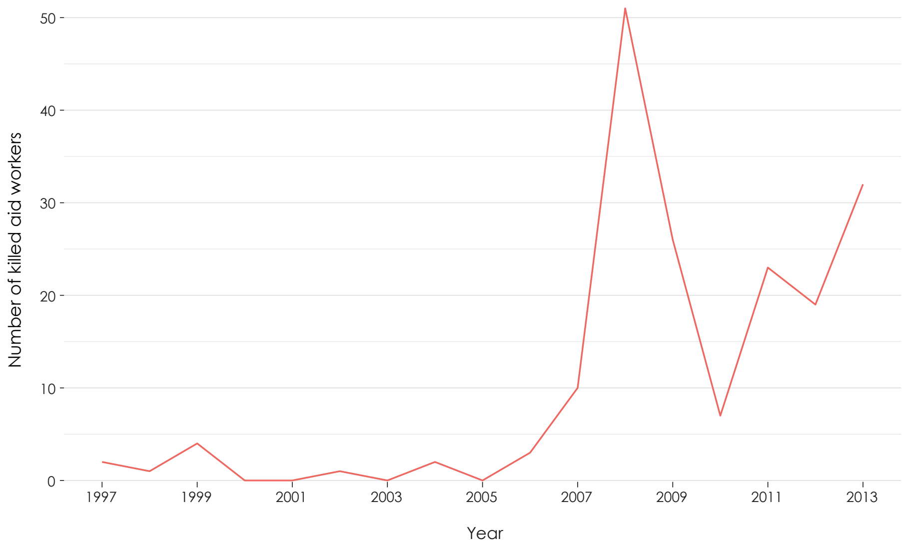


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

surprising peak between 2007 and 2009. Although we can also see a steady increase after the fall from that peak, prior to 2007 there were very few attacks. The year 2008 presents itself as a clear outlier in this plot. The data reveals that 32 cases, more than half of the total number of cases in 2008, occurred in Somalia. Strangely, the attacks mostly happened after May, when the UN-led Djibouti peace talks started (Kasaija 2010). Kasaija (2010) argues that increased violence, including violence against aid workers, may have been a result of certain groups being left out of the peace talks. Figures A.2 and A.3 in the Appendix show the trends of the two most affected countries, Somalia and Sudan.

Figure 6.2 shows the distribution of the independent variable territorial control according to number of cells in control. As shown before, the numbers of cells in contested territory is relatively small, thus it makes sense that the trend of government- and rebel-held territory is somewhat inverted. Insurgent groups are clearly on the rise again since 2005, with more territory in rebel control than in government control as of 2013. The data shows that many of the poorly populated cells in the Sahara in fact fall under rebel territory. This is not so surprising, because insurgent groups tend to steer some of their activities into areas that are hard to find but easy to control.

Figure 6.2: Cell frequency of territorial control in Africa, 1997-2013

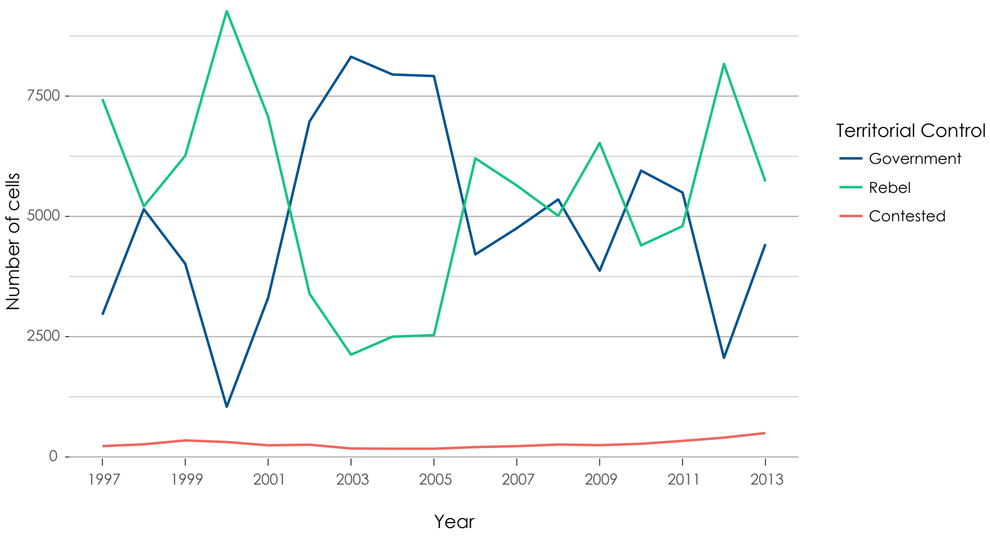


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

Figure 6.3: Trend of deadly attacks against aid workers according to territorial control in Africa, 1997-2013

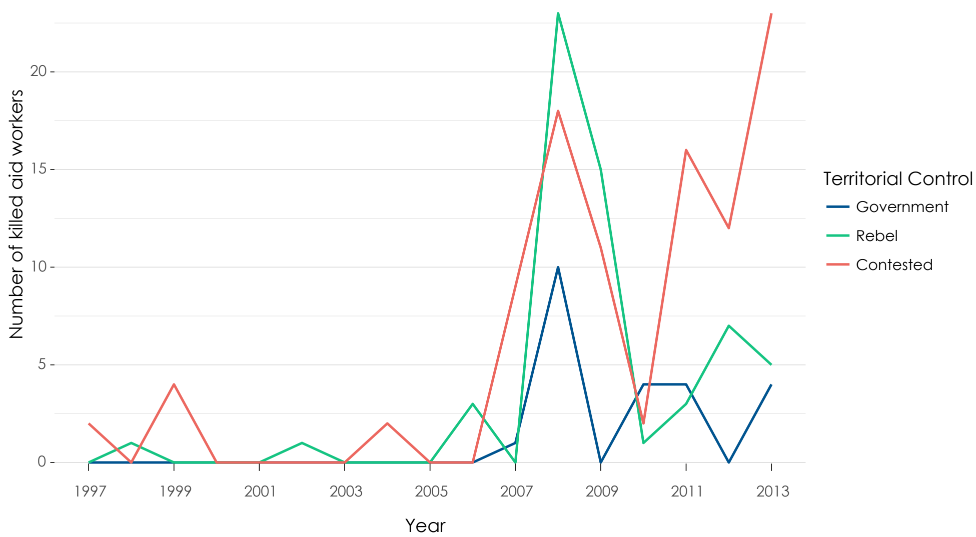


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

Breaking up this figure into the respective territorial controls reveals more information about the relationship between the predictor and the outcome. Figure 6.3 shows the trend over time in attacks against aid workers according to territorial control. Firstly, government territory generally experiences fewer attacks against aid workers compared to the two other categories. Secondly, it seems that the all-time peak in 2008 is due to heavy fighting, because both contested territory and rebel-held territory is part of that peak. Thirdly, after the numbers came back to normal in around 2010, aid workers were most endangered in contested territory.

As previously mentioned in the data Chapter, one reason for the seemingly low numbers of attacks prior to 2007 could be due to incomplete reports on attacks. The further back one goes, the bigger this issue becomes. In general, the trend in attacks against aid workers in Africa is upward, similar to how it is on the global scale. However, the timing is different, as before 2007 there were very few attacks on the whole continent. Furthermore, the trends between the different categories of territorial control are not parallel. This indicates that there might indeed be different territorial dynamics leading to attacks.

Figure 6.4 illustrates a map of Africa with the regional distribution of all deadly attacks against aid workers between 1997 and 2013. The dark blue cells indicate cells that were affected by a conflict between 1997 and 2013, as described by the conflict variable in the data Chapter. The red dots mark the location of attacked aid workers. The map indeed shows that most attacks occurred in active conflict zones. Furthermore, there is a clear cluster of attacks around conflict zones in Central and East Africa, notably in the DRC, Uganda, Kenya, Somalia, Sudan, and South Sudan. The map does not show dynamic changes. It could be that a conflict was ongoing in a respective cell during different years than when the aid worker or workers were attacked. However, it still gives a clear picture about the correlation between active conflict zones and attacks against aid workers.

6.2 Regression analysis

6.2.1 Conflict model

As a preliminary analysis, I ran a model that tests the effect of conflict on violence against aid workers. The conflict model has previously been tested by Hoelscher et al. (2015), but only on a nation-state level. As a consequence, they could only show that violence against aid workers is indeed more likely in conflict affected countries, but

Figure 6.4: Geographical distribution of aid workers killed in Africa, 1997 - 2013

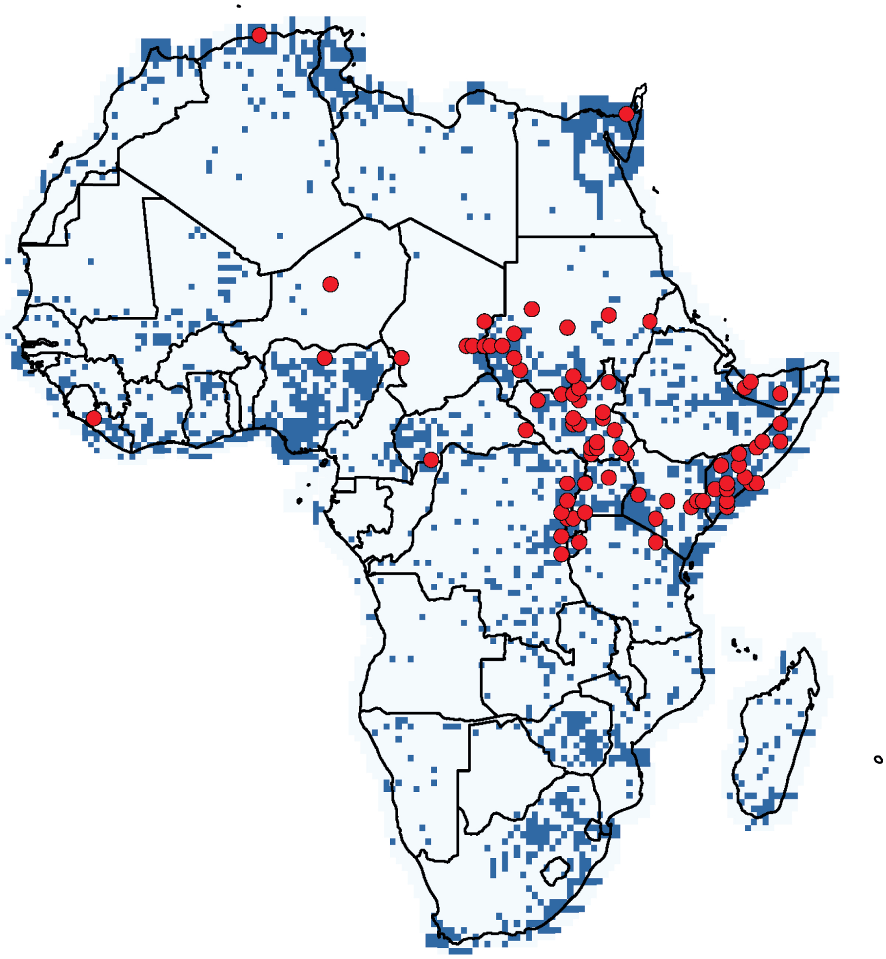


Figure made by author. Blue cells indicate active conflict zones, red dots indicate deadly attacks against aid workers.

not whether actual conflict zones are more dangerous. Furthermore, they tested it on general acts of violence, including wounded and kidnapped aid workers. Thus I wanted to retest the model on a more disaggregated level.

My theory is based on the assumption that contested territory in conflict zones is more dangerous for aid workers than non-contested territory. Yet non-contested territory can still lie in conflict zones. As a first step, I want to test whether conflicts indeed have an impact on deadly attacks against aid workers when tested with subnational data. This is somewhat different from Hoelscher et al.'s study because it directly tests conflict affected zones and not the country as a whole. I am aware that I do not work with the same model specifications, because I cannot include the same control variables. However, the analysis should still reveal whether the theory holds. Recalling

Table 6.1: Regression: Conflict model

	Dependent variable:	
	killed aid workers	
	(1)	(2)
Conflict zone	0.631	2.534***
	(0.507)	(0.253)
Violence against civilians	2.424***	
	(0.501)	
Conflict intensity	0.00005	0.0003**
	(0.0001)	(0.0001)
Nightlights	4.248	4.266
	(3.414)	(3.268)
Population density	0.00002	0.00002
	(0.0001)	(0.0001)
Urban land	0.307***	0.367***
	(0.089)	(0.092)
Time lag kills	1.547***	1.185***
	(0.314)	(0.348)
Neighbour cell kills	0.852***	0.893***
	(0.130)	(0.140)
Constant	−37.227	−37.154
	(4.069^6)	(4.069^6)
Observations	180,607	180,607
Log Likelihood	-701.788	-716.689
Akaike Inf. Crit.	1,531.575	1,559.379
Note:	*p<0.05; **p<0.01; ***p<0.001	

Standard errors in brackets, country dummies not shown

the independent variable conflict, it is a binary variable that is coded 1 for every cell year unit that experienced active fighting.

The first column in the conflict model in Table 6.1 indicates that only violence against civilians has a significant impact on violence against aid workers. The effect of the conflict predictor might be blurred by the violence against civilians predictor because of the high correlation between the two variables (also shown in the correlation matrix). The inherent nature of violence against civilians presupposes an active conflict, as explained earlier. Thus, the significantly positive effect of violence against civilians also shows that active conflict zones do have an impact on violence against aid workers. It may make sense to exclude the variable in this analysis because of the high correlation with the independent variable. Running the model again without the control variable violence against civilians, there is a seemingly larger effect from conflict on deadly attacks against aid workers. This is well in line with the map in Figure 6.4 that showed the distribution of conflict cells and attacks.

Furthermore, Urban land has a positive, although minor effect on violence against aid workers. The large standard errors in the constant (or intercept) estimate might seem peculiar. The model is run with country dummies for the fixed effects. This means that every country has its own intercept (I have excluded them from the table for better readability). Thus, the constant does not report the intercept of the estimated model in the usual sense of the term. The constant is the average of the individual intercepts. The large standard error may be due to the highly varied individual intercepts.

6.2.2 Territorial model

Table 6.2 shows the territorial control model. Column 1 shows the short regression with only the independent variable as well as the lagged dependent variable included. Column 2 shows a model with all control variables except violence against civilians, and column 3 shows a model with all control variables except conflict intensity. This is because I wanted to test the model each time with only one of the two control variables that are highly correlated with each other and see whether the effect holds. Model 4 shows the full model with all control variables.

Throughout all four model specifications, contested territory has a significant positive effect on the 0.05% level of violence against aid workers, although the size of the coefficient of contested territory slightly decreases from 2.73 (model 2) to 1.43 (model 3 and 4) when controlling for violence against civilians. Furthermore, rebel-held territory does not have a significant impact on violence against civilians. Again, we cannot directly interpret the constant as an intercept because of the fixed effects model. Checking for the single intercepts from the country dummies shows that none of them seem to have an impact, meaning that government-controlled territory has no impact on violence against aid workers.

In column 2, the effect of contested territory on violence against aid workers lies at 2.73. The model also shows a rather small but significant effect of urban area on violence against aid workers. This means that in urban areas aid workers are more likely to getting attacked as compared to non-urban areas. This could however also be biased due to the fact that the model cannot control for total aid workers deployed, and urban areas with a higher population density are more likely to have a higher number of aid workers present. The second model also shows some impact of economic development

Table 6.2: Regression: Territorial model

	Dependent variable:			
	killed aid workers			
	(1)	(2)	(3)	(4)
Rebel-held territory	0.113	0.108	0.171	0.171
	(0.299)	(0.296)	(0.301)	(0.301)
Contested territory	3.265***	2.731***	1.429***	1.432***
	(0.325)	(0.325)	(0.360)	(0.361)
Conflict intensity		0.00002		−0.00004
		(0.0001)		(0.0002)
Violence against civilians			2.316***	2.317***
			(0.286)	(0.286)
Nightlights		7.182*	4.796	4.780
		(3.078)	(3.374)	(3.377)
Population density		−0.00001	0.00002	0.00002
		(0.0001)	(0.0001)	(0.0001)
Urban land		0.340***	0.251**	0.251**
		(0.092)	(0.087)	(0.087)
Time lag kills	1.622***	1.431***	1.347***	1.346***
	(0.375)	(0.339)	(0.295)	(0.295)
Neighbour cell kills	0.884***	0.862***	0.826***	0.826***
	(0.151)	(0.138)	(0.123)	(0.123)
Constant	−37.061	−37.388	−37.323	−37.372
	(4.069^6)	(4.069^6)	(4.069^6)	(4.069^6)
Observations	180,607	180,607	180,607	180,607
Log Likelihood	-738.563	-721.170	-694.222	-694.213
Akaike Inf. Crit.	1,597.125	1,570.341	1,516.445	1,518.425

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors in brackets, country dummies not shown

on attacks against aid workers. This is somewhat surprising, as it shows that more developed areas seem to have more attacks against aid workers. Again, model 2-4 show a significant effect of urban land on violence against aid workers.

The significant positive effect of economic development and urban areas diminishes with the inclusion of violence against civilians as a control variable in the model, as shown in column 3 and 4. Model 2 and 4 show that conflict intensity seems to have no influence on violence against aid workers. Violence against civilians, on the other hand, has a significant positive effect that is bigger than contested territory and, as shown in model 3 and 4, takes away some of the explanatory power of the territorial predictor.

Table A.1 in the Appendix shows the main model without fixed effects. Interestingly, government held territory shows a highly significant negative effect, suggesting that aid workers are more safe in government controlled territory. Further, rebel-held territory seems to have a positive but small effect on violence against aid workers. As shown in Section 6.1, Somalia seems to be a stark outlier with more than 30 cases in one year. Table A.2 in the Appendix shows the main model whereby Somalia is excluded from the data. The results seem to hold, the same predictors as in the main model show significance. Thus, although Somalia is a clear outlier in the data, it does not seem to influence the results. This is in line with the NBRM that is supposed to correct for outliers, as described in Chapter 5.

By just looking at the coefficients and standard errors, we cannot tell for sure whether there is an actual positive or negative effect. Table 6.3 shows the confidence intervals for the main territorial control model. The certainty of the estimated effect seems quite robust. The confidence intervals of contested territory and violence against civilians moves in positive values. If a positive estimator showed a negative lower bound, it could mean that the effect might as well be zero. This is the case for rebel-held territory. Thus, the model correctly predicted no significance for rebel-held territory. I have included violence against civilians in this overview because it also showed a highly significant estimate. I will come back to the implications of this result in the next Chapter.

Table 6.3: Confidence intervals, territorial model

	Estimate	2.5 %	97.5 %
Rebel-held territory	0.171	−0.418	0.761
Contested territory	1.432	0.725	2.140
Violence against civilians	2.317	1.756	2.878

The interpretation of the coefficients from the NBRM is rather cumbersome; the size of the coefficient does not say much about the effect on the dependent variable as opposed to an OLS estimate. The dependent variable is an overdispersed count variable. The NBRM models the logarithm of the expected count as a function of the independent variable. The coefficient can be interpreted as follows: for a one-unit change in the independent variable, the difference in the log of the expected counts is expected to change by the value of the coefficient, ceteris paribus (Long 1997: 224). In order to make the effect of the coefficient more understandable, one can calculate the incident rate ratios (IRR). The IRR is the ratio of the rate of counts between two levels of the independent variable (Hilbe 2014: 60).

Table 6.4: Incidence rate ratio territorial model

	IRR Estimate
Contested territory	4.189
Violence against civilians	10.141

Table 6.4 shows the IRR for the territorial control model. Contested territory bears a risk of being attacked that is 4.1 times higher than in government held territory. It is important to mention that violence against civilians seems to have an even bigger effect on violence against aid workers, with an incident rate ratio of 10.14.

6.3 Robustness tests

I already discussed the model fit of a negative binomial regression in Chapter 5. Due to the highly skewed count outcome, there are no alternative models available that would make sense testing for. However, the robustness of the previous results can still be tested by varying model specifications.

6.3.1 Alternative territorial model: Binary independent variable

The three-level categorical independent variable differentiates between government- and rebel-held territory. Neither rebel- nor government-held territory showed a significant effect on violence against aid workers. To test this again on a more general level summarised as non-contested territory, I work with a binary predictor that combines rebel- and government held territory. Table 6.5 shows a model similar to that of column 4 in Table 6.2. The only difference is that the independent variable is the binary contested territory variable. The results from the territorial model seem to be robust even when replacing the treatment with a binary variable. Contested territory is still showing a significant positive effect on violence against aid workers. Yet again, violence against civilians is highly significant, too. Interestingly, the effect of urban areas seems to hold in this model, too.

Table 6.5: Regression: Binary predictor territorial model

	Dependent variable:
	killed aid workers
contested	1.327^{***}
	(0.301)
Violence against civilians	2.313^{***}
	(0.286)
Conflict intensity	-0.00003
	(0.0002)
Nightlights	4.730
	(3.397)
Population density	0.00002
	(0.0001)
Urban land	0.253^{**}
	(0.087)
Time lag kills	1.347^{***}
	(0.296)
Neighbour cell kills	0.834^{***}
	(0.123)
Constant	-37.283
	(4.069^{6})
Observations	180,607
Log Likelihood	-694.377
Akaike Inf. Crit.	1,516.754
Note:	*p<0.05; **p<0.01; ***p<0.001
	Standard errors in brackets, Country dummies not shown

6.3.2 Alternative territorial model: Incident dependent variable

As mentioned earlier in the data Chapter, the mechanisms explaining the magnitude of violence may be different from mechanisms explaining the incidence of violence. According to my theory I would not expect a different outcome concerning contested territory. However, it could be that the estimate for government- or rebel-held territory would show a different behavior when testing for the incidents. To test for this, I run the model from Table 6.2 specified in column 4 with a binary dependent variable. The variable is coded 1 if one or more aid workers were killed in the respective cell year unit. As a consequence, the model is specified as a logit model.

Contested territory shows a significant positive effect on violence against aid workers and so does violence against civilians. Remarkably, economic development, measured by nightlight emissions, also seems to have a rather big effect on the incident of violence against civilians. Similar to the main territorial model, rebel-held territory does not have an effect on the incidence of violence against civilians. In this model, the effect of urban land has changed to a non-significant result. This means that non-contested territory is no more or less secure in terms of incidents or magnitude of violence.

Table 6.6: Regression: Incident territorial model, logit

	Dependent variable:
	incident killed aid workers
Rebel-held territory	-0.012
	(0.285)
Contested territory	0.911^{**}
	(0.326)
Violence against civilians	2.089^{***}
	(0.266)
Conflict intensity	-0.0002
	(0.0002)
Nightlights	11.722^{**}
	(4.195)
Population density	0.00002
	(0.0001)
Urban land	-0.016
	(0.098)
Time lag kills	0.562^{***}
	(0.115)
Neighbour cell kills	0.310^{***}
	(0.073)
Observations	180,607
R^2	0.001
Max. Possible R^2	0.007
Log Likelihood	-532.967
Wald Test	244.060^{***} (df = 9)
LR Test	218.820^{***} (df = 9)
Score (Logrank) Test	626.952^{***} (df = 9)
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Similar to the negative binomial model, in a logit model the coefficients cannot be interpreted directly; the size of the coefficient does not say much about the effect on the dependent variable. Instead, the model calculates the logarithmized probability that event 1 occurs in relation to the probability that event 0 occurs. The difference between these probability occurrences is the so-called odds ratio (Manderscheid 2012). This measure indicates the ratio of the probability of 1 over the probability of 0 for a binary variable (Davies et al. 1998).

The odds ratios show the effect size of the logistic model in more detail. The probability that contested territory has a positive impact on violence against aid workers is 2.48 times higher compared to government held territory. Violence against civilians increases the probability of the occurrence of an attack by 8.07. Higher economic development lets the probability of violence against aid workers skyrocket by 123,263.

The results show that when measured for the incidence of violence against aid workers, economic development seems to have a bigger effect size than when measured for the magnitude of violence against aid workers. The predictors that have previously been significant on the magnitude of violence against aid workers, namely contested territory and violence against civilians, hold their effect when tested for the occurrence of the event.

6.3.3 Alternative territorial model: Interaction term with conflict zones

As shown in the conflict model in Table 6.1, conflict-affected cells indeed show a much higher possibility of aid workers getting killed. Furthermore, most peaceful cells are coded as government-held territory. The nature of the unconditional fixed effects model makes it more difficult to evaluate the effect of government held territory on violence against aid workers. But if the main model is run without fixed effects, government-held territory shows a highly significant negative effect on violence against aid workers. It is thus not clear whether government troops in conflicts are unlikely to attack aid workers or whether the effect is spurred by the many peaceful cells. There are two options when accounting for this issue. The first is to include an interaction term with the conflict dummy, the second one is a subanalysis with the conflict-affected cells only. I tested for both.

Table 6.7 shows the main territorial model with an interaction term between contested territory and conflict. In this analysis, the dummy for contested territory, instead of the three-level territorial variable, is the independent variable. It is easier to interpret the interaction term with only a two-level binary variable. It also decreases the risk for perfect collinearity between the predictors and the interaction. Furthermore, the inherent nature of an interaction term prerequisites the possibility of a zero outcome in both variables that are part of the interaction. This is not possible with the territorial variable that puts territory into three different categories.

Table 6.7: Regression: Killed aid workers, interaction term

	Dependent variable:
	attacks against aid workers
Violence against civilians	2.313***
	(0.286)
Conflict intensity	−0.00003
	(0.0002)
Nightlights	4.730
	(3.397)
Population density	0.00002
	(0.0001)
Urban land	0.253**
	(0.087)
Time lag kills	1.347***
	(0.296)
Neighbour cell kills	0.834***
	(0.123)
Contested territory*Conflict	1.327***
	(0.301)
Constant	−37.179
	(4.069^6)
Observations	180,607
Log Likelihood	-694.377
Akaike Inf. Crit.	1,516.754
Note:	*p<0.05; **p<0.01; ***p<0.001
Standard errors in brackets, country dummies not shown	

The regression shows a positive impact of violence against civilians and population density on violence against aid workers. Additionally, the interaction between contested territory and conflict has a positive effect on violence against civilians, too. This means that if, and only if, the conflict dummy takes the value 1 for active conflict zones, then contested territory has a positive effect on violence against aid workers. Table A.3 in the Appendix shows the interaction model without fixed effects. Interestingly, the constant, here government held territory, shows a highly negative effect on violence against aid workers. This is consistent with the main territorial model when run without fixed effects. This is insofar interesting in that the negative effect in the full model might be due to the many peaceful cells in government controlled territory. In Table 6.7, however, these cells are not included in the analysis.

6.3.4 Subanalysis conflict zones only

The other possibility to test for conflict-affected cells only is by doing an analysis with a subset of the data for conflict-affected cells only. I have excluded country fixed effects for this model because there might be some imbalance for the cells included, since only conflict-affected cells are included. This means that countries with large and intense conflicts are overrepresented, and countries with minor conflicts might only have few cells included in the analysis. Having a separate intercept for each country then might not lead to efficient results. Over all four models, the effect seems to be similar to the initial territorial model with the full dataset. Furthermore, column four shows similar results to the model in Table 6.7 with the interaction term.

Following these tests, it seems that excluding the peaceful cells does not change the effects of contested territory on violence against aid workers. It still seems to be the most dangerous territory for humanitarians to operate in. It is also interesting that violence against civilians seems to have an equally consistent effect over all models. Peculiarly, all control variables lose their effects in this model.

6.4 Matching

Although the effect of contested territory seems to have a significant positive effect across the different model specifications, the size of the effect varies across the models. Matching methods offer a way to overcome the difficulties of making valid causal claims by reducing the number of assumptions. Model dependency could, for example, be if the range of the control group exceeds the range of the treated group. Matching aims to eliminate the dependence between the treatment and control groups (Ho et al. 2007).

The key challenge of causal inference is to separate possible treatment effects from characteristics of units that may be correlated with the treatment status. In the previous analysis, violence against civilians seems to explain a large share of the variance in the outcome. As explained before, this could be due to a so-called confounding effect, whereby territorial control has an effect on violence against civilians, and this in turn affects violence against aid workers. If the units were exactly identical before the treatment, then the differences after the treatment can be assigned exclusively to the treatment. A causal interpretation can only be given when all suitable control variables are included into the analysis and can therefore perfectly account for the relevant selection into treatment. In other words, the techniques assume there is no omitted variable

Table 6.8: Regression: Conflict zones only territorial model

	Dependent variable:			
	killed aid workers			
	(1)	(2)	(3)	(4)
Rebel-held territory	-0.333	-0.402	-0.411	-0.411
	(0.509)	(0.500)	(0.487)	(0.487)
Contested territory	1.322^{**}	1.041^{*}	1.084^{**}	1.089^{**}
	(0.420)	(0.416)	(0.415)	(0.416)
Conflict intensity		0.00002		-0.00005
		(0.0001)		(0.0002)
Violence against civilians			2.194^{***}	2.198^{***}
			(0.439)	(0.440)
Nightlights		-1.761	-2.801	-2.847
		(4.770)	(5.089)	(5.105)
Population density		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
Urban land		0.176	0.153	0.154
		(0.128)	(0.125)	(0.126)
Time lag kills	1.027^{**}	0.976^{**}	1.293^{***}	1.294^{***}
	(0.359)	(0.326)	(0.286)	(0.286)
Neighbour cell kills	0.517^{***}	0.505^{***}	0.387^{**}	0.387^{**}
	(0.150)	(0.141)	(0.137)	(0.138)
Constant	-37.430	-37.269	-38.394	-38.443
	(9.490^{6})	(9.483^{6})	(8.468^{6})	(8.202^{6})
Observations	13,249	13,249	13,249	13,249
Log Likelihood	-432.871	-421.826	-405.371	-405.354
Akaike Inf. Crit.	975.742	961.652	928.743	930.708

Note: *p<0.05; **p<0.01; ***p<0.001

Standard errors in brackets, country dummies not shown

bias (Angrist and Pischke 2014). With matching, one tries to uncover causal effects by balancing the treatment variable on all relevant and observed covariates, so that the treatment and the control groups become as similar as possible. Matching forms a quasi-experimental contrast between the treatment and control groups by sampling comparable treatment and control cases from a larger pool of such cases. Matching enables us to compare units that are actually comparable, by finding a possible counterfactual average effect to the average treatment effect in the control group. In other words, it allows us to compare apples with apples and not with oranges (Morgan and Winship 2007). The goal of this pre-processing technique is to obtain better causal effect estimates with less bias and variance. Matching supplements regression analysis when the treatment is not randomized. In many datasets, the control group is much larger than the treatment group. This is true for the case at hand, with only 4,593 cells in contested territory. Matching is a strategic subsampling that selects a non-treated case for each treated case (Morgan and Winship 2007).

Matching is not an independent data analysis tool, but rather a pre-processing technique. After matching data, one can continue with statistical analysis such as regressions. Furthermore, matching reduces model dependency, allowing more flexibility in the structure of a model. Matching increases internal validity because the units are better comparable. Then again, matching has some drawbacks. The process excludes observations that do not match. These observations are units without counterfactuals in either group (Morgan and Winship 2007). A common notion in statistics is that the more data one has, the better. Yet Ho et al. (2007) explain that even though matching discards data, estimators are still more efficient.

6.4.1 Coarsened exact matching

Exact matching matches the treated group with the control group on identical values. Since this is hardly feasible in practice, most common matching techniques pair on distributions (Ho et al. 2007). This matching with distant metrics measures the distance between treatment and control group and discards those units that are too far away.

Coarsened exact matching (CEM) conducts exact matching but within stratum of the control variables. In other words, a set of strata is being created in which all observations have the same values on the control variables. Observations from the control group are given a weight, so that the control and treatment groups are of similar size even when their numbers differ. The advantage is that this technique also works well for multicategory treatments. The disadvantage is that CEM might discard observation from the treatment group (Ho et al. 2007; G. King et al. 2010). Table 6.9 shows an overview of the matched data according to the CEM technique. 8,482 cases from the control group and 4,559 from the treatment group were matched. The matched data has a total of 13,041 observations, including 68 attacks against aid workers.

Figure 6.5 shows which cells are included in the matched dataset. The map shows a clear cluster around East, Central, and West Africa, the regions with the highest numbers of attacks against aid workers.

Table 6.9: Matched data, sample sizes

	Control	Treated
All	176,014	4,593
Matched	8,482	4,559
Unmatched	167,532	34
Discarded	0	0

Figure 6.5: Geographical distribution of matched cells

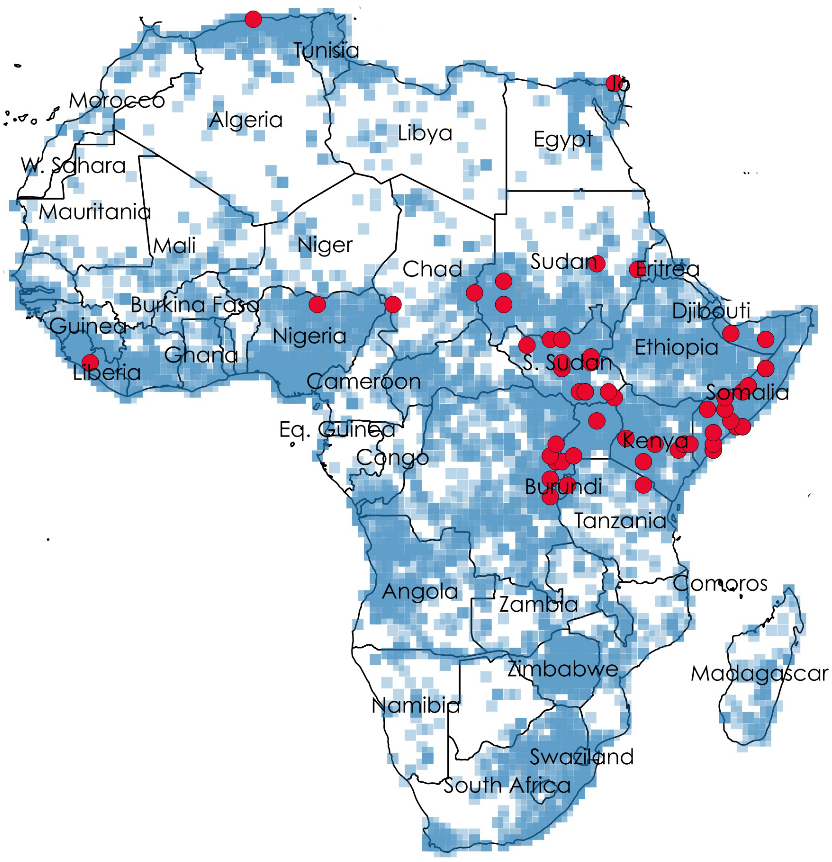


Figure made by author. Blue cells indicate matched cells (intensity according to frequency), red dots indicate deadly attacks against aid workers.

6.4.2 Imbalance

With matching, one tries to improve the balance between the treatment and the control group according to the values of the independent variable and the control variables.

King et al. (2010) emphasize that the group of control variables included is secondary, and one should try different specifications and decide which model improves the balance best. In order to be able to differentiate between treatment and control group, I use my binary independent variable contested territory. Imbalance occurs when the distribution of the covariates differs between the treatment and control group. By dropping and weighting units, matching can improve this balance. The measure $\mathcal{L}_1$ indicates the imbalance between treatment and control group, where 1 is perfect imbalance and 0 is perfect balance. Before matching, my data shows an almost perfect imbalance with a $\mathcal{L}_1 = 0.970$. After matching on the full model, the balance improves to $\mathcal{L}_1 = 0.484$. This remarkable improvement is depicted in the histograms in Figure 6.6. The propensity scores show the probability of being treated for each unit in the respective group. The difference between the treatment and control group concerning the probability of being treated for a unit is closer after the matching. This means that selection into treatment bias has been reduced.

Figure 6.6: Propensity scores control and treatment group

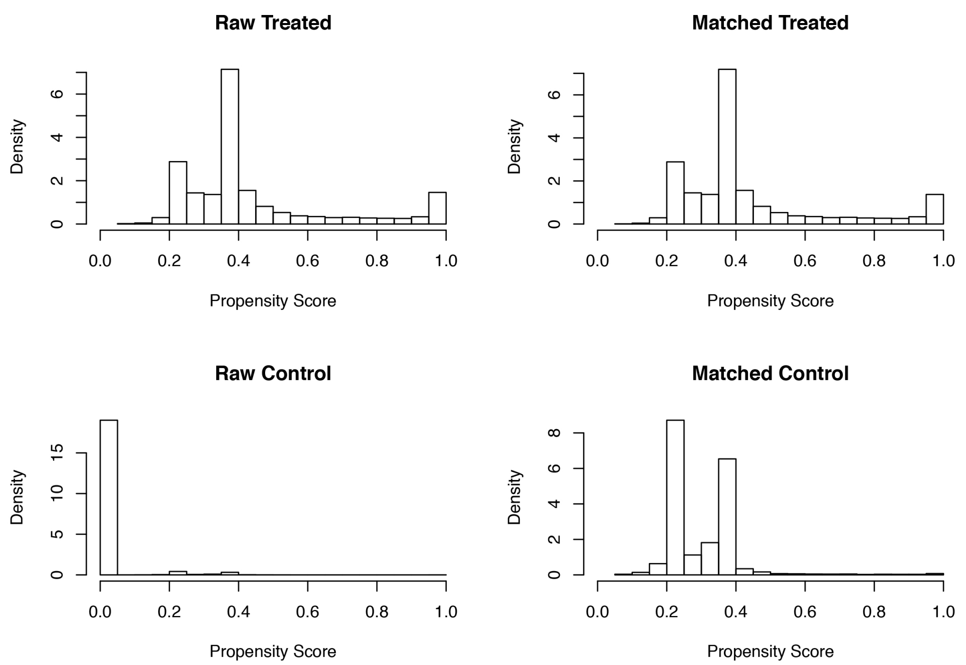
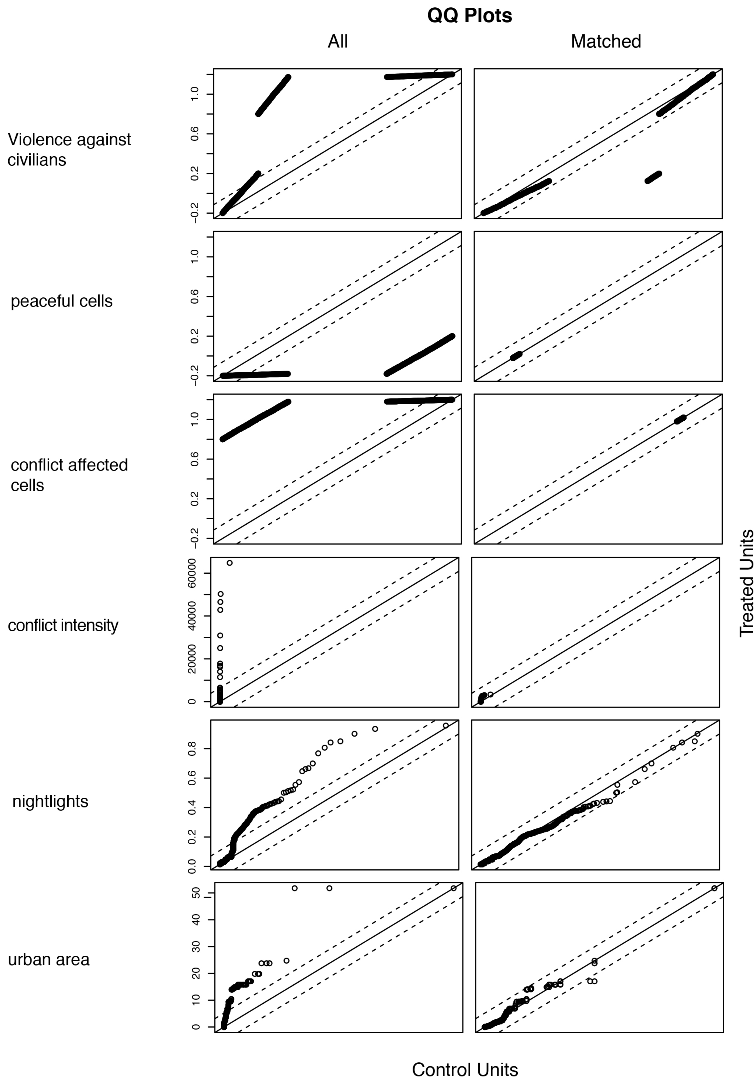


Figure 6.7 shows the Q-Q plots of the main variables before and after matching. The Q-Q plot, or quantile-quantile plot, is a scatterplot created by plotting two sets of quantiles against one another. The plots show the quantiles from the control units on the x-axis plotted against the quantiles from the treatment unit on the y-axis. If they

both have the same distribution, the points should form a more or less straight line. We can see that for the matched data, the lines of all variables have become straighter as compared to the unmatched data. The variable population density is excluded from the graph because the points all clustered at a very low point in the left corner, not leaving much room for interpretation.

Figure 6.7: Q-Q plots showing imbalance between treatment and control group before and after matching



6.4.3 Matched regression

Table 6.10 shows the negative binomial regression with the matched and weighted data. The direction of the effects and their significant levels are mostly similar to column 4 of the territorial model. Interestingly, the size of the violence against civilians predictor is smaller with the weighted data. Similar to the models that tested for conflict affected cells, rebel-held territory shows no effect on violence against aid workers.

Table 6.10: Regression: Territorial model, matched data

	Dependent variable:
	killed aid workers
Rebel-held territory	-0.346
	(0.495)
Contested territory	0.960^{*}
	(0.429)
Violence against civilians	1.966^{***}
	(0.395)
Conflict intensity	0.001
	(0.001)
Nightlights	-3.227
	(5.213)
Population density	0.001
	(0.001)
Urban land	0.163
	(0.127)
Time lag kills	1.229^{***}
	(0.285)
Neighbour cell kills	0.376^{**}
	(0.137)
Constant	-37.701
	(7.842^{6})
Observations	13,041
Log Likelihood	-406.020
Akaike Inf. Crit.	932.041
Note:	*p<0.05; **p<0.01; ***p<0.001

Standard errors in brackets, country dummies not shown

Table 6.11 shows the IRR's from the matched model. The effect size of contested territory on violence against aid workers is very similar when compared to the initial territorial model. In contested territory, aid workers have a 2.6 higher risk ratio of being attacked. Furthermore, the effect of violence against civilians decreased to an 7.1 risk ratio after matching.

Table 6.11: Incidence rate ratios, matched model

	IRR Estimate
Contested territory	2.611
Violence against civilians	7.141

6.5 Summary

This Chapter demonstrates a consistently robust effect of contested territory on violence against aid workers through an array of alternative model specifications. In all tested models, the coefficient for contested territory is positively significant. Furthermore, the effect of violence against civilians holds in every model. Even when applying pre-process matching in an attempt to make the treatment group more comparable to the control group, the results hold. It is to mention, however, that the significance of contested territory slightly decreases after matching. In conclusion, the strong statistical performance of contested territory on violence against aid workers is quite firmly established. What remains is to assess the implications of these results and the possible limitations they have.

Chapter 7

Conclusion and discussion

As the preceding analysis has demonstrated, contested territory shows an impressively robust effect tested throughout plausible alternative specifications. In this Chapter, I first give a summary of the work done in this thesis. Secondly, I discuss how the effects affirm the theory. Thirdly, I want to shed light on some limits to the analysis. I also discuss a set of possible policy implications for humanitarian organizations based on the effects I have found. Lastly, I provide some recommendations for further possible research on the topic.

7.1 Summary of the thesis

The intention of this thesis is to contribute to the young body of literature examining the micro-dynamics in conflicts leading to violence against aid workers. The hypothesis guiding this thesis states: *Violence against aid workers is more likely in contested territory than in non-contested territory*. The results of my analysis show robust evidence confirming this hypothesis.

With a theoretical framework on the basis of the logic of violence against civilians, this thesis explains violence against aid workers in terms of undermining the enemy's civilian base of support. I argue that violence against aid workers is a strategy to undermine popular support of the enemy in a more efficient way, as opposed to large scale violence against civilians.

In an attempt to measure this effect, publicly available data was used to undertake a quantitative analysis on the subnational level in Africa. The highly disaggregated data on the 0.5 longitude/latitude measure allowed for a detailed analysis of conflict dynamics related to territorial control. The unit of analysis contained gid year entities, with 180,607 observations over the course of 17 years in Africa. Due to the fact that this study was undertaken on a subnational level, it is possible to link violence against aid workers directly to territorial control of armed groups. This allows for more detailed deductions about the micro-dynamics of conflicts.

Due to the highly skewed count outcome, a negative binomial model is used for the main analysis. In the first step, the effect of conflict on violence against aid workers is tested to reaffirm the assumption that territories with ongoing conflicts are indeed more prone to experience violence against aid workers. The result of this analysis supported the assumption that humanitarians are more in danger in active conflict zones.

In a second step, the main territorial model with the three-level categorical independent variable is tested. The positive effect of contested territory on violence against aid workers was robust throughout various model specifications. Furthermore, violence against civilians seems to work as an additional predictor throughout all models. This does not mean that my theory is spurious. Violence against civilians is possibly more likely when armed groups want to undermine their enemies' civilian base of support.

The effect was not only tested with different model specifications, but also by applying a number of robustness tests with different models altogether. First, the independent variable is modified to a binary predictor that differentiates between contested and controlled territory, summarizing government- and rebel-held territory. Here again the effect of contested territory on violence against aid workers is positively correlated. In another model, I adjusted the dependent variable into a binary incidence variable, accounting for every incidence but not the magnitude of violence against civilians. Because of the binary outcome, the model is estimated with a logistic regression. Again, contested territory showed a stable positive effect on violence against aid workers.

In a third robustness check, an interaction term based on the conflict variable is applied. This allowed for the testing of the effect of violence against aid workers in interaction with conflict-affected cells. A forth robustness check was undertaken with a subset of the data of conflict-affected cells only. These two checks tested for a possibly biased effect of government territory on violence against aid workers. Most of the peaceful cells are coded as either government- or rebel-held territory, and as such the effect of territory under full control on violence against aid workers could have been flawed. Yet when controlling for conflict, government- and rebel-held territory is still uncorrelated with violence against aid workers, implying that it seems to be safer for aid workers in non-contested territory, even if there is an ongoing conflict with heavy fighting.

Lastly, due to the highly diverse cells in the analysis, I undertook pre-process matching. The aim of this process is to make the data more comparable between the treatment and control groups. Although matching excludes a high number of observations, the results might be more efficient in terms of comparability. Matching helps reduce selection into treatment bias. The result of the matched regression was in line with the previous analysis. Although after matching the contested territory predictor shows a smaller significance level, the result still holds.

Throughout the six territorial models, the estimated effect seems robust in terms of direction, although the size of the effect shows minor variations. The outcome of my analysis therefore shows that violence against aid workers is indeed more likely in contested territory, as opposed to rebel- or government-held territory. Urban land showed an effect too, although on a smaller significant level. Furthermore, the effect did not hold when tested on the incident model or in the subanalysis with the conflict zones only or with the matched data.

7.2 What do the effects say about the theory?

The analysis in the previous Chapter shows that contested territory indeed increases the likelihood for attacks against aid workers, whereas non-contested territory seems to have little effect or even a negative effect. This result holds for both specifications of the independent variable.

One may argue violence against aid workers is naturally more likely in contested territory because it is more dangerous in general, and that the estimated effect is made up of many cross-fire events but not intentional attacks. However, the way the model is specified should control for unfortunate cross-fire events. The categories for rebel- or government-held territory in the independent variable account for territorial control or major activities, but not for conflict. This means that government- or rebel-held territory experiences equally violent episodes as compared to contested territory. What is more, when one group takes control over a territory in armed combat, the battle is likely to be very severe.

To eliminate the possibility of spurious results from the many peaceful cells in government-held territory, I undertook the analysis on a subset with only conflict-affected cells. The estimation shows the average effect of the treated unit, in this case contested territory, compared to the control groups with non-contested territory. If my effect was influenced by unfortunate cross-fire effects, then it should also show a significant effect in government- or rebel-held territory. If the attacks were not intentional, they should happen more randomly without systematic clustering related to contested territory.

The results from the model without fixed effects are quite interesting concerning the government-held territory variable. The model predicts better safety for humanitarians in government-held territory, even in active conflict zones. One possible explanation may be that state forces are better at shielding their territory against outside intruders. Another explanation could be there are fewer needs for humanitarian organizations in state territory. The government might still be able to provide state-run services. A third explanation might be a result of conflict dynamics. Rebel groups might be less likely to have heavy weapons equipment to launch remote attacks, such as air strikes, in territory far away from their control.

Apart from territorial contestation, violence against civilians seems to be a strong predictor for violence against aid workers, too. This could interfere with my hypothesis because it could mean that violence against civilians is a stronger predictor for violence against aid workers. Yet this is not necessarily a threat to the inference. In line with the theory, the underlying mechanism for attacking aid workers is to weaken popular support of the enemy. Thus, violence against civilian seems to be a legitimate control for the model, even if it is highly significant. If an armed group is indeed interested in weakening the civilian base of its enemy, it does not seem conspicuous that these cases also experience violence against civilians. It would be interesting to see whether the magnitude of violence against civilians predicts the outcome in a different way than the occurrence, but due to data restrictions this was not testable.

The effect of urban land in the main model could be due to the higher population density and overall crime rate in urban areas. Also, the effect does not hold in a number of more fine-grained robustness tests. There might be a correlation with total aid workers deployed in the respective area.

7.3 Threats to causal inference

Theories help us to define causal patterns and see causal processes. They are speculations about the answers we expect to receive from our data (G. King et al. 1994). With inferences researchers draw conclusions from things they can observe about things they cannot observe. Causal inference describes the process of inferring from facts we do know to facts we cannot observe. As explained earlier, threats to causal inference can happen either on the theoretical or empirical level. This includes data collecting, measurement errors, the choice of research method, and interpretation of results. In the following paragraphs I will evaluate the validity, reliability, and replicability of my study.

Gerring (2005) presents a framework to assess causality of a given study. His first criterion concerns plenitude. This is particularly important for a large-N study. The more cases our analysis contains, the more confident our results are in terms of causal effects. Since this study is based on 180,607 observations over the course of 17 years, the principle of plenitude is fulfilled.

The second criterion concerns comparability. This means the study is limited to a less heterogeneous sample in order to ensure comparability between units and treatment groups. The applied pre-process matching technique aimed to reach this principle.

The third criterion is independence. This concerns endogeneity, a condition in which the model is influenced by factors from within the model, such as reverse causation. As shown in the literature review, some authors claim that the presence of humanitarian organizations might negatively affect conflicts. Armed groups might be artificially sustained by humanitarian aid which may prolong a conflict. However, it is unlikely that the killings of aid workers has an impact on territorial control. Thus, the only way this could threaten the argument in this thesis is if the number of humanitarian aid workers killed is a direct function of the number of humanitarians deployed. Furthermore, I have controlled for autocorrelation in space and time with time lag and neighbor cell lag variables.

The fourth criterion is representativeness. Although the study tests violence against aid workers in a rather large sample concerning cell year observations, it only tests for Africa. This would not be too worrisome if one could assume that Africa is a good representation of general trends in violence against aid workers. However, the fact that the study excludes the Middle East region, which has some of the most severe cases, sheds doubt on that claim. The conflict dynamics in Afghanistan, Iraq, and Syria may be somewhat different from the dynamics in African wars. At this stage, it remains rather difficult to name the exact reasons because of the ongoing chaotic situations that led to little reliable research output from these regions for the time being. Thus, a global generalizability of this study remains questionable. However, it may be valid to say that conflicts with similar dynamics as we can see Somalia or South Sudan, for example, might show similar patterns concerning violence against aid workers, no matter whether they can be found outside of Africa.

The fifth criterion is variation. Although my dependent variable has limited variations in relation to all the zero count cases, the negative binomial model choice adjusts for this shortcoming.

The sixth criterion concerns transparency. Since this thesis is not based on primary data but rather publicly accessible secondary data, there is little threat to transparency in this work. However, I cannot judge how transparent the data gathering process is for the datasets used.

The seventh criterion concerns replicability. Only the independent variable territorial control was coded specifically for this work. The coding process is well documented in the data Chapter and anyone repeating the same process should come to the same results as I did in this thesis.

In sum, I have limited the technical and theoretical threats to my study as much as possible. Thus, as long as the theory is not falsified in further research with more detailed data, my causal claim seems to hold.

7.4 Policy implications

The analysis at hand shows that aid workers are most in danger in contested territory. Humanitarian organizations should take this fact into consideration when planning their operations. They should acknowledge the fact that their presence is being politicized, and they are targeted strategically by armed groups as leverage to undermine popular support of their enemy.

The services provided by humanitarian organizations are lifesaving, which is of particular value in violent conflicts. But when humanitarians become the targets themselves, they will not be able to deliver these services to those who are most vulnerable. As such, humanitarian organizations should reconsider their strategies for operational decisions in order to minimize the risk of being attacked. Furthermore, humanitarian organizations may train their staff better for the increased risks in contested territory and make them aware of the mechanisms leading to this violence. Awareness is key for humanitarians on the ground.

The international community could also tackle the problem with more tangible measures. Available data only captures serious events, such as deaths, serious injuries, and kidnappings for a prolonged period. More extensive data that allows for further exploration of security incidents could lead to better early warning about escalation of threats. There is a clear need to improve the available data to include the frequency of incidents, the type of organization involved in each incident, and any correlation between attacks against aid workers and attacks against other groups such as journalists. Better data would also allow for comparison of deliberate versus cross-fire events, as well as the development of trends.

Without an international mechanism for systematic monitoring, underreporting will remain a problem. There is a clear need to enhance the available data. Better data enables researchers to understand the motivations and dynamics of attacks, as well as to assess the effectiveness of prevention strategies. Problematically, the humanitarian community is a highly fragmented industry with few international organizations, and a majority of smaller or local NGOs. Bringing these actors together in order to gather more reliable data requires an internationally connected actor. Only an officially mandated international actor would have the resources and capacities to fulfill this task. The authority to standardize practices among a whole industry would be a key point in that endeavor.

Better data could also improve compliance with international humanitarian law. Solving the problem of accountability is crucial to improving the fragile situation for aid workers. Yet outside actors cannot interfere in domestic jurisdiction of sovereign states. An evaluation of each incident from an independent body would pressure states to comply.

There have been a number of interesting developments concerning data on the humanitarian sector. After the World Humanitarian Summit, the UN and a number of partner organizations founded a new data exchange platform called Humanitarian Data Exchange (HDX 2017). The platform might provide better-quality data for future studies in the field.

7.5 Further research

One major limitation of this study is the lack of the control variable total aid workers deployed in a respective place. The issue was briefly addressed in the data Chapter. It could be that my results are severely flawed because of this issue. It may be likely, for example, that in highly conflictive regions, such as South Sudan, more aid workers are deployed in the first place. This in turn increases the likelihood of one of them being hit in cross-fire incidents of a conflict. On the other hand, not that many aid agencies deploy their personnel in direct conflict zones. An exception to this might be the International Committee of the Red Cross, or Doctors Without Borders. Furthermore, by applying fixed effects to my panel analysis, I control for unobserved confounders that differ across units. This also controls for countries with more aid workers present. Of course, this cannot control for the within-unit differences, meaning that the number of aid workers is unlikely to be stable across cells even within a country. As long as there is not more accurate data available on the number of aid workers deployed, there is little one can do to overcome this issue.

A second limitation to the study is the lack of information on the identity or affiliation of perpetrators. For this reason, this study could only test on territorial control and not perpetrator affiliation. As a consequence, the results of the study only reveal in what territory aid workers are most in danger, but not who is most likely to be the attacker. With the data at hand, one cannot make inferences concerning whether government forces or rebel groups are more likely to attack aid workers.

As a result, we do not know whether it is only the tactic of one side in contested territory to attack aid workers and less so for the other side. According to my theory, attacking humanitarians is a way to undermine the enemy's civilian support base. It follows that the group in control is less likely to attack humanitarians. In light of this, it is vital to know who the perpetrator is. It might be that there are different strategies among groups and according to territorial control. For example, in contested territory it might be more likely that humanitarians are being directly attacked and killed. In rebel-held territory, it could be more likely that government forces are attacking the infrastructure instead of the personnel.

The previously mentioned cases of air attacks against hospitals and refugee centers could be understood in this light. We have also seen this tactic outside of Africa, notably in Syria. Government forces using air attacks against health centers in order to cut whole populations off from medical services has become a popular tactic to displace civilians. Unfortunately, these are mere speculations based on the theory of this thesis. As long as there is no data that reveals the identity of the perpetrator, there is no way to make this inference with a sufficient degree of certainty.

Furthermore, the occupation of targeted aid workers is not specified. Drawing inferences related to the aid workers' professional activities is therefore not feasible. For example, we cannot say whether medical personnel are more likely to being attacked as opposed to nutrition logisticians or camp officers. This could be an interesting gap to fill. If the vulnerability of victims depends on their occupation, we might also be able to better understand why they are being attacked.

Ideally, future research should address these shortcomings. However, without improvement on the data side, it will remain difficult to address these issues. There are, however, some limitations to this study that could be addressed with the available data. For example, there might be different mechanisms leading to attacks against expatriate staff as opposed to native workers. Another neglected issue concerns gender-based violence. Although rape is not always reported, some incidents contain descriptive information about gender-based violence. In 2016, concerned women from the humanitarian sector came together and set up the Humanitarian Women's Network (HWN).

HWN has petitioned the Inter-Agency Standing Committee (IASC), which is led by the UN and acts as a forum for coordination between different humanitarian agencies and NGOs, in order to address the issue. An internal survey among female humanitarians found that over fifty percent of the respondents experienced some sort of sexual assault during their work.

Moreover, future research should address conflict dynamics outside of Africa. This would ensure better generalizability and shed light on violence against aid workers on a global level. As mentioned earlier, most incidents take place in conflicts in the Middle East, namely Afghanistan, Iraq and Syria. If the results from this study are indeed showing a general pattern of violence against aid workers the results should hold when testing them in the aforementioned cases in the Middle East.

Lastly, researchers may attempt to further disaggregate the time unit to months or weeks. With cell years units, we are still not able to directly link violent incidents against aid workers to conflict incidents. This may be of less concern for the territorial model, since territorial control is something more static. However, the first model that tested the correlation between active conflict zones and violence against aid workers may yield different results when tested on a more fine-grainedtime unit.

The young research field on violence against aid workers will show many exciting opportunities for researchers in the future. Quantitative research in particular may become a growing field with the development of more accurate data.

Bibliography

Abbott, Marianne (2006). “Dangerous Intervention: An Analysis of Humanitarian Fatalities in Assistance Contexts.” The Ohio State University.

Al Jazeera (2017). “ICRC: Six Red Cross Aid Workers Killed in Afghanistan.” In: *Al Jazeera and news agencies*.

Amnesty International (2015). *Don’t We Matter? Four Years of Unrelenting Attacks Against Civilians of Sudan’s South Kordofan.* AFR 54/2162/2015. Amnesty International Ltd.

Anderson, Mary B (1999). *Do No Harm: How Aid Can Support Peace - or War*. Lynne Rienner Publishers.

Angrist, Joshua D. and Jörn-Steffen Pischke (2014). *Mastering ’Metrics: The Path from Cause to Effect*. Princeton ; Oxford: Princeton University Press. 304 pp.

Arjona, Ana, Laia Balcells, and Patricia Justino (2014). “Wartime Institutions: A Research Agenda.” In: *Journal of Conflict Resolution* 58.8, pp. 1360–1389.

Arjona, Ana, Nelson Kasfir, and Zachariah Mampilly (2015). *Rebel Governance in Civil War*. Cambridge University Press. 329 pp.

Azam, Jean-Paul and Anke Hoeffler (2002). “Violence Against Civilians in Civil Wars: Looting or Terror?” In: *Journal of Peace Research* 39.4, pp. 461–485.

Balcells, Laia (2010). “Rivalry and Revenge: Violence against Civilians in Conventional Civil Wars.” In: *International Studies Quarterly* 54.2, pp. 291–313.

Barber, Ben (1997). “Feeding Refugees, or War?” In: *Foreign Affairs* (July/August 1997).

Barnett, Katy (2004). “Security Report for Humanitarian Organizations.” In: *ECHO Security Review. Brussels*.

BCC (2017). “Nigeria Air Strike Error Kills Dozens in Refugee Camp.” In: *BBC News. Africa*.

Buchanan, Cate and Robert Muggah (2005). *No Relief: Surveying the Effects of Gun Violence on Humanitarian and Development Personnel*. Humanitarian Practice Network.

Buhaug, Halvard, Kristian Skrede Gleditsch, Helge Holtermann, Gudrun Østby, and Andreas Forø Tollefsen (2011). "It's the Local Economy, Stupid! Geographic Wealth Dispersion and Conflict Outbreak Location." In: *Journal of Conflict Resolution* 55.5, pp. 814–840.

Buhaug, Halvard and Päivi Lujala (2005). "Accounting for Scale: Measuring Geography in Quantitative Studies of Civil War." In: *Political Geography* 24.4, pp. 399–418.

Cederman, Lars-Erik and Kristian Skrede Gleditsch (2009). "Introduction to Special Issue on "Disaggregating Civil War"." In: *Journal of Conflict Resolution* 53.4, pp. 487–495.

Center for International Earth Science Information Network (CIESIN) and Centro Internacional de Agricultura Tropical (CIAT) (2005). *Population Count Grid Future Estimates, v3: Gridded Population of the World (GPW), v3 | SEDAC*. URL: `http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count-future-estimates` (visited on 04/06/2017).

Clausewitz, Carl von (1989). *On War*. Princeton University Press. 752 pp.

Collier, Paul and Anke Hoeffler (1998). "On Economic Causes of Civil War." In: *Oxford Economic Papers* 50.4, pp. 563–573.

Cook, Dennis and P. Prescott (1981). "On the Accuracy of Bonferroni Significance Levels for Detecting Outliers in Linear Models." In: *Technometrics* 23.1, pp. 59–63. JSTOR: `1267976`.

Davies, H., I. K. Crombie, and M. Tavakoli (1998). "When Can Odds Ratios Mislead?" In: *BMJ* 316.7136, pp. 989–991.

Duffield, Mark (1997). "NGO Relief in War Zones: Towards an Analysis of the New Aid Paradigm." In: *Third World Quarterly* 18.3, pp. 527–542.

Eck, Kristine and Lisa Hultman (2007). "One-Sided Violence Against Civilians in War: Insights from New Fatality Data." In: *Journal of Peace Research* 44.2, pp. 233–246.

Ensuring the Protection Aid Workers: Why a Special Mandate Holder Is Necessary (2015). Discussion Paper.

Fast, Larissa (2010). "Mind the Gap: Documenting and Explaining Violence against Aid Workers." In: *European Journal of International Relations* 16.3, pp. 365–389.

— (2014). *Aid in Danger: The Perils and Promise of Humanitarianism*. Philadelphia: University of Pennsylvania Press. 336 pp.

Galula, David (2006). *Counterinsurgency Warfare: Theory and Practice*. Greenwood Publishing Group. 134 pp.

Gerring, John (2005). “Causation: A Unified Framework for the Social Sciences.” In: *Journal of Theoretical Politics* 17.2, pp. 163–198.

Graham-Harrison, Emma (2016). “Aleppo Hospitals Are Latest Casualty in Attacks by the Syrian Regime.” In: *The Guardian. Global*.

Green, Donald P., Soo Yeon Kim, and David H. Yoon (2001). “Dirty Pool.” In: *International Organization* 55 (02), pp. 441–468.

Guevara, Ernesto Che (1968). *Der Guerillakrieg [La Guerra de Guerillas (1960)]*. Ed. by Horst Kurnitzky.

HDX (2017). *Humanitarian Data Exchange*. URL: `https://data.humdata.org/` (visited on 05/15/2017).

Hegre, Håvard and Nicholas Sambanis (2006). “Sensitivity Analysis of Empirical Results on Civil War Onset.” In: *Journal of Conflict Resolution* 50.4, pp. 508–535.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil (2011). “A Bright Idea for Measuring Economic Growth.” In: *The American economic review* 101.3, pp. 194–199.

Hilbe, Joseph M. (2011). *Negative Binomial Regression*. 2nd ed. Cambridge, UK ; New York: Cambridge University Press. 570 pp.

— (2014). *Modeling Count Data*. New York, NY: Cambridge University Press. 300 pp.

Ho, Daniel E., Kosuke Imai, Gary King, and Elizabeth A. Stuart (2007). “Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference.” In: *Political Analysis* 15.3, pp. 199–236.

Hoelscher, Kristian, Jason Miklian, and Haavard Nygaard (2015). *Understanding Violent Attacks Against Humanitarian Aid Workers*. SSRN Scholarly Paper ID 2700772. Rochester, NY: Social Science Research Network.

Hultman, Lisa (2008). “Targeting the Unarmed : Strategic Rebel Violence in Civil War.”

Humanitarian Outcomes (2016). *Aid Worker Security Database*. URL: `https://aidworkersecurity.org` (visited on 09/11/2016).

ICRC (2011). *Health Care in Danger: A Sixteen-Country Study*. International Committee of the Red Cross.

International Committee of the Red Cross (ICRC) (1949). *Geneva Convention Relative to the Protection of Civilian Persons in Time of War (Fourth Geneva Convention)*.

Jentzsch, Corinna, Stathis Kalyvas, and Livia Isabella Schubiger (2015). “Militias in Civil Wars.” In: *Journal of Conflict Resolution* 59.5, pp. 755–769.

Johnston, Patrick (2007). “Negotiated Settlements and Government Strategy in Civil War: Evidence from Darfur.” In: *Civil Wars* 9.4, pp. 359–377.

Kalyvas, Stathis (2006). *The Logic of Violence in Civil War*. 1st ed. Cambridge; New York: Cambridge University Press. 508 pp.

Kasaija, Apuuli Phillip (2010). "The UN-Led Djibouti Peace Process for Somalia: Results and Problems." In: *Journal of Contemporary African Studies* 28.3, pp. 261–282.

Kasfir, Nelson (2015). "Rebel Governance – Constructing a Field of Inquiry: Definitions, Scope, Patterns, Order, Causes." In: *Rebel Governance in Civil War*. Cambridge University Press.

Keele, Luke (2015). "The Discipline of Identification." In: *PS: Political Science & Politics* 48 (01), pp. 102–106.

Kennedy, Peter (2008). *A Guide to Econometrics*. 6th ed. Malden, MA: John Wiley & Sons. 600 pp.

Kilcullen, David (2011). *The Accidental Guerrilla: Fighting Small Wars in the Midst of a Big One*. Oxford University Press. 377 pp.

King, Dennis (2002). "Paying the Ultimate Price: An Analysis of Aid-Worker Fatalities." In: *Humanitarian Exchange* 21.

King, Gary, Matthew Blackwell, Stefano Iacus, and Giuseppe Porro (2010). *Cem: Coarsened Exact Matching in Stata*.

King, Gary, Robert Keohane, and Sidney Verba (1994). *Designing Social Inquiry: Scientific Inference in Qualitative Research*. Princeton University Press.

Krulak, Charles C. (1999). *The Strategic Corporal: Leadership in the Three Block War*.

Lichbach, Mark Irving (1998). *The Rebel's Dilemma*. University of Michigan Press. 544 pp.

Lischer, Sarah Kenyon (2006). *Dangerous Sanctuaries: Refugee Camps, Civil War, and the Dilemmas of Humanitarian Aid*. Cornell University Press. 222 pp.

— (2007). "Military Intervention and the Humanitarian Force Multiplier." In: *Global Governance: A Review of Multilateralism and International Organizations* 13.1, pp. 99–118.

Loertscher, Seth and Daniel Milton (2015). *Held Hostage: Analyses of Kidnapping Across Time and Among Jihadist Organizations - Islamic Terrorism, Al Qaeda, ISIS, ISIL, Taliban, Boko Haram, Al Nusra, Al-Shabaab, Historical Perspective, Pirates*. The Combating Terrorism Center at West Point. 464 pp.

Long, J. Scott (1997). *Regression Models for Categorical and Limited Dependent Variables*. SAGE Publications. 336 pp.

Mahoney, James and Gary Goertz (2006). "A Tale of Two Cultures: Contrasting Quantitative and Qualitative Research." In: *Political Analysis* 14.3, pp. 227–249.

Mampilly, Zachariah (2009). “A Marriage of Inconvenience: Tsunami Aid and the Unraveling of the LTTE and the GoSL’s Complex Dependency.” In: *Civil Wars* 11.3, pp. 302–320.

Manderscheid, Katharina (2012). *Sozialwissenschaftliche Datenanalyse mit R*. Wiesbaden: VS Verlag für Sozialwissenschaften.

Mason, T. David (1996). “Insurgency, Counterinsurgency, and the Rational Peasant.” In: *Public Choice* 86 (1/2), pp. 63–83.

McVeigh, Karen (2017). “Seven Dead in Worst Attack on Aid Workers since South Sudan War Began.” In: *The Guardian. Global development*.

Meiyappan, Prasanth and Atul K. Jain (2012). “Three Distinct Global Estimates of Historical Land-Cover Change and Land-Use Conversions for over 200 Years.” In: *Frontiers of Earth Science* 6.2, pp. 122–139.

Migdal, Joel S. (2015). *Peasants, Politics and Revolution: Pressures Toward Political and Social Change in the Third World*. Princeton University Press. 312 pp.

Milton, Daniel, Megan Spencer, and Michael Findley (2013). “Radicalism of the Hopeless: Refugee Flows and Transnational Terrorism.” In: *International Interactions* 39.5, pp. 621–645.

Moore, R Scott (2007). “The Basics of Counterinsurgency.” In: *Small Wars Journal* 14.

Morgan, Stephen and Christopher Winship (2007). *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. 1 edition. New York: Cambridge University Press. 328 pp.

Narang, Neil (2013). “Biting the Hand That Feeds: An Organizational Theory Explaining Attacks Against Aid Workers in Civil Conflict.” In: *Draft for Princeton Foreign Aid Conference April 2013*, p. 41.

Narang, Neil and Jessica Stanton (2004). “A Strategic Logic of Attacking Aid Workers: Evidence from Violence in Afghanistan, 2008–2012.” In: *International Studies Quarterly*.

Naylor, R Thomas (1997). “Mafias, Myths, and Markets: On the Theory and Practice of Enterprise Crime.” In: *Transnational Organized Crime* 3.3, pp. 1–45.

OECD (2017). *Humanitarian Assistance*. URL: `http://www.oecd.org/dac/stats/humanitarian-assistance.htm` (visited on 04/06/2017).

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joachim Carlsen (2009). “Armed Conflict Location and Event Dataset (ACLED) Codebook.” In: *Center for the Study of Civil War, International Peace Research Institute, Oslo (PRIO): Version*, pp. 1–2006.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen (2010). "Introducing Acled: An Armed Conflict Location and Event Dataset Special Data Feature." In: *Journal of peace research* 47.5, pp. 651–660.

Rieff, David (2009). *Humanitarianism in Crisis*. URL: https://www.foreignaffairs.com/articles/2002-11-01/humanitarianism-crisis (visited on 02/08/2016).

Rubenstein, Leonard S. and Melanie D. Bittle (2010). "Responsibility for Protection of Medical Workers and Facilities in Armed Conflict." In: *The Lancet* 375.9711, pp. 329–340.

Salehyan, Idean and Kristian Skrede Gleditsch (2006). "Refugees and the Spread of Civil War." In: *International Organization* 60 (02), pp. 335–366.

Scott, Andrew MacKay and Donald P Clark (1970). *Insurgency*. University of North Carolina Press.

Searcey, Dionne (2017). "Nigerian Jet Mistakenly Bombs Refugee Camp, Killing Scores." In: *The New York Times*.

Staniland, Paul (2012). "States, Insurgents, and Wartime Political Orders." In: *Perspectives on Politics* 10.2, pp. 243–264.

Stock, James H. and Mark W. Watson (2015). *Introduction to Econometrics, Update*. 3rd edition. Boston: Pearson. 840 pp.

Stoddard, Abby, Adele Harmer, and Victoria DiDomenico (2009). *Providing Aid in Insecure Environments: Trends in Violence against Aid Workers and the Operational Response*. Overseas Development Institute London.

Stoddard, Abby, Adele Harmer, and Katherine Haver (2006). *Providing Aid in Insecure Environments: Trends in Policy and Operations*. Overseas Development Institute London.

Terry, Fiona (2011). "The International Committee of the Red Cross in Afghanistan: Reasserting the Neutrality of Humanitarian Action." In: *International Review of the Red Cross* 93.881, pp. 173–188.

The Guardian (2016). "UN Peacekeepers in South Sudan Ignored Rape and Assault of Aid Workers." In: *The Guardian. World news*.

The PLOS Medicine Editors (2014). "Health Care in Danger: Deliberate Attacks on Health Care during Armed Conflict." In: *PLoS Medicine* 11.6.

The World Bank (2017). *World Bank Data*. URL: http://data.worldbank.org (visited on 01/25/2017).

Tollefsen, Andreas Forø (2012). "PRIO-GRID Codebook." In: *Oslo: PRIO*.

Tollefsen, Andreas Forø, Håvard Strand, and Halvard Buhaug (2012). "PRIO-GRID: A Unified Spatial Data Structure." In: *Journal of Peace Research* 49.2, pp. 363–374.

Torrenté, Nicolas de (2004). “Humanitarianism Sacrificed: Integration’s False Promise.” In: 18.2, pp. 3–12.

Tse-Tung, Mao and Zedong Mao (1961). *On Guerrilla Warfare*. University of Illinois Press.

UNOCHA (2016). *South Sudan Humanitarian Bulletin*. Text 16.

Urdal, Henrik (2008). “Population, Resources, and Political Violence: A Subnational Study of India, 1956–2002.” In: *Journal of Conflict Resolution* 52.4, pp. 590–617.

Uvin, Peter (1999). *The Influence of Aid in Situations of Violent Conflict*. OECD Development Assistance Committee Informal Task Force on Conflict, Peace and Development Co-operation. 48 pp.

Valentino, Benjamin, Paul Huth, and Dylan Balch-Lindsay (2004). “Draining the Sea: Mass Killing and Guerrilla Warfare.” In: *International Organization* 58.2, pp. 375–407.

Waghelstein, John (1985). “El Salvador: Observations and Experiences in Counterinsurgency.” In: *US Army War College, Carlisle Barracks, Penn*.

Weidmann, Nils, Doreen Kuse, and Kristian Skrede Gleditsch (2010). “The Geography of the International System: The CShapes Dataset.” In: *International Interactions* 36.1, pp. 86–106.

Weinstein, Jeremy (2006). *Inside Rebellion: The Politics of Insurgent Violence*. Cambridge University Press. 428 pp.

Weissman, Fabrice (2004). *In the Shadow of "Just Wars": Violence, Politics and Humanitarian Action*. Ed. by Médicines sans Frontiers. Ithaca, N.Y: Cornell Univ Pr. 400 pp.

Weng, Qihao (2014). *Global Urban Monitoring and Assessment through Earth Observation*. CRC Press. 412 pp.

WHO (2012). *World Health Assembly Closes with New Global Health Measures*. URL: http://www.who.int/mediacentre/news/releases/2012/wha65_closes_20120526/en/ (visited on 02/08/2016).

Wood, Reed (2010). “Rebel Capability and Strategic Violence against Civilians.” In: *Journal of Peace Research* 47.5, pp. 601–614.

Wood, Reed and Christopher Sullivan (2015). “Doing Harm by Doing Good? The Negative Externalities of Humanitarian Aid Provision during Civil Conflict.” In: *The Journal of Politics* 77.3, pp. 736–748.

Zambernardi, Lorenzo (2010). “Counterinsurgency’s Impossible Trilemma.” In: *The Washington Quarterly* 33.3, pp. 21–34.

Appendix A

Appendix

Figure A.1: Key AWSD Dataset

Key for organisation type	
UN:	United Nations
INGO:	International non-governmental organisation
LNGO and NRCS:	Local non-governmental organisation or National Red Cross / Red Crescent Society
ICRC:	International Committee of the Red Cross
IFRC:	International Federation of Red Cross and Red Crescent Societies
Key for means of attack	
AB:	Aerial bombardment/missile/mortar/RPG/lobbed grenade
BA:	Bodily assault/beating/stabbing with non-fire weapons or no weapons
B:	Bombing (set explosives with a stationary target: building, facility, home)
BBIED:	Body-borne IED
CX:	Complex attack (explosives in conjunction with small arms)
RIED:	Roadside IED
VBIED:	Vehicle-born IED (unknown whether remote control or suicide)
VBIED-RC:	Vehicle-borne IED (remote control detonation)
VBIED-S:	Vehicle-borne IED (suicide)
K:	Kidnapping (not killed)
KK:	Kidnap-killing
RSA:	Rape or serious sexual assault
LM:	Landmine or UXO detonation
S:	Shooting (small arms / light weapons, e.g. pistols, rifles, machine guns)
U:	Unknown
Key for attack context	
Am:	Ambush/attack on road
C:	Combat (or police operations) / Crossfire
IA:	Individual attack or assassination
MV:	Mob violence, rioting
R:	Raid (armed incursion by group on home, office, or project site)
D:	Detention (by official government forces or police, where abuse takes place)
U:	Unknown
Key for location	
H:	Home (private home, not compound)
OC:	Office or organization compound/residence
PS:	Project site (village, camp, distribution point, hospital, etc.)
P:	Other public location (street, market, restaurant, etc.)
R:	Road (in transit)
C:	Custody (official forces/police)
U:	Unknown

A.1 Descriptive trends Somalia and Sudan

Figure A.2: Trend of deadly attacks against aid workers according to territorial control in Somalia, 1997-2013

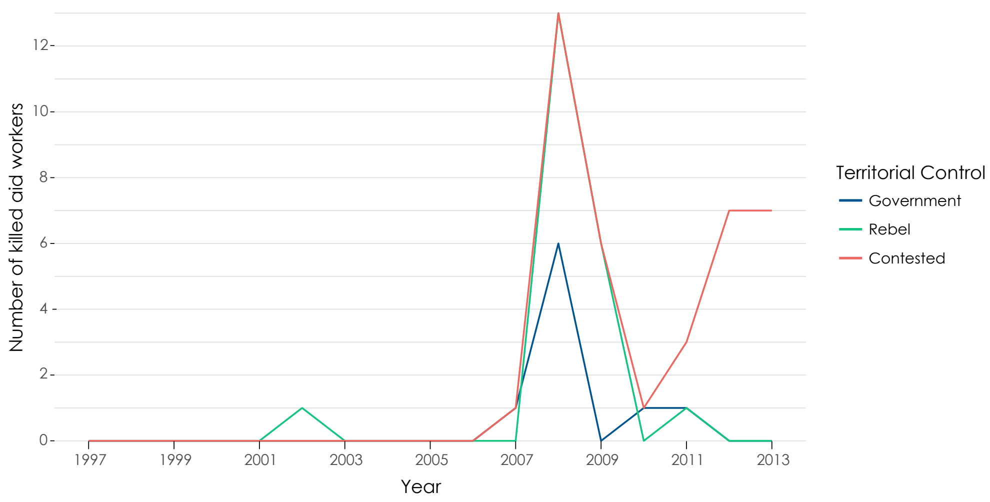


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

Figure A.3: Trend of deadly attacks against aid workers according to territorial control in Sudan, 1997-2013

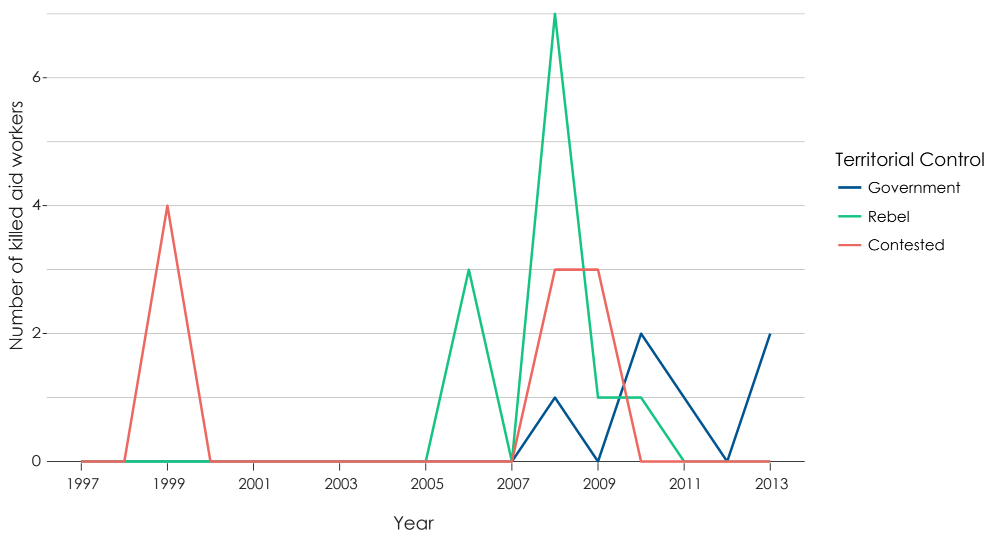


Figure made by author. Datasource: (Humanitarian Outcomes 2016)

A.2 Further regression models

Table A.1: Regression: Territorial model, without fixed effects

	Dependent variable:			
	attacks against aid workers			
	(1)	(2)	(3)	(4)
Rebel-held territory	0.545	0.554*	0.567*	0.567*
	(0.279)	(0.279)	(0.284)	(0.284)
Contested territory	3.962***	3.797***	2.043***	2.054***
	(0.312)	(0.314)	(0.353)	(0.354)
Conflict Intensity		−0.00001		−0.0001
		(0.0001)		(0.0003)
Violence against civilians			2.779***	2.782***
			(0.273)	(0.273)
Nightlights		6.130**	2.989	2.969
		(1.924)	(2.105)	(2.107)
Population density		0.00000	0.00002	0.00002
		(0.0001)	(0.0001)	(0.0001)
Urban land		−0.003	−0.0002	0.0001
		(0.058)	(0.055)	(0.055)
Time lag kills	3.149***	3.099***	2.354***	2.349***
	(0.492)	(0.481)	(0.378)	(0.378)
Neighbour cell kills	1.853***	1.887***	1.583***	1.584***
	(0.190)	(0.185)	(0.149)	(0.149)
Constant	−8.346***	−8.655***	−8.853***	−8.853***
	(0.226)	(0.248)	(0.262)	(0.262)
Observations	180,607	180,607	180,607	180,607
Log Likelihood	-839.297	-834.042	-792.514	-792.450
Akaike Inf. Crit.	1,688.594	1,686.083	1,603.027	1,604.899

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors in brackets

Table A.2: Regression: Territorial model, without Somalia

	Dependent variable:			
	killed aid workers			
	(1)	(2)	(3)	(4)
Rebel-held territory	0.488	0.498	0.516	0.516
	(0.367)	(0.362)	(0.363)	(0.363)
Contested territory	3.981***	3.251***	1.822***	1.827***
	(0.426)	(0.422)	(0.450)	(0.451)
Conflict intensity		0.00002		−0.00005
		(0.0002)		(0.0003)
Violence against civilians			2.468***	2.470***
			(0.351)	(0.351)
Nightlights		8.130*	4.706	4.684
		(3.530)	(3.861)	(3.866)
Population density		−0.00003	0.00000	0.00000
		(0.0002)	(0.0001)	(0.0001)
Urban land		0.396***	0.267**	0.267**
		(0.115)	(0.102)	(0.102)
Time lag kills	1.518*	1.266*	0.350	0.349
	(0.661)	(0.581)	(0.504)	(0.504)
Neighbour cell kills	0.356	0.440	0.374	0.374
	(0.301)	(0.264)	(0.234)	(0.234)
Constant	−37.316	−37.676	−37.529	−37.555
	(4.069^{6})	(4.069^{6})	(4.069^{6})	(4.069^{6})
Observations	176,510	176,510	176,510	176,510
Log Likelihood	-526.974	-513.917	-495.095	-495.082
Akaike Inf. Crit.	1,171.949	1,153.834	1,116.190	1,118.164

Note: *p<0.05; **p<0.01; ***p<0.001

Standard errors in brackets, country dummies not shown

Table A.3: Regression: Killed aid workers, interaction term, no fixed effects

	Dependent variable:
	attacks against aid workers
Violence against civilians	2.781***
	(0.273)
Conflict intensity	−0.0001
	(0.0003)
Nightlights	3.113
	(2.083)
Population density	0.00002
	(0.0001)
Urban land	−0.005
	(0.054)
Time lag kills	2.357***
	(0.379)
Neighbour cell kills	1.613***
	(0.149)
Contested territory*Conflict	1.716***
	(0.300)
Constant	−8.522***
	(0.183)
Observations	180,607
Log Likelihood	-794.524
Akaike Inf. Crit.	1,607.048
Note:	*p<0.05; **p<0.01; ***p<0.001

A.3 R-Script Regressions

Note: The datasets and all R-Scripts, including data preparation and diagnostics, for this thesis can be downloaded from the following Dropbox folder: https://www.dropbox.com/sh/899kr4bofq08l8w/AAAIh0XJzwbVm3M8NvRuirRqa?dl=0.

```
# Conflict Model
#-------------------------------
require(MASS)

nbm.conf.fe <- glm.nb(total.killed ~ conflict +  onsesided + fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1+neigbor.killed + gwno,
control = glm.control(maxit = 30), data=data)

nbm.conf2.fe <- glm.nb(total.killed ~ conflict +  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1 + neigbor.killed +gwno,
control = glm.control(maxit = 30), data=data)

# Territorial Model
#-------------------------------
nbm.pl.fe <- glm.nb(total.killed ~ territory + total.killed1+ neigbor.killed + gwno,
control = glm.control(maxit = 50), data=data)

nbm.full.fe <- glm.nb(total.killed ~ territory + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1 + neigbor.killed +gwno,
control = glm.control(maxit = 100), data=data)

nbm1.fe <- glm.nb(total.killed ~ territory +  fatalities + nlights_calib_mean + popden + urban_gc +
total.killed1+neigbor.killed +gwno,
control = glm.control(maxit = 30), data=data)

nbm2.fe <- glm.nb(total.killed ~ territory + onesided + nlights_calib_mean + popden + urban_gc +
total.killed1+neigbor.killed + gwno,
control = glm.control(maxit = 30), data=data)

# Sub Analysis Conflict zones only
#-------------------------------
conflict <- subset(data, subset=data$conflict==1)

nbm.sub <- glm.nb(total.killed ~ territory + total.killed1 +neigbor.killed +gwno,
control = glm.control(maxit = 30), data=conflict)

nbm.sub.fe <- glm.nb(total.killed ~ territory + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1+neigbor.killed+gwno,
control = glm.control(maxit = 30), data=conflict)

nbm1.sub.fe <- glm.nb(total.killed ~ territory +  fatalities + nlights_calib_mean + popden +
urban_gc +
total.killed1+neigbor.killed+gwno,
control = glm.control(maxit = 30), data=conflict)
summary(nbm1.sub.fe) #Best FIT

```

```r
nbm2.sub.fe <- glm.nb(total.killed ~ territory + onesided + nlights_calib_mean + popden + urban_gc +
total.killed1+neigbor.killed+gwno,
control = glm.control(maxit = 30), data=conflict)

# Interaction Term
#-------------------------------
nbm.int <- glm.nb(total.killed ~ contested:conflict + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1+neigbor.killed +gwno,
control = glm.control(maxit = 30), data=data)

# Binary Predictor Model
#-------------------------------
nbm.full.dich <- glm.nb(total.killed ~ contested + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1 +neigbor.killed+gwno,
control = glm.control(maxit = 30), data=data)

# Incidence Model (logit Regression)
#-------------------------------
logit <- clogit(attack ~ territory + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1+neigbor.killed+strata(gwno),
data=data)

# CEM Matching
#-------------------------------
library(cem)
library(MatchIt)

matched <- matchit(contested ~ onesided  + conflict + fatalities + nlights_calib_mean +
popden + urban_gc, data = data, method = "cem")
matchdata <- match.data(matched)

# Territorial model, matched data
#-------------------------------
mod <- glm.nb(total.killed ~ territory + onesided+  fatalities + nlights_calib_mean +
popden + urban_gc + total.killed1+neigbor.killed+gwno,
control = glm.control(maxit = 100), data=matchdata, weights=(matchdata$weights))
```